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Empirical Analysis of Mobility Behavior in the Presence of Pigovian Transport Pricing

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Forschungsprojekt ASTRA 2017/006 auf Antrag des Bundesamts für Strassen (ASTRA)

July 2021 **1704**

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Abstract

Abstract – English

This study investigates and analyzes the effect of *Pigovian transport pricing* in Switzerland, i.e., personalized pricing of all external costs in transport. The project's core is a virtual transport pricing based on the observed transport behavior of the participants in the experiment. The empirical work of the project was conducted by ETH Zurich, University of Basel, and ZHAW from September 2019 to January 2020. The project was funded by the Swiss Competence Center for Energy Research (SCCER CREST-Mobility Joint Activity), the Swiss Federal Roads Office, and the Swiss Federal Office of Transport.

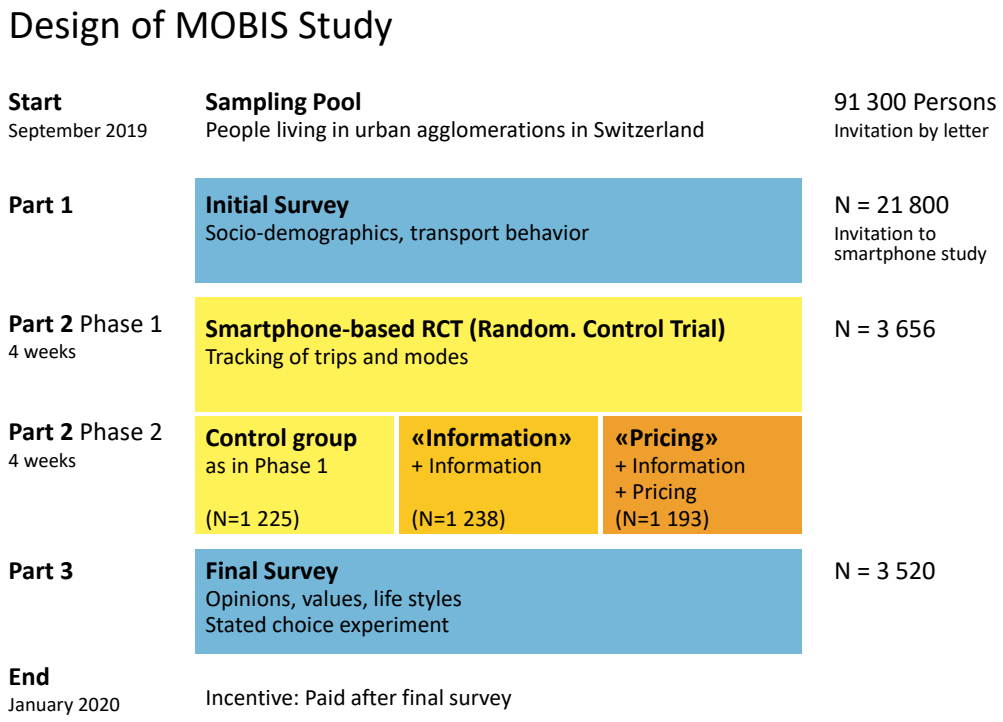
Pigovian transport pricing is a nearly 100-year-old idea (Pigou, 1920; Vickrey, 1963) to reduce the external costs of transport to an economy-wide optimum. External costs are all societal burdens that the users themselves do not bear. Ideally, transport pricing takes into account all external costs: emissions of pollutants, noise and greenhouse gases, safety risks and health effects, lack of seats in public transport, and congestion on the roads, but also the operating and maintenance costs for the transport infrastructure. Implementing the idea was technologically impractical for a long time, but this hurdle has fallen due to digitization in recent years. Partial implementations of transport pricing are increasing worldwide, e.g. as congestion pricing in Singapore, London, Stockholm, or as road pricing on German or French highways.

In Switzerland, only surveys and modeling studies have been conducted so far (Vrtic *et al.*, 2010; INFRAS, 2019). The MOBIS study went one step further and tested the impact of Pigovian transport pricing in an experiment with 3,700 participants in metropolitan areas in the French and German-speaking parts of Switzerland. It is the largest and most comprehensive transport pricing experiment in the transport sector to date and allows the robust estimation of the effect size for the agglomeration areas in Switzerland.

The figure below shows the structure and flow of the MOBIS study. The core of the experiment is the four weeks during which participants are randomly divided into three equal groups (pricing, information and control groups) and subjected to an information or pricing treatment. To measure the effect of this treatment using a difference-in-differences approach, all participants were previously observed, without treatment, for four weeks. Suitable participants were identified and invited through an initial representative survey. Regular use of a car (at least two days per week) was a condition for participation in the study. At the end of the study, participants received an incentive payment of CHF 100.

After the four-week observation period, the information group received regular information about the amount of external costs their behavior had caused. These external costs were converted to money and presented, but participants did not pay for these costs. The pricing group received the same information for the second phase of the experiment and a budget from which the external costs were deducted. This personalized budget was slightly more than each participant's actual external costs during the first four weeks of the study. As an incentive to reduce the external costs of their transportation behavior, this group was allowed to keep the unspent portion of the budget. In this sense, Pigovian transport pricing was implemented for this group.

The core result of the study is the significant reduction in external costs observed for participants in the pricing group. These participants measurably changed their behavior through shifts in route choice, departure time choice, and mode choice. In particular, participants who understood the concept of external costs in the experiment are responsible for the observed reduction. The short-term price elasticity is -0.31, which is at the same level as for gasoline price increases. Participants in the information group also showed reductions, but not to a statistically significant extent. The results were tested for robustness in a series of tests and confirmed.



The MOBIS study shows that Pigovian transport pricing in Switzerland would have the intended effects and that these could be enhanced by targeted information. It also seems plausible that longer-term adjustments in behavior, which could not be tested in this experiment, would lead to a larger effect.

Kurzfassung – Deutsch

Die vorliegende Studie untersucht und analysiert die Wirkung eines *Pigovian Transport Pricings* in der Schweiz, d.h. die personalisierte Bepreisung aller externer Kosten im Verkehr. Der Kern des Projekts ist ein virtuelles Transport Pricing auf der Grundlage des beobachteten Verkehrsverhaltens der Teilnehmer des Experiments. Die empirischen Arbeiten des Projekts wurden von der ETH Zürich, der Universität Basel und der ZHAW von September 2019 bis Januar 2020 durchgeführt. Das Projekt wurde vom Swiss Competence Center for Energy Research (SCCER CREST-Mobility Joint Activity), dem Bundesamt für Strassen und dem Bundesamt für Verkehr finanziert.

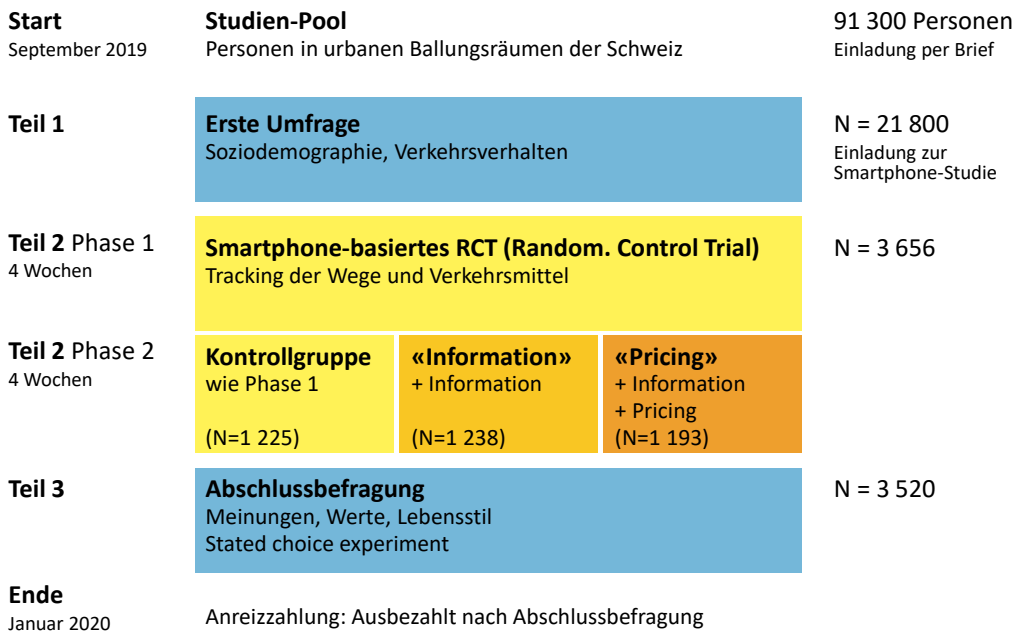
Pigovian Transport Pricing ist eine fast 100-jährige Idee (Pigou, 1920; Vickrey, 1963), um die externen Kosten des Verkehrs auf ein volkswirtschaftliches Optimum zu reduzieren. Die externen Kosten sind alle gesellschaftlichen Lasten, welche nicht von den Nutzern selbst getragen werden. Im Idealfall berücksichtigt Transport Pricing alle externen Kosten: Emissionen von Schadstoffen, Lärm und Treibhausgasen, Sicherheitsrisiken und Gesundheitseffekte, Sitzplatzmangel im öffentlichen Verkehr und Stau auf den Strassen, aber auch die Betriebs- und Unterhaltskosten für die Verkehrsinfrastruktur. Die Umsetzung der Idee war technologisch lange nicht praktikabel, aber diese Hürde ist durch die Digitalisierung der letzten Jahre gefallen. Partielle Implementierungen von Transport Pricing nehmen weltweit zu, z.B. in der Form von Congestion Pricing in Singapur, London, Stockholm oder als Road Pricing auf deutschen oder französischen Autobahnen.

In der Schweiz sind bisher erst Befragungen und Verkehrsmodellstudien durchgeführt worden (Vrtic *et al.*, 2010; INFRAS, 2019). Die MOBIS Studie geht einen Schritt weiter und testet die Wirkung von Pigovian Transport Pricing in einem Experiment mit 3'700 Teilnehmern in den Ballungsräumen der Romandie und der Deutschschweiz. Es ist das bis anhin grösste und umfassendste Transport Pricing Experiment im Verkehrssektor und erlaubt eine robuste Schätzung der Effektgrösse für die Agglomerationsräume in der Schweiz.

Das Design der Mobis-Studie (siehe Abbildung) zeigt den Ablauf und die Struktur des Projekts. Der Kern des Experiments sind die vier Wochen, in denen die zugeteilten Informationen und Preise ihre Wirkung auf je ein Drittel der Teilnehmer entwickeln. Die Teilnehmer wurden zufällig den Interventionen "Pricing" und "Information" sowie einer Kontrollgruppe zugeteilt. Vorab wurden alle Teilnehmer vier Wochen beobachtet, sodass die Studie die Wirkung durch einen Difference-in-Differences-Ansatz unabhängig von saisonalen und anderen Einflüssen messen konnte. Geeignete Teilnehmer wurden im Rahmen einer ersten repräsentativen Befragung identifiziert und eingeladen. Die regel-mässige Nutzung eines Autos (an mindestens zwei Tagen pro Woche) war eine Bedingung für die Teilnahme an der Studie. Am Ende der Studie wurde den Teilnehmern eine Anreizzahlung von CHF 100 überwiesen.

Nach der vierwöchigen Beobachtungsphase erhielt die Informations-Gruppe regelmässige Informationen über die Menge der externen Kosten, die ihr Verhalten verursacht hatte. Diese externen Kosten wurden in Geld umgerechnet und präsentiert, aber die Teilnehmer mussten nicht für diese Kosten bezahlen. Die Pricing-Gruppe erhielt für die 2. Phase es Experiments dieselben Informationen und zusätzlich ein Budget, von dem die verursachten externen Kosten abzogen wurden. Die Höhe dieses personalisierten Budgets entsprach etwas mehr als den externen Kosten der einzelnen Probanden während den ersten vier Wochen der Studie. Als Anreiz die externen Kosten ihres Verkehrsverhaltens zu senken, durfte diese Gruppe den nicht ausgegebenen Teil des Budgets behalten. In diesem Sinne wurde für diese Gruppe ein Pigovian Transport Pricing implementiert.

Das Kernergebnis der Studie ist die signifikante Reduktion der externen Kosten, welche für die Probanden in der Pricing-Gruppe beobachtet wurde. Die Teilnehmer änderten ihr Verhalten messbar durch Verschiebungen in der Routenwahl, der Wahl der Abfahrtszeit und der Verkehrsmittelwahl. Es sind insbesondere die Personen, die das Konzept der externen Kosten im Experiment verstanden hatten, welche für die Reduktion verantwortlich sind. Die kurzfristige Preiselastizität liegt bei -0.31 und damit in der Grössenordnung von Benzinpreiserhöhungen. Die Teilnehmer der Informationsgruppe zeigten ebenfalls Reduktionen,



aber nicht in einem statistisch signifikanten Ausmass. Die Ergebnisse wurde in einer Reihe von Tests auf ihre Robustheit geprüft und bestätigt.

Die MOBIS Studie zeigt, dass Pigovian Transport Pricing in der Schweiz die beabsichtigten Wirkungen hätte, und dass diese durch gezielte Informationen verstärkt werden könnten. Es erscheint auch plausibel, dass längerfristige Anpassungen im Verhalten, welche in diesem Experiment nicht getestet werden konnten, zu einer verstärkten Wirkung führen würden.

Résumé abrégé – Français

La présente étude analyse l'effet d'une *tarification pigovienne des transports* en Suisse, c'est-à-dire la tarification individualisée de tous les coûts externes des transports. Le cœur de l'étude consiste en une tarification virtuelle du transport, fondée sur le comportement, en termes de déplacements, des participants à l'étude. La partie expérimentale du projet a été effectuée conjointement par l'École polytechnique fédérale de Zurich, l'Université de Bâle et la Haute école des sciences appliquées de Zurich de septembre 2019 à janvier 2020. Le projet a été financé par le Swiss Competence Center for Energy Research (SCCER CREST-Mobility Joint Activity), par l'Office Fédéral des Routes et par l'Office Fédéral des Transports.

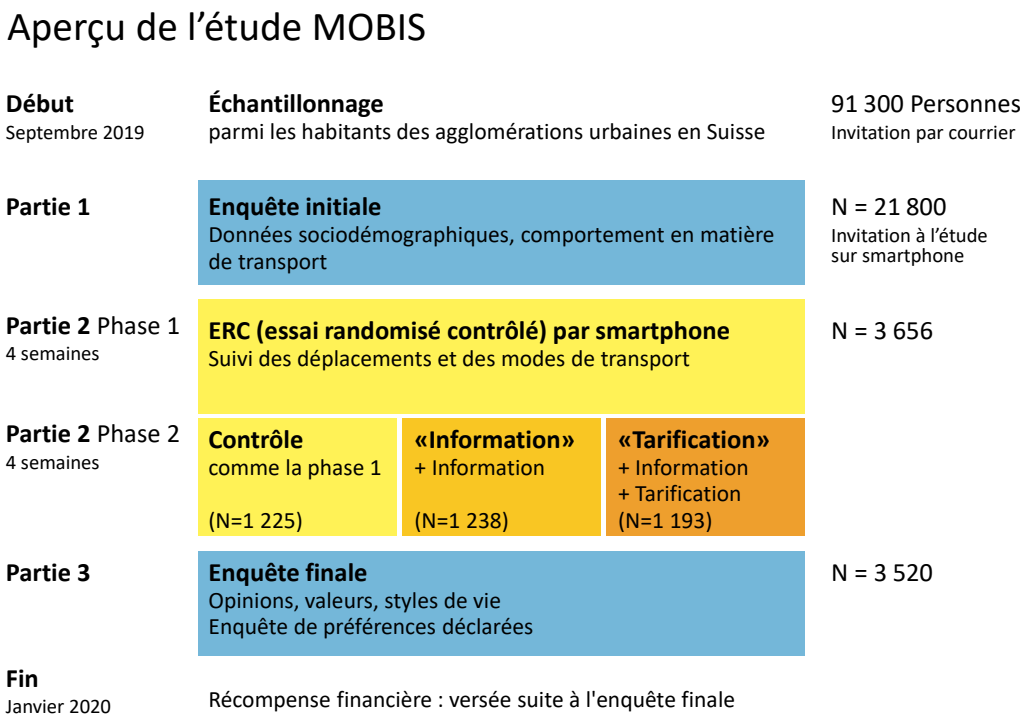
La tarification pigovienne des transports est une idée qui a été proposée pour la première fois il y a près de cent ans (Pigou, 1920; Vickrey, 1963) dans le but de réduire les coûts externes des transports à un optimum économique. Par coûts externes, on entend toutes les charges liées aux déplacements qui ne sont pas payées par les utilisateurs eux-mêmes. Idéalement, la tarification des transports devrait prendre en compte tous les coûts externes : émissions de polluants, de gaz à effet de serre, de bruit, risques pour la sécurité, effets sur la santé, manque de places assises dans les transports publics, embouteillages, mais aussi les coûts de fonctionnement et de maintenance des infrastructures. Pendant longtemps, la mise en œuvre de cette idée a été irréalisable d'un point de vue technologique ; cet obstacle a cependant été levé récemment avec la digitalisation continue de la société. On observe aujourd'hui toujours plus de mises en œuvre partielles de la tarification des transports autour du monde, sous la forme, par exemple, de péages urbains à Singapour, Londres ou Stockholm, ou encore de péages routiers sur les autoroutes allemandes ou françaises.

En Suisse, jusqu'à présent, seuls des sondages et des études de modélisation du trafic ont été effectués (Vrtic *et al.*, 2010; INFRAS, 2019). L'étude MOBIS va plus loin en évaluant l'impact d'une tarification pigovienne des transports par une expérience menée sur 3 700 participants, recrutés dans les agglomérations urbaines de Suisse romande et alémanique. À ce jour, il s'agit de l'expérience la plus importante et la plus complète dans le domaine de la tarification des transports. Elle permet une estimation fiable de l'ampleur de l'effet de cette mesure dans les agglomérations suisses.

Le schéma ci-dessous montre la structure et le déroulement de l'étude MOBIS. Les quatre semaines pendant lesquelles les participants, après avoir été répartis aléatoirement en trois groupes de même taille (groupe de tarification, d'information et de contrôle), sont soumis à un traitement d'information ou de tarification constituent le point central de l'expérience. Afin que l'étude puisse mesurer les effets de cette nouvelle information ou tarification par la méthode des doubles différences, tous les participants avaient été observés au préalable, sans traitement, pendant quatre semaines. Les participants éligibles ont été identifiés puis invités à l'étude suite à une enquête initial représentative : un usage régulier de la voiture - au moins deux jours par semaine - était une condition nécessaire à la participation à l'étude. À la fin de l'étude, les participants ont reçu une récompense financière de 100 CHF.

Suite à la période d'observation de quatre semaines, les membres du groupe d'information ont reçu des informations régulières sur les coûts externes engendrés par leur comportement en matière de mobilité. Ces coûts externes, convertis en francs suisses, leur étaient présentés, mais ils ne devaient pas les payer. Les membres du groupe de tarification ont reçu les mêmes informations lors de la deuxième phase de l'expérience, ainsi qu'un budget duquel les coûts externes ont été déduits. Le montant de ce budget personnalisé était légèrement supérieur aux coûts externes réels engendrés par chaque participant pendant les quatre premières semaines de l'expérience. Pour encourager la réduction des coûts externes des transports, les membres du groupe de tarification ont été informés que la partie économisée de leur budget leur serait versée à la fin de l'étude, mettant ainsi en application un système de tarification pigovienne des transports.

Le résultat principal de l'étude est la réduction significative des coûts externes des transports qui a été observée pour les membres du groupe de tarification. Les participants ont changé de façon mesurable leur comportement, à travers des changements dans le choix



d'itinéraire, de l'horaire de départ, et du mode de transport utilisé. En particulier, une grande part de cette réduction est attribuable aux individus qui ont le mieux compris le concept des coûts externes des transports. L'élasticité des prix à court terme est de -0.31, du même ordre de grandeur que les effets habituellement observés lors de l'augmentation des prix du carburant. Les coûts externes ont aussi diminué pour les participants du groupe d'information, mais pas à un niveau statistiquement significatif. La robustesse des résultats a été évaluée et confirmée par une série de tests.

L'étude MOBIS a montré que la tarification pigovienne des transports aurait les effets attendus en Suisse et que ces derniers pourraient être améliorés par la diffusion ciblée d'informations. Il semble également plausible que des ajustements de comportement à plus long terme, qui n'ont pas pu être évalués dans cette expérience, mènent à des effets encore plus importants.

Versione ridotta – Italiano

Il presente studio analizza l'effetto di una *tariffazione pigouviana dei trasporti* in Svizzera, ovvero la tariffazione personalizzata di tutti i costi esterni riconducibili al traffico. Lo studio è centrato su una tariffazione virtuale del trasporto che si basa direttamente sui comportamenti dei partecipanti all'esperimento. Svoltesi nel periodo tra settembre 2019 e gennaio 2020, le analisi empiriche per il progetto sono state effettuate dal Politecnico Federale di Zurigo, dall'Università di Basilea e dall'Università di Scienze Applicate di Zurigo. Il progetto è stato finanziato dal Swiss Compentence Center for Energy Research (SCCER CREST-Mobility Joint Activity), dall'Ufficio federale delle strade e dall'Ufficio federale dei trasporti.

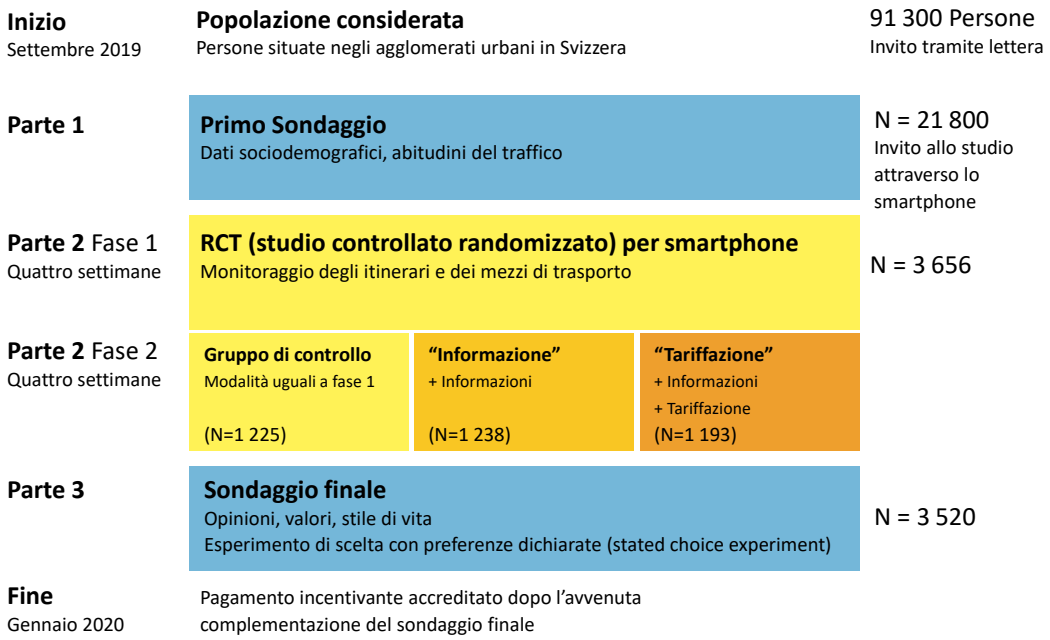
Il concetto di tariffazione pigouviana dei trasporti risale a quasi cento anni fa (Pigou, 1920; Vickrey, 1963) e mira a ridurre i costi esterni del traffico ad un optimum economico. Per costi esterni si intendono tutti gli oneri sociali che non sono sostenuti dagli stessi utenti. Idealmente, la tariffazione dei trasporti tiene conto di tutti i costi esterni: emissioni di sostanze inquinanti, rumore e gas serra, rischi per la sicurezza ed effetti sulla salute, mancanza di posti nel trasporto pubblico e congestione sulle strade. Vengono inoltre considerati i costi operativi e di manutenzione delle infrastrutture di trasporto. Per molto tempo, l'implementazione dell'idea è stata tecnologicamente impraticabile, ma negli ultimi anni questo ostacolo si è dissolto a causa della continua digitalizzazione. Infatti, l'attuazione parziale di pedaggi avviene in misura crescente in tutto il mondo. Basta solo considerare il pedaggio urbano a Singapore, Londra e Stoccolma o il pedaggio stradale sulle autostrade tedesche o francesi.

Sebbene in Svizzera siano già stati realizzati studi e sondaggi relativi a modelli del traffico (Vrtic *et al.*, 2010; INFRAS, 2019), lo studio MOBIS è andato oltre. MOBIS ha infatti testato l'impatto di una tariffazione pigouviana dei trasporti in un esperimento con 3'700 partecipanti nelle aree metropolitane della Svizzera francofona e germanofona. Fino ad oggi, si tratta del più grande e completo esperimento di tariffazione nel settore dei trasporti. Esso permette una stima affidabile dell'effetto per le aree di agglomerazione elvetiche.

L'illustrazione sottostante mostra la struttura e i processi dello studio MOBIS. La parte cruciale dell'esperimento si è svolta nell'arco di quattro settimane. Durante questo periodo i partecipanti all'esperimento sono stati divisi in tre gruppi di uguali dimensioni ("Gruppo di tariffazione", "Gruppo d'informazione", "Gruppo di controllo"). La collocazione degli individui a questi gruppi è avvenuta in modo casuale. Allo stesso tempo, sono state assegnate delle informazioni e dei prezzi che hanno influito su ciascun gruppo. In antecedenza alle collocazioni sperimentali, tutti i partecipanti sono stati osservati per quattro settimane per far sì che il metodo "differenza-nelle-differenze" permettesse una misurazione indipendente da effetti stagionali e di altre tipologie. I candidati ritenuti idonei per il progetto sono stati individuati ed invitati attraverso un primo sondaggio rappresentativo. Una condizione necessaria per la loro partecipazione allo studio era l'utilizzo regolare di un'automobile (almeno due giorni a settimana). A seguito della partecipazione allo studio, i partecipanti sono stati ricompensati con un pagamento pari a cento franchi.

Dopo la fase osservazionale di quattro settimane, i membri del gruppo d'informazione hanno ricevuto un riscontro regolare riguardante il valore monetario dei costi esterni attribuiti ai loro comportamenti, senza però dover effettivamente pagare per essi. Nella seconda fase dell'esperimento i partecipanti al gruppo di tariffazione hanno ottenuto le stesse informazioni. Inoltre, ciascun soggetto di quest'ultimo gruppo poteva disporre di un budget da cui, in seguito, si sarebbero dedotti i costi esterni. In ogni caso, l'importo di questo budget personalizzato era leggermente superiore ai costi esterni accumulati nelle prime quattro settimane dello studio. Per incentivare la riduzione di costi esterni del traffico dei membri del gruppo di tariffazione è stato consentito di trattenere le quote del loro budget in eccedenza rispetto ai propri costi esterni. Dunque, per questo gruppo si è attuata una tariffazione dei trasporti ai sensi di Pigou.

Il risultato centrale dello studio è stato la riduzione significativa dei costi esterni osservata per gli individui appartenenti al gruppo di tariffazione. Essi hanno cambiato i loro comportamenti in modo misurabile, ossia attraverso cambiamenti nella scelta degli itinerari, degli



orari di partenza o dei mezzi di trasporto utilizzati. In aggiunta, una grande parte della riduzione è riferibile ai soggetti che hanno interiorizzato il concetto dei costi esterni nell'ambito sperimentale. A breve termine, l'elasticità del prezzo ammonta a -0,31 ed è quindi paragonabile agli effetti solitamente innescati da aumenti del prezzo del carburante. Sebbene non in misura statisticamente significativa, anche i membri del gruppo d'informazione si sono adoperati per la riduzione dei loro costi esterni. La robustezza dei risultati è stata esaminata e riconfermata in una serie di test.

Per la Svizzera lo studio MOBIS dimostra che un sistema di tariffazione dei trasporti in conformità con il concetto di Pigou eserciterebbe gli effetti desiderati. Inoltre, si è costatato che quest'ultimi possono essere amplificati attraverso la diffusione mirata di informazioni. Infine, sembra plausibile assumere che a lungo termine adattamenti comportamentali, che per via delle tempistiche delle esperimento non potevano essere testati, portino ad un'ulteriore intensificazione di questi effetti.

Executive summary

Executive Summary – English

Transport systems face many challenges. With population growth and increasing overall mobility, transport networks are reaching their capacity limits (ARE, 2016). The resulting road congestion is a considerable source of time loss for drivers: The total monetized time loss in 2017 due to congestion in Switzerland was estimated to be 1,420 million CHF (ARE, 2019). Switzerland has strongly invested in road and rail networks to accommodate the increasing demand in transport. However, augmenting the capacity of private and public transport is costly and faces physical limitations. Furthermore, increasing road capacity induces demand and thus results in little improvement in congestion in the long term (Duranton and Turner, 2011).

The transport sector is also among the largest contributors of local air pollution and greenhouse gas emissions. While there has been significant progress in the industrial, services and households sectors, emissions in the transport sector have remained roughly constant as gains in efficiency have been neutralized by an increase in distance traveled (IEA, 2020). In Switzerland, CO_2-emissions from the transport sector in 2019 were on the same level as in 1990.[1] Health costs from traffic-related air pollution amount to 2,200 million CHF annually (Federal Office for Spatial Development, 2020).

Congestion, averse effects of climate change, and health effects from traffic emissions have something in common: They constitute externalities, or *external costs of transport*. Whereas transport users pay the private costs of transport, reflected in the prices for fuel, transit tickets, vehicle purchase and maintenance, among others, the external costs are borne by "others", i.e. society at large. Thus, external costs typically do not affect the decision about where, when and how to travel. This results in a market failure which implies a need for policy interventions, above and beyond the existing regulatory framework.

External costs of transport have been, for the most part, addressed by “command-and-control” policies, such as speed limits, emission limits or mandatory vehicle inspections. In theory, however, price instruments reflecting the external - or "true" - costs of transport are a more efficient means of regulation, as they allow people to retain high-utility trips while reducing those that they view as less important. With fully rational and completely informed individuals, reflecting the full marginal costs and benefits in the price of each trip will lead to the "optimal" level of congestion and pollution.[2] Pricing based on the full marginal costs of transport leads to an efficient use of the existing transport system and thus, among other things, to a reduction in the need for an expansion of the network.

Traditionally, the most prevalent examples of price-based instruments in the transport sector have been fuel taxes, road tolls and registration fees. However, the motivation behind them is often the recovery of the cost of road construction rather than optimizing travel behavior. As such, they typically do not fully reflect external costs of transport (Parry and Small, 2005). An exception is the Swiss "heavy vehicles charge", which is explicitly motivated by internalizing the external costs of freight transport, specifically as they pertain to impacts on the alpine ecosystem. Recently, congestion charges have been introduced by a growing number of cities around the world. Congestion fees are effective at reducing congestion and at least partially internalize external costs of urban driving (Small, 2008). However, the fixed nature of such fees cannot fully address the time-varying nature of congestion, and they abstract from any other external costs associated with driving and other modes of transport.

For Switzerland, the previous studies on transport pricing are restricted to surveys and mod-

[1] Transport emissions in Switzerland (without international aviation) were 14.9 and 15.0 million tCO_2-equivalents in 1990 and 2019, respectively. See `https://www.bfs.admin.ch/bfs/de/home/statistiken/raum-umwelt/klimabezogene-indikatoren/menschliche-einwirkungen.html`.

[2] From a societal point of view, the optimal level of pollution is generally not zero, but defined by the quantity at which the marginal cost of reducing pollution is equal to the marginal benefits of doing so.

eling studies (e.g., Vrtic *et al.*, 2010; INFRAS, 2019). Empirical studies on transport pricing include computations of the overall, or aggregate effects of congestion charge schemes, for example, in Singapore (Agarwal and Koo, 2016), London (Leape, 2006) or Stockholm (Eliasson *et al.*, 2009). In contrast, field experiments tracking individual travel behavior allow to control for individual characteristics, allowing for more refined and more robust analyses.

For example, before-vs.-after experiments in Denmark and Australia installed GPS receivers in vehicles and drivers were then exposed to different peak and off-peak pricing schemes (Nielsen, 2004; Martin and Thornton, 2017b). Both studies report a reduction in the number of car trips during peak hours. In Singapore, commuters responded to a monetary reward by shifting their departure time in public transport (Pluntke and Prabhakar, 2013). These earlier studies focused on a single mode of transport and could therefore not identify effects on mode choice (i.e. modal shifts), even though the expectation is that pricing will affect travel behavior across all modes (car, public transport and non-motorized modes) (Tirachini and Hensher, 2012). In the “Spitsmijden” experiment in the Netherlands, commuters responded to financial and in-kind rewards by shifting departure times, switching to other modes of transport and by working from home (Ben-Elia and Ettema, 2011b). The only previous large-scale study in the transport sector that included a control group is a randomized controlled trial which found no effect of informational treatments (i.e., no financial incentives) on carpooling and commuting behavior among employees of five large employers (Kristal and Whillans, 2020).

This summary describes the results from the research project “Mobility Behavior in Switzerland” (MOBIS), which conducted a randomized controlled trial (RCT) that simulated a “Pigovian” transport pricing scheme (also known as "polluter pays"), based on the external costs of transport. [3] The transport pricing scheme used in the experiment fully internalized the marginal external costs in the domains of congestion, climate change and health in the user price. Travel of study participants was tracked by means of a smartphone app, based on which the associated external costs were computed. The transport pricing treatment was implemented by providing a third of the participants with a transport budget, from which the external costs caused by their travel were subtracted. To simulate the financial incentive of Pigovian transport pricing, participants got to keep any savings resulting from changes in their travel behavior. To differentiate the pricing effect from a pure information effect, or other confounding factors, the experiment included a second treatment group in which the respondents were provided with the same information about the external costs of transport as the pricing group, but without having to pay anything, as well as a control group. The experiment found an elasticity of -0.31 for total external costs associated with the pricing treatment. In other words, introducing a transport pricing scheme based on external costs that raises transport costs, on average, by 10 % would lead to a reduction in the external costs of transport by 3.1%. MOBIS was carried out jointly by researchers from ETH Zurich, the University of Basel, the ZHAW and was supported by the Swiss Federal Office of Roads (ASTRA), the Swiss Federal Office of Transport (BAV) and Innosuisse. To the best of our knowledge, MOBIS is the first multimodal randomized controlled trial of a Pigovian transport pricing intervention.

The MOBIS experiment

The aim of the MOBIS experiment was to investigate the effectiveness of transport pricing and information with regards to changing transport behavior towards optimized and more sustainable travel patterns. The study sample was recruited among individuals living in urban agglomerations in the German- and French-speaking parts of Switzerland. Addresses were provided by the Swiss Federal Office of Statistics, which maintains a comprehensive registry of inhabitants, and by a private vendor.

The initial screening survey was answered by 21,800 participants and contained questions about travel behavior, socio-demographics and a number of transport policy issues. Poten-

[3] This term is due to Arthur Pigou, who first formulated the concept of internalizing the external costs associated with an activity by imposing the marginal social damage as a corrective tax (Pigou, 1920). The Pigovian tax is a standard concept in economics and is often referred to as the “polluter pays” principle.

tial participants for the experiment had to fulfill a number of inclusion criteria, such as using a car on at least two days per week and being between 18 and 65 years old.

From the initial survey, over 4,000 participants were recruited for the transport pricing experiment, although at the time of recruitment the nature of the study was not revealed to them nor that they were part of an experiment. The participants in the experiment agreed to download a tracking app on their smartphones and to have their daily travel tracked over a period of 8 weeks. In return for participating during the entire study, they received CHF 100. 3,656 participants successfully completed the experiment, and almost all of them also filled in the final survey. The MOBIS sample differs from the general population due to its age restriction and the focus on drivers, but is otherwise quite similar as the sample for the initial survey is drawn from a representative study pool.

Figure I – Design of the MOBIS study

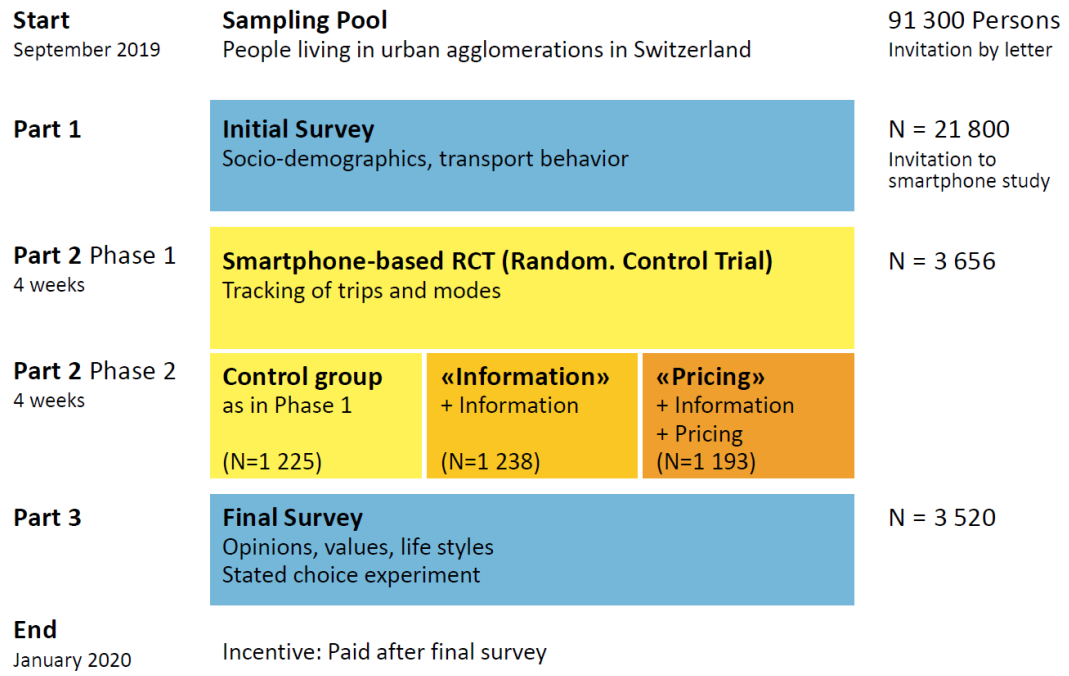


Figure I provides an overview of the study design. The recruitment took place on a rolling basis between August and November of 2019. Once a participant registered the first track on the app, he or she automatically became part of the sample. The study consisted of 4 weeks of observation for all participants, followed by another 4 weeks of treatment (or continued observation for the control group). Assignment to the groups was randomized.

The app recorded each trip and imputed the mode of transport based on the route, speed and acceleration patterns. The overall accuracy of the mode detection was over 90%. Participants were able to review and correct the mode assignment manually. For each trip, the associated external costs of transport were computed and monetized based on cost factors published by the Swiss Federal Office of Spatial Development (ARE).

During the observation period, participants were presented with a weekly summary of their travel by mode of transport. The control group continued to receive only this information until the end of the study.

On study day 29, the participants assigned to the “Information only” group received an e-mail that informed them about the external costs of transport, how they are calculated and monetized, and how they could be reduced. Once per week, the participants were presented with a summary of the external costs that they had produced during the previous

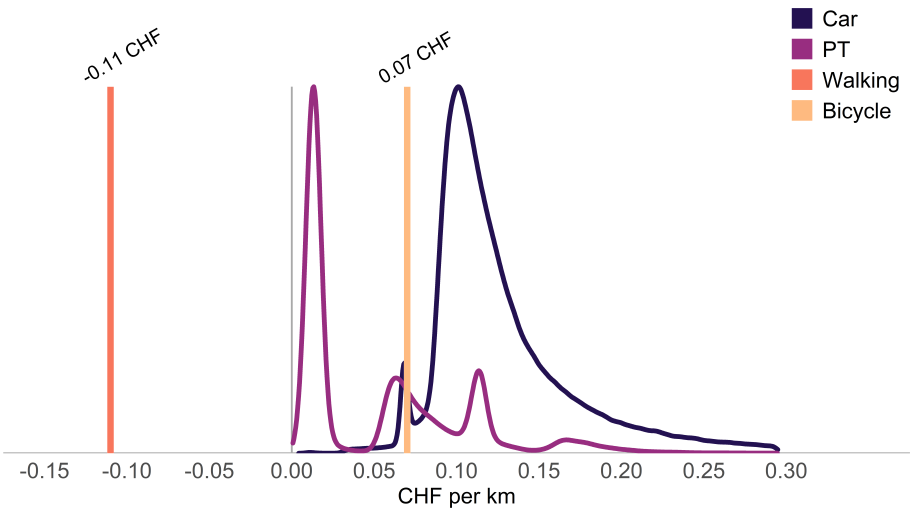
week. The external costs were presented by mode of transport and by cost domain, such as health, climate and congestion. The participants assigned to the "Pricing" group received the same information about the external costs, but in addition were provided a budget from which their external costs of transport would be deducted. The participants were informed that as of now (i.e., day 29), their budget would be used to pay for the external costs caused by their travel, but that any money remaining in their account by the end of the study was theirs to keep. These individualized budgets were computed based on each participants' external costs during the observation period, plus a 20 % buffer.[4] This treatment thus simulated transport pricing based on the marginal external costs.

The average treatment effect is computed by comparing participants in the two treatment groups with the participants in the control group that started the experiment on the same day. Including a control group allowed for the control of seasonal trends and other temporal factors that could influence the generation of external costs of transport and thus bias the results. The study concluded just before the onset of the COVID-19 pandemic in March 2020.[5]

Calculation of external costs of transport

The health, carbon emissions, and congestion related external costs of transport were imputed for the recorded daily trips using an automated data pipeline. To calculate the external costs of congestion and emissions, GPS tracks were aligned to the Swiss road network (Karich and Schröder, 2014) and processed using modules developed on top of the MATSim transport model framework (Horni *et al.*, 2016a). Emission factors were taken from the Handbook Emission Factors for Road Transport (HBEFA) version 3.3 and applied using the MATSim emissions module. For congestion, an average marginal cost approach incorporating spillback effects and flow congestion was applied (Kaddoura, 2015) and monetized using standard factors used by the Swiss government (Federal Roads Office - ASTRA, 2017).

Figure II – Distribution of external costs-per-person-km charges applied in MOBIS



For health effects from active transport (i.e., walking and bicycling), standard per-km values were used. The health effects include injury costs (most of which are external to the people hurt due to coverage by the Swiss health care system), but also the external portion of health benefits in the form of reduced mortality and morbidity risks as a consequence of

[4] The average budget was CHF 144, but for some participants it exceeded CHF 700.

[5] About a third of the participants agreed to re-start tracking, as part of an effort to study travel patterns in response to COVID-19 policies. Preliminary results of this ongoing study are reported in (Molloy *et al.*, 2020).

physical activity. Whereas walking is associated with net external benefits, current estimates imply that external crash costs outweigh the external health benefits from cycling, such that bicycling was associated with small net external costs in the experiment.[6]

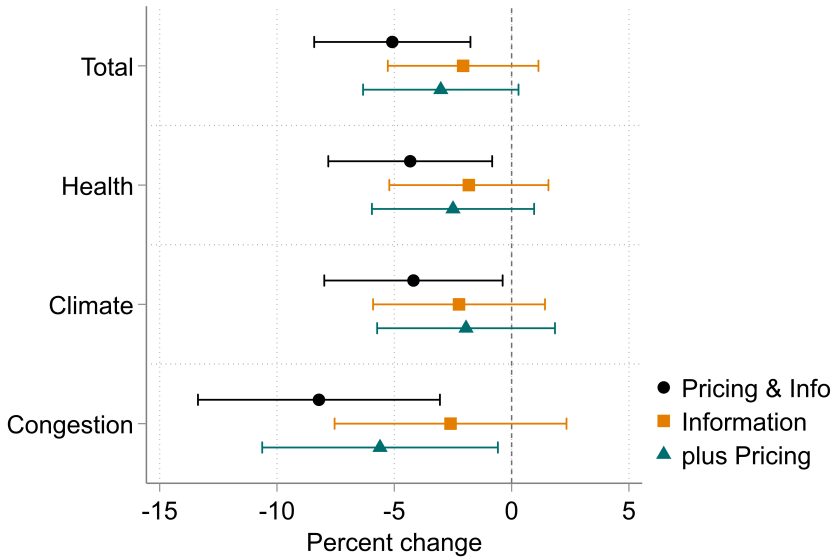
For the external costs of public transport (PT), pollution emissions were calculated on a per-km basis. Noise externalities were not considered as reference values were not available. To approximate crowding costs (i.e. congestion in PT), a zonal peak-hour surcharge pricing scheme was developed for the national PT network. Throughout the experiment, the participants in the treatment groups had access to an interactive map which showed them where and when the pricing surcharge applied.[7]

Figure II shows the distribution of the monetized external costs charges, on a per-person-kilometer basis, for each mode of transport. Whereas the per-km values for active transport are fixed, the external costs associated with driving and public transport (PT) are continuous as the congestion component varies over time and space and different types of PT are associated with different levels of health and climate externalities. The figure shows their distribution, as applied to the trips observed during the experiment.

Results

Figure III shows the average treatment effects observed in the experiment. Transport pricing, as implemented in the MOBIS experiment (i.e. pricing + information), significantly reduced the external costs of transport overall as well as for each of the three cost domains: health, climate and congestion. On average, the respondents in the pricing group reduced their external costs of transport by 5.1%, relative to the control group. This effect is statistically highly significant ($p<0.01$) and corresponds to an elasticity of -0.31.[8] The point estimates for information only suggest that there could be an information effect without pricing, but it is weaker and not statistically significant.

Figure III – Treatment effect on the external costs of transport



Note: The figure shows the average treatment effect for overall travel in the *pricing group* and in the *information group*, relative to the *control group* (dotted 0-mark). The green bars denote the causal effect of adding a price to existing information. The bars denote 95%-confidence intervals.

[6]Most of the positive health effects are in the form of lower morbidity and mortality risks, which are private (not external) benefits.

[7]The peak-hour pricing surcharge applied a 0.10 CHF/km surcharge on PT trips between those zones with a larger demand in peak hours compared to off-peak.

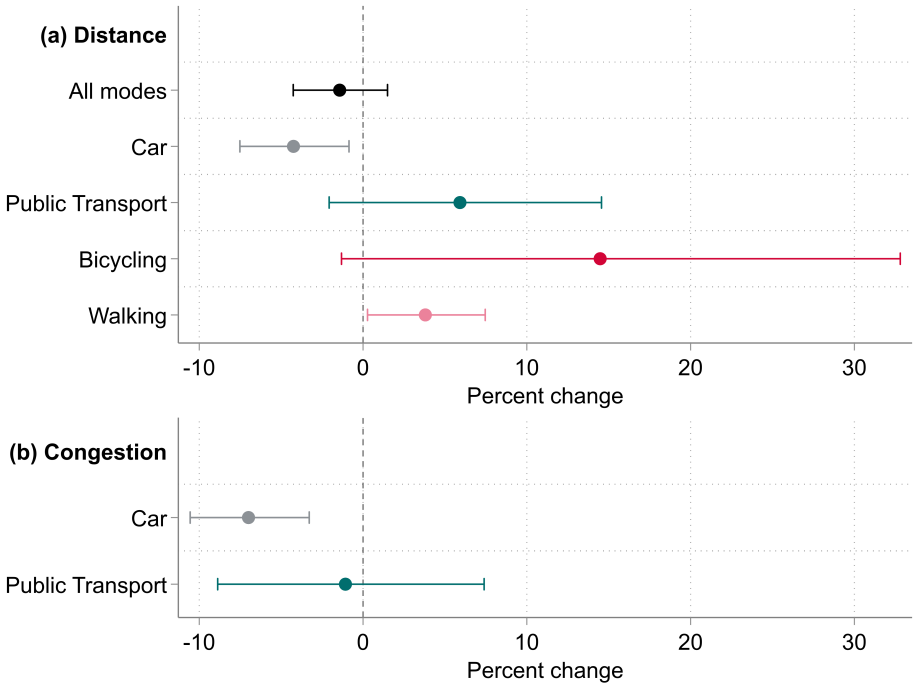
[8]Factoring in the external costs of transport increases total costs by 16.4%, such that the resulting elasticity is (-5.1/16.4 =) -0.31.

The figure also shows the differential effect between the two treatments, which is the causal effect of adding pricing to the information about the external costs of transport (this interpretation is possible because the informational content in both treatments was the same). The effect is statistically significant for congestion, but not for health and climate costs.

The effect of Pigovian transport pricing is relatively homogeneous across the sample with respect to the most important socio-demographic characteristics such as age, income, education etc. We found two exceptions: The treatment effect was stronger for men than for women, and it was not statistically significant for the French-speaking participants. However, we stress that these are latent constructs. The difference could be mediated by unobserved variables (e.g., taking care of children or working in certain jobs) or due to methodological issues, for example how information was translated into the different languages.

Furthermore, we found that the effect was driven by those participants who correctly identified the definition of *external costs of transport*. This definition had been explained to the participants at the beginning of the treatment phase. A corresponding question was inserted in the final survey to capture differences with regards to reading instructions or pre-existing knowledge. Those who responded correctly reacted strongly to the pricing treatment, whereas those that chose an incorrect answer did not respond at all to the pricing. This finding indicates that a conceptual understanding of the pricing scheme, or its justification, is essential for it to work.

Figure IV – Mechanisms underlying the reduction in external costs



Note: The bars denote 95%-confidence intervals. Panel (a) shows the average treatment effect from pricing on the daily distance, overall and by mode. Panel (b) displays the effect on congestion (cars) and crowding (public transport).

Although we find no statistically significant effect of the information-only treatment for the sample overall, some subgroups did respond to the information treatment (although to a lesser extent than to pricing). These subgroups include men and participants that scored high on an "altruistic" scale.[9] This implies that an information-only intervention would result in an effect at least for a part of the population.

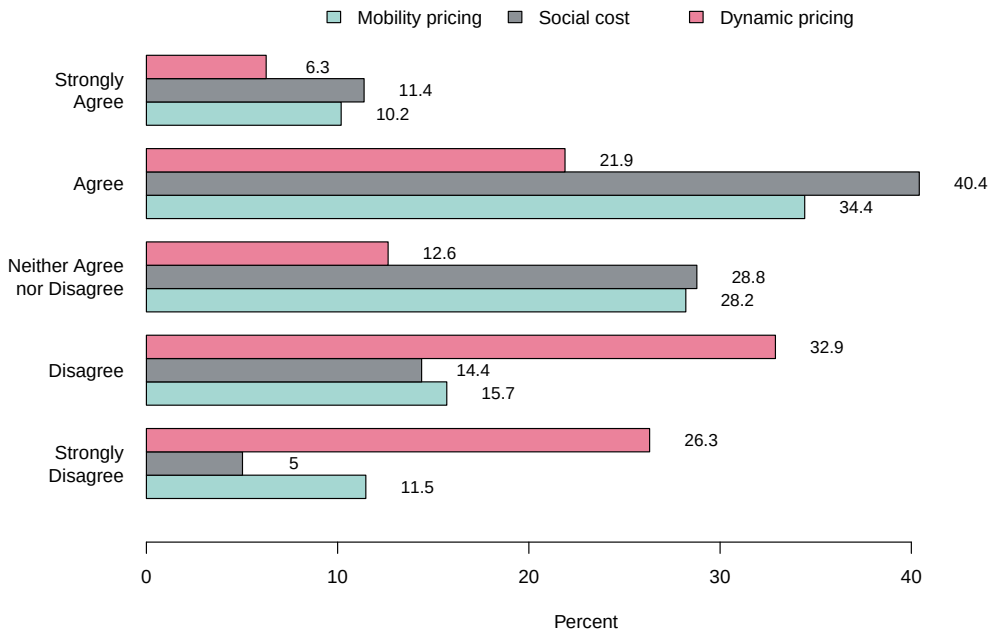
[9] In the final survey conducted after the experiment was concluded, a battery of questions was asked to elicit respondents' personal values (Schwartz, 1992; De Groot and Steg, 2010). Using this methodology, respondents were assigned a numerical value along four dimensions labeled "altruistic", "egoistic", "hedonic" and "biospheric".

There are several ways in which people can reduce their external costs of transport. Pricing did not significantly reduce overall daily travel distances, but there is a significant reduction in daily car distance countered by increases in public transport, as well as bicycling and walking (Fig. IVa). The effect can be seen both in terms of the average distance on travel days (the "intensive margin") and on the probability to travel (the "extensive margin"). For example, the negative effect on average car distance is a combination of shorter distances traveled and a lower probability of using the car in the first place.

The pricing treatment also significantly reduced congestion costs per km of car travel, implying that modal shift is not the only mechanism responsible for the reduction in external costs (Fig. IVb). We measured a significant shift in the departure times for car trips in the morning peak, but not in the evening. In contrast, there was no reduction in crowding and no departure time shift for public transport.

Even if Pigovian transport pricing works, implementing it may face challenges of implementation not only in terms of technology and data confidentiality, but also in terms of social acceptability. In the introduction survey, we included three questions designed to elicit respondents' preferences about a possible introduction of transport pricing. In order not to reveal the purpose of the experiment, these questions were part of a much larger number of queries posed to the respondents. The three questions aimed at the same concept but were worded differently.

Figure V – Support for transport pricing



Note: The figure shows participants' level of agreement with the following policies and statements: (i) Introduction of time- and route-specific mobility pricing, made revenue-neutral by lowering other taxes; (ii) the price for mobility should reflect the social cost (e.g., health, environment, congestion); (iii) the transport network should be used more efficiently by introducing dynamic pricing.

A majority of the respondents were either positive or neutral if the question was worded with respect to social costs or externality pricing (Fig. V). However, if the focus was placed on the time-varying nature of this pricing (but without mention of social aspects), a majority was opposed. This suggests that transport pricing could in principle find a political majority, but that it depends on how the pricing scheme is communicated.

There were no statistically significant differences along the other three "values" dimensions.

Discussion

The MOBIS experiment implemented transport pricing based on the social marginal costs of transport. The external costs were greatest for health, followed by congestion and climate costs. Pricing reduced all dimensions of external costs significantly, but it was particularly effective in reducing congestion, both in absolute terms and relative to providing information alone. The information-only treatment had an effect for subgroups of the population (such as altruists), but was not statistically significant for the overall sample. The reduction in the external costs is due to a combination of a shift away from driving towards other modes, and towards less congested times and possibly routes. The effect is quite homogeneous across other socio-demographic characteristics such as age, income, education or household size, but we found a significant difference between the genders and language regions. The elasticity estimate is comparable to results based on toll pricing (Bain, 2019), but lower than earlier estimates based on before-vs.-after studies (Leape, 2006; Nielsen, 2004). MOBIS is the first multimodal RCT about pricing in a transport setting and thus different to uni-modal pricing schemes, where the lack of pricing for alternative modes may have inflated the mode shift effects.

By design, drivers were over-represented in this study. As driving produces the largest external costs, the observed short-term elasticity therefore may lead to over-estimating pricing effects in the general population. Furthermore, since the pricing scheme in the experiment consisted of taking money away from a given budget, loss aversion may have increased the effect relative to a tax (Tversky and Kahneman, 1991). On the other hand, there are a number of arguments for expecting larger effects in the long run than during this 8-week trial. With a permanent introduction of transport pricing, additional margins of response would become available such as the choice of work and home locations, changes in long-term activity routines, vehicle/transit pass ownership or negotiations with employers about work hours and location. Furthermore, the behavioral response was limited to respondents that understood the concept of external costs underlying the experiment. Whereas it is to be expected that not everyone pays close attention to the “rules” in a short study, a general introduction of transport pricing would presumably have a greater salience.

The MOBIS experiment shows that Pigovian transport pricing works in practice. By making it multimodal, the applied pricing scheme is not exclusively a tax on drivers, as is sometimes argued, but it equally prices the external costs across all modes of transport.[10] The required technology is available, and a number of countries have computed the external costs of transport within their borders. The COVID-19 pandemic has demonstrated that patterns of living, working and traveling are susceptible to change. It seems justified to expect people to respond to the price incentives in similar, albeit less dramatic ways. Furthermore, a transition away from the current transport funding mechanism that relies mostly on fuel taxes is unavoidable due to shifts in modes, fuel types and vehicle technologies. Pigovian transport pricing is an alternative funding mechanism that can also be implemented in the presence of a sizable electric vehicle fleet.

A Pigovian pricing scheme as used in the MOBIS experiment would face a number of challenges for practical implementation including privacy concerns, social acceptability, technical constraints of assessing the tax on a real-time basis (Verhoef, 2000). However, even a simplified pricing scheme should be guided by the marginal external costs of transport to increase the efficiency of the transport system. A key challenge will be to agree on the price setting (e.g., the value of time or the social cost of carbon) within the political process. Furthermore, it is well-known that fuel taxes are regressive (Eidgenössisches Finanzdepartement (EFD), 2013; ECOPLAN, 2012; ECOPLAN, EPFL & FHNW, 2019), and thus the distributional aspects of a cost-based pricing scheme deserve further investigation. Efforts to advance such a scheme will need to be complemented with ancillary measures to counteract adverse distributional implications. In principle, however, we believe that Pigovian transport pricing could be politically feasible, at least in Switzerland.

[10] We stress that the scheme is not an average cost pricing scheme, as it excludes any fixed costs such as the costs of infrastructure in public transport (which are heavily subsidized in Switzerland) or any generalized costs of the road network not covered by the fuel excise tax. Whereas the fixed costs are important for planning the expansion of the transport network, they are not relevant for individual travel decision at a given point in time.

Multimodal transport pricing based on the external costs of transport is feasible and has the desired effect of shifting modes, departure times and routes. It thus leads to a more efficient use of the transport system and a reduction in the need for network expansions. If implemented in an equitable way, transport pricing could become a key pillar of sustainable transport policy.

Zusammenfassung – Deutsch

Verkehrssysteme stehen vor vielen Herausforderungen. Mit dem Bevölkerungswachstum und der steigenden Gesamtmobilität stossen die Verkehrsnetze an ihre Kapazitätsgrenzen (ARE, 2016). Der daraus resultierende Stau auf den Strassen ist eine erhebliche Quelle von Zeitverlusten für Autofahrer: Der gesamte monetarisierte Zeitverlust durch Stau in der Schweiz wurde 2017 auf 1'420 Millionen CHF geschätzt (ARE, 2019). Die Schweiz hat stark in das Strassen- und Schienennetz investiert, um die steigende Verkehrsnachfrage zu bewältigen. Die Erhöhung der Kapazität des privaten und öffentlichen Verkehrs ist jedoch kostspielig und stösst an physikalische Grenzen. Darüber hinaus führt die Erhöhung der Strassenkapazität zu erhöhter Nachfrage und führt daher langfristig kaum zu einer Verbesserung der Verkehrslage.

Der Verkehrssektor gehört auch zu den grössten Verursachern von lokaler Luftverschmutzung und Treibhausgasemissionen. Während in den Sektoren Gewerbe, Dienstleistungen und Haushalte erhebliche Fortschritte erzielt wurden, sind die Emissionen im Verkehrssektor in etwa konstant geblieben, da Effizienzgewinne durch eine Zunahme der zurückgelegten Kilometer ausgeglichen wurden (IEA, 2020). In der Schweiz lagen die CO_2-Emissionen des Verkehrssektors im Jahr 2019 auf dem gleichen Niveau wie im Jahr 1990.[11] Die Gesundheitskosten durch verkehrsbedingte Luftverschmutzung belaufen sich jährlich auf 2'200 Millionen CHF (Federal Office for Spatial Development, 2020).

Stau, die negativen Auswirkungen des Klimawandels und die gesundheitlichen Auswirkungen von Verkehrsemissionen haben eine Gemeinsamkeit: Sie stellen externe Effekte oder *externe Kosten des Verkehrs* dar. Während die Verkehrsteilnehmer die privaten Kosten des Verkehrs tragen, die sich u.a. in den Preisen für Treibstoff, Fahrkarten, Fahrzeugkauf und -unterhalt niederschlagen, werden die externen Kosten von "Anderen", d. h. der Gesellschaft insgesamt, getragen. Externe Kosten haben somit typischerweise keinen Einfluss auf die Entscheidung, wo, wann und wie man reist. Dies führt zu einem Marktversagen, das einen Bedarf an politischen Interventionen über den bestehenden Regulierungsrahmen hinaus impliziert.

Externe Kosten des Verkehrs wurden bisher grösstenteils durch Regulierungen angegangen wie z.B. Geschwindigkeitsbegrenzungen, Abgasgrenzwerte oder obligatorische Fahrzeuginspektionen. Theoretisch sind jedoch Preisinstrumente, die die externen - oder "wahren" - Kosten des Verkehrs widerspiegeln, ein effizienteres Mittel der Regulierung, da sie es den Menschen ermöglichen, Fahrten mit hohem Nutzen beizubehalten, während sie diejenigen reduzieren, die sie als weniger wichtig erachten. Bei vollständig rationalen und vollständig informierten Individuen führt die Berücksichtigung der vollen Grenzkosten und -nutzen im Preis jeder Fahrt zum "optimalen" Niveau von Stau und Umweltverschmutzung.[12] Eine Preisgestaltung, die sich an den vollen Grenzkosten des Verkehrs orientiert, führt zu einer effizienten Nutzung des bestehenden Verkehrssystems und damit u.a. zu einer Verringerung der Notwendigkeit eines Netzausbaus.

Traditionell sind die gängigsten Beispiele für preisbasierte Instrumente im Verkehrssektor Treibstoffsteuern, Strassenbenutzungsgebühren und Zulassungsgebühren. Die Motivation dahinter ist jedoch oft die Deckung der Kosten für den Strassenbau und nicht die Optimierung des Reiseverhaltens. Als solche spiegeln sie typischerweise die externen Kosten des Verkehrs nicht vollständig wider (vgl. Parry and Small (2005)). Eine Ausnahme ist die Schweizer "Schwerverkehrsabgabe", die explizit durch die Internalisierung der externen Kosten des Güterverkehrs motiviert ist, insbesondere was die Auswirkungen auf das alpine Ökosystem betrifft. In jüngster Zeit wurden von einer steigenden Anzahl Städten weltweit Staugebühren eingeführt. Staugebühren sind wirksam bei der Reduzierung von Stau und internalisieren zumindest teilweise die externen Kosten des städtischen Fahrens. Die kon-

[11] Die Verkehrsemissionen in der Schweiz (ohne den internationalen Luftverkehr) betrugen 1990 und 2019 14,9 bzw. 15,0 Millionen tCO_2-Äquivalente. Siehe `https://www.bfs.admin.ch/bfs/de/home/statistiken/raum-umwelt/klimabezogene-indikatoren/menschliche-einwirkungen.html`.

[12] Aus gesellschaftlicher Sicht ist das optimale Niveau der Umweltverschmutzung im Allgemeinen nicht Null, sondern durch die Menge definiert, bei der die Grenzkosten der Reduzierung der Umweltverschmutzung gleich dem Grenznutzen dieser Reduzierung sind.

stante Natur solcher Gebühren kann jedoch die zeitlich variierende Natur von Stau nicht vollständig berücksichtigen, und sie ignorieren alle anderen externen Kosten, die mit dem Autofahren und anderen Verkehrsmitteln verbunden sind.

In der Schweiz beschränken sich Studien zur Bepreisung des Verkehrs auf Befragungen und Modellierungen (e.g., Vrtic *et al.*, 2010; INFRAS, 2019). Internatinoal liegen empirische Studien vor, welche eine Berechnung der Effekte von Staugebührenregelungen vornehmen, zum Beispiel in Singapur (Agarwal and Koo, 2016), London (Leape, 2006) oder Stockholm (Eliasson *et al.*, 2009). Im Gegensatz dazu erlauben Feldexperimente, die das individuelle Reiseverhalten verfolgen, das Kontrollieren für individuelle Eigenschaften, was nuanciertere und robustere Analysen ermöglicht.

Zum Beispiel wurden in Vorher-Nachher-Experimenten in Dänemark und Australien GPS-Empfänger in Fahrzeuge eingebaut und die Fahrer wurden dann verschiedenen Preisschemen zu Spitzenzeiten und ausserhalb der Spitzenzeiten ausgesetzt (Nielsen, 2004; Martin and Thornton, 2017b). Beide Studien berichten von einer Verringerung der Anzahl der Autofahrten während der Hauptverkehrszeiten. In Singapur reagierten Pendler auf eine monetäre Belohnung, indem sie ihre Abfahrtszeit mit öffentlichen Verkehrsmitteln verschoben (Pluntke and Prabhakar, 2013). Diese früheren Studien konzentrierten sich auf ein einzelnes Verkehrsmittel und konnten daher keine Auswirkungen auf die Verkehrsmittelwahl (d. h. Verkehrsmittelverlagerungen) feststellen, obwohl die Erwartung besteht, dass das Preissystem das Reiseverhalten über alle Verkehrsmittel (Auto, öffentliche Verkehrsmittel und nicht-motorisierte Verkehrsmittel) hinweg beeinflusst (Tirachini and Hensher, 2012). Im "Spitsmijden"-Experiment in den Niederlanden reagierten Pendler auf finanzielle Belohnungen und Sachleistungen, indem sie die Abfahrtszeiten verschoben, auf andere Verkehrsmittel umstiegen und von zu Hause aus arbeiteten (Ben-Elia and Ettema, 2011b). Die einzige frühere gross angelegte Studie im Verkehrssektor, die eine Kontrollgruppe einschloss, ist eine randomisierte kontrollierte Studie, die keinen Effekt von Informationsbehandlungen (d.h. ohne finanzielle Anreize) auf das Fahrgemeinschafts- und Pendelverhalten von Angestellten von fünf grossen Arbeitgebern fand (Kristal and Whillans, 2020).

Diese Zusammenfassung erläutert die Ergebnisse des Forschungsprojekts "Mobility Behavior in Switzerland" (MOBIS), das eine randomisierte kontrollierte Studie (RCT) durchführte. Darin wurde ein Pigou-Verkehrsbepreisungssystem simuliert, das auf den externen Kosten des Verkehrs basiert und somit eine Anwendung des Verursacherprinzips ist.[13] Die im Experiment verwendete Verkehrsbepreisung internalisierte die externen Grenzkosten in den Bereichen Stau, Klima und Gesundheit vollständig in den Benutzerpreis. Die Fahrten der Studienteilnehmer wurden mittels einer Smartphone-App erfasst, auf deren Basis die zugehörigen externen Kosten berechnet wurden. Die Bepreisung wurde umgesetzt, indem einem Drittel der Teilnehmer ein Transportbudget zur Verfügung gestellt wurde, dem die durch ihre Fahrten verursachten externen Kosten belastet wurden. Um den finanziellen Anreiz eines Verkehrsbepreisungssystems zu simulieren, durften die Teilnehmer alle Einsparungen, die sich aus der Änderung ihres Reiseverhaltens ergaben, behalten. Um den Preiseffekt von einem reinen Informationseffekt oder anderen Störfaktoren zu unterscheiden, enthielt das Experiment eine zweite Behandlungsgruppe, in der die Probanden die gleichen Informationen über die externen Kosten des Verkehrs erhielten wie in der Preisgruppe, aber nichts bezahlen mussten, sowie eine Kontrollgruppe. Das Experiment fand eine Elastizität von (minus) 0,31 für die Bepreisung mit den externen Kosten. Mit anderen Worten: Die Einführung eines auf externen Kosten basierenden Bepreisungssystems, das die Transportkosten im Durchschnitt um 10% erhöht, würde zu einer Reduzierung der externen Kosten des Transports um 3,1% führen. MOBIS wurde gemeinsam von Forschern der ETH Zürich, der Universität Basel und der ZHAW durchgeführt und von den Bundesämtern für Strassen (ASTRA) und Verkehr (BAV) sowie von Innosuisse unterstützt. Unseres Wissens ist MOBIS die erste multimodale randomisierte kontrollierte Studie einer Pigou-Verkehrsbepreisungs-Intervention.

[13] Dieser Begriff geht auf Arthur Pigou zurück, der als erster das Konzept der Internalisierung der mit einer Aktivität verbundenen externen Kosten formulierte, indem er den marginalen sozialen Schaden als korrigierende Steuer auferlegte (Pigou, 1920). Die Pigou-Steuer ist ein Standardkonzept in den Wirtschaftswissenschaften und wird oft als "Verursacherprinzip" bezeichnet.

Das MOBIS-Experiment

Ziel des MOBIS-Experiments war, die Wirkung von Verkehrsbepreisung und -informationen in Bezug auf die Veränderung des Verkehrsverhaltens hin zu optimierten und nachhaltigeren Reisemustern zu untersuchen. Die Studienstichprobe wurde unter Personen rekrutiert, die in städtischen Agglomerationen in der deutsch- und französischsprachigen Schweiz leben. Die Adressen wurden vom Bundesamt für Statistik, das ein umfassendes Einwohnerregister führt, und von einem privaten Anbieter zur Verfügung gestellt.

Eine erste Umfrage wurde von 21'800 Teilnehmern beantwortet und enthielt Fragen zum Reiseverhalten, zur Soziodemografie und zu einer Reihe von verkehrspolitischen Themen. Potenzielle Teilnehmer für das Experiment mussten eine Reihe von Einschlusskriterien erfüllen, wie z. B. die Nutzung eines Autos an mindestens zwei Tagen pro Woche und ein Alter zwischen 18 und 65 Jahren.

Aus der anfänglichen Umfrage wurden über 4'000 Teilnehmer für das Bepreisungsexperiment rekrutiert, wobei ihnen zum Zeitpunkt der Rekrutierung weder die Art der Studie noch die Tatsache, dass sie Teil eines Experiments waren, mitgeteilt wurde. Die Teilnehmer des Experiments erklärten sich bereit, eine Tracking-App auf ihr Smartphone herunterzuladen und ihre täglichen Fahrten über einen Zeitraum von 8 Wochen erfassen zu lassen. Als Gegenleistung für die Teilnahme an der gesamten Studie erhielten sie 100 CHF. 3'656 Teilnehmer schlossen das Experiment erfolgreich ab, und fast alle von ihnen füllten auch die abschliessende Umfrage aus. Die MOBIS-Stichprobe unterscheidet sich von der Allgemeinbevölkerung durch die Altersbeschränkung und den Fokus auf Autofahrer, ist aber ansonsten vergleichbar, da die Stichprobe für die Erstbefragung aus einem repräsentativen Studienpool gezogen wurde.

Abbildung I – Design der MOBIS-Studie

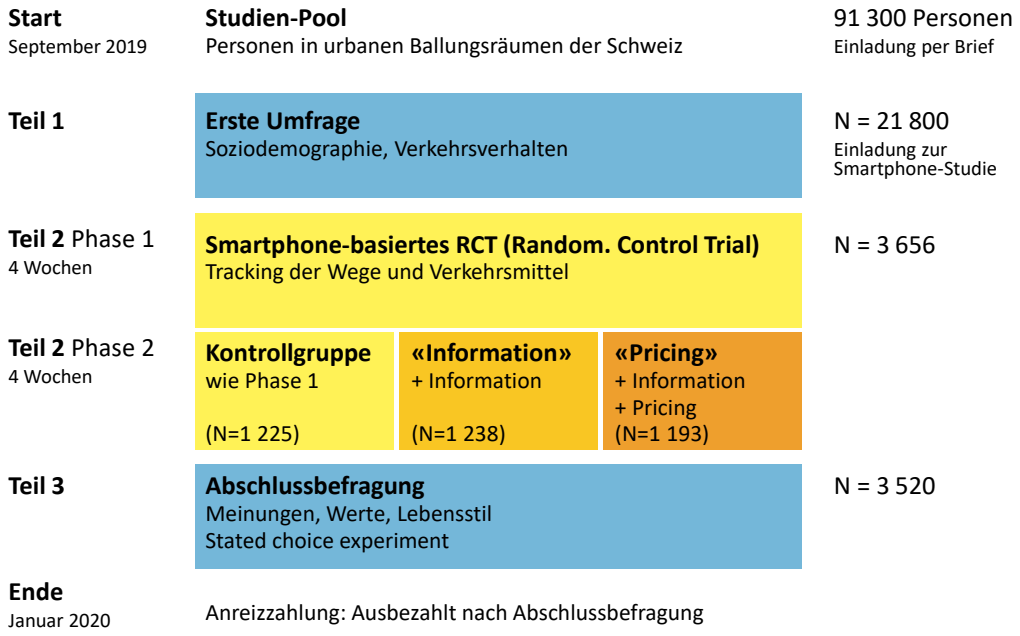


Abbildung I gibt einen Überblick über das Studiendesign. Die Rekrutierung fand zwischen August und November 2019 auf kontinuierlicher Basis statt. Sobald ein Teilnehmer den ersten Track in der App registriert hatte, wurde er automatisch Teil der Stichprobe. Die

Studie bestand aus 4-wöchigen Beobachtungsphase für alle Teilnehmer, gefolgt von einer 4-wöchigen Interventionsphase (bzw. fortgesetzter Beobachtung in der Kontrollgruppe). Die Zuweisung zu den Gruppen erfolgte vollständig randomisiert.

Die App zeichnete jede Fahrt auf und ermittelte das Verkehrsmittel anhand der Route, der Geschwindigkeit und der Beschleunigungsmuster. Die Gesamtgenauigkeit der Verkehrsmittelerkennung lag bei über 90%. Die Teilnehmer hatten die Möglichkeit, die Verkehrsmittelzuordnung manuell zu überprüfen und zu korrigieren. Für jede Fahrt wurden die damit verbundenen externen Kosten des Transports berechnet und monetarisiert, basierend auf Kostenfaktoren publiziert vom Bundesamt für Raumentwicklung (ARE).

Während des Beobachtungszeitraums erhielten die Teilnehmer eine wöchentliche Zusammenfassung ihrer Fahrten nach Verkehrsmitteln. Die Kontrollgruppe erhielt weiterhin nur diese Informationen bis zum Ende der Studie.

Am Studientag 29 erhielten die Teilnehmer, die der Informations-Gruppe zugeordnet waren, eine E-Mail, die sie über die externen Kosten des Verkehrs informierte, wie diese berechnet und monetarisiert werden und wie sie reduziert werden können. Einmal pro Woche wurde den Teilnehmern eine Zusammenfassung der externen Kosten präsentiert, die sie in der vorangegangenen Woche produziert hatten. Die externen Kosten wurden nach Verkehrsträger und in den Kategorien Gesundheit, Klima und Stau dargestellt. Die Teilnehmer, die der Bepreisungs-Gruppe “(Pricing)” zugewiesen wurden, erhielten die gleichen Informationen über die externen Kosten, bekamen aber zusätzlich ein Budget, von dem ihre externen Kosten des Transports abgezogen werden sollten. Die Teilnehmer wurden darüber informiert, dass ihr Budget ab sofort (d. h. ab Tag 29) für die externen Kosten ihrer Reise verwendet werden würde, dass aber der Restbetrag, der am Ende der Studie auf ihrem Konto verbleiben würde, ihnen ausbezahlt wird. Diese individualisierten Budgets wurden auf der Grundlage der externen Kosten jedes Teilnehmers während der Beobachtungsphase berechnet, zuzüglich eines Puffers von 20%.[14] Diese Intervention simulierte also ein Transportbepreisungssystem auf Basis der externen Grenzkosten.

Der durchschnittliche Behandlungseffekt wurde berechnet, indem die Teilnehmer der beiden Behandlungsgruppen mit den Teilnehmern der Kontrollgruppe verglichen wurden, die das Experiment am selben Tag begonnen hatten. Die Einbeziehung einer Kontrollgruppe ermöglichte die Kontrolle von saisonalen Trends und anderen zeitlichen Faktoren, die die Entstehung von externen Kosten des Transports beeinflussen und somit die Ergebnisse verzerren könnten. Die Studie endete kurz vor dem Ausbruch der COVID-19-Pandemie im März 2020.[15]

Berechnung der externen Kosten des Verkehrs

Die gesundheits-, emissions- und stauabhängigen externen Kosten des Verkehrs wurden für die aufgezeichneten täglichen Fahrten mit Hilfe einer automatisierten Datenpipeline berechnet. Um die externen Kosten von Stau und Emissionen zu berechnen, wurden GPS-Tracks an das Schweizer Strassennetz (Karich and Schröder, 2014) angepasst und mit Modulen verarbeitet, die auf der Grundlage des MATSim-Verkehrsmodells (Horni *et al.*, 2016a) entwickelt wurden. Die Emissionsfaktoren wurden dem Handbook Emission Factors for Road Transport (HBEFA) Version 3.3 entnommen und mit dem MATSim Emissionsmodul angewendet. Für Stau wurde ein durchschnittlicher Grenzkostenansatz angewendet, der Rückstaueffekte und Stau im Verkehrsfluss einbezieht (Kaddoura, 2015), ergänzt durch Daten, die in der Einführungserhebung erhoben wurden, und monetarisiert mit Standardfaktoren, die vom Bundesamt für Raumentwicklung (ARE) verwendet werden (Federal Roads Office - ASTRA, 2017).

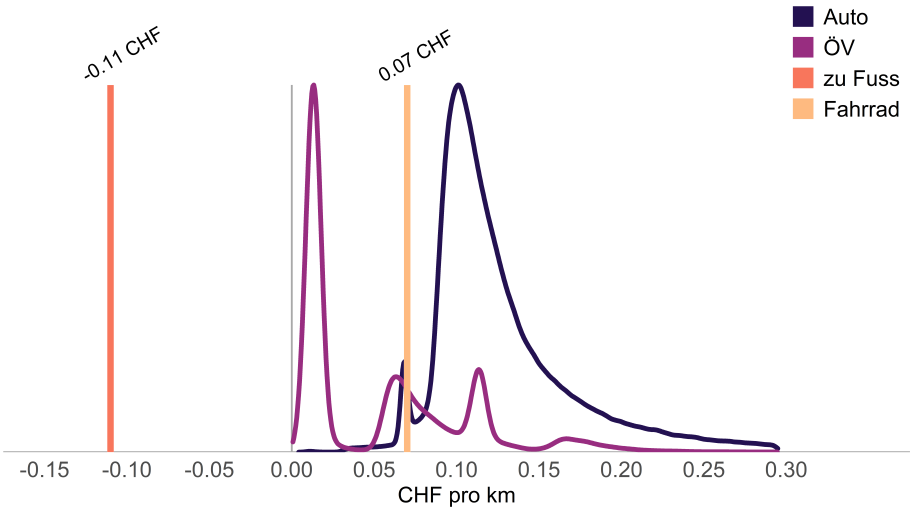
Für die Gesundheitseffekte des aktiven Verkehrs (d. h. Zu Fuss gehen und Radfahren) wurden Standardwerte pro Kilometer verwendet. Die Gesundheitseffekte beinhalten Ver-

[14] Das durchschnittliche Budget betrug CHF 144, aber bei einigen Teilnehmern überstieg es CHF 700.

[15] Ungefähr ein Drittel der Teilnehmer erklärte sich bereit, das Tracking erneut zu starten, um das Reiseverhalten als Reaktion auf die COVID-19-Massnahmen zu untersuchen. Vorläufige Ergebnisse dieser laufenden Studie werden in der Publikation (Molloy *et al.*, 2020) berichtet.

letzungskosten (die aufgrund der Deckung durch das Schweizer Gesundheitssystem grösstenteils extern zu den verletzten Personen sind), aber auch den externen Anteil des Gesundheitsnutzens in Form von reduzierten Mortalitäts- und Morbiditätsrisiken als Folge der körperlichen Aktivität. Während das Zufussgehen mit einem externen Nettonutzen verbunden ist, implizieren aktuelle Schätzungen, dass die externen Unfallkosten den externen Gesundheitsnutzen des Radfahrens überwiegen, so dass das Radfahren im Experiment mit geringen externen Nettokosten verbunden war.[16]

Abbildung II – Verteilung der in MOBIS angewandten externen Kosten pro Personenkilometer



Für die externen Kosten des öffentlichen Verkehrs (ÖV) wurden die Schadstoffemissionen auf einer Pro-km-Basis berechnet. Lärm-Externalitäten wurden nicht berücksichtigt, da keine Referenzwerte verfügbar waren. Um Kosten durch Kapazitätsgrenzen (*Crowding*) zu approximieren, wurde ein zonales Preisschema für Hauptverkehrszeitzuschläge für das nationale ÖV-Netz entwickelt. Während des gesamten Experiments hatten die Teilnehmer der Behandlungsgruppen Zugang zu einer interaktiven Karte, die ihnen zeigte, wo und wann der Preiszuschlag galt.[17]

Abbildung II zeigt die Verteilung der monetarisierten externen Kosten pro Personenkilometer für jedes Verkehrsmittel. Während für den Langsamverkehr konstante Werte pro km angewandt wurden hängen die externen Kosten für das Autofahren und für den ÖV von der Verkehrsbelastung ab und variieren daher über Zeit und Raum (verschiedene Träger des öffentlichen Verkehrs verursachen zudem unterschiedliche externe Kosten). Die Abbildung zeigt ihre Verteilung aufgrund der während des Experiments beobachteten Fahrten.

Ergebnisse

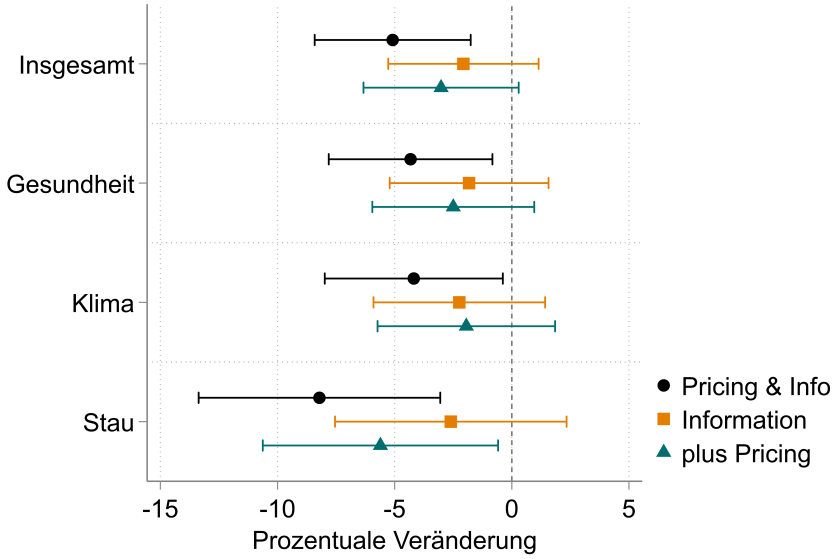
Abbildung III zeigt die durchschnittlichen Behandlungseffekte, die im Experiment beobachtet wurden. Die Bepreisung des Verkehrs, wie sie im MOBIS-Experiment umgesetzt wurde (d. h. Bepreisung + Information), reduzierte die externen Kosten des Verkehrs insgesamt sowie für jeden der drei Bereiche Gesundheit, Klima und Stau signifikant. Im Durchschnitt reduzierten die Befragten in der Bepreisungsgruppe ihre externen Kosten des Verkehrs um 5,1%, relativ zur Kontrollgruppe. Dieser Effekt ist statistisch hoch signifikant ($p<0{,}01$) und

[16] Die meisten positiven Gesundheitseffekte liegen in Form von geringeren Morbiditäts- und Mortalitätsrisiken vor, die einen privaten (nicht externen) Nutzen darstellen.

[17] Der Hauptverkehrszeitzuschlag wendete einen Aufschlag von 0,10 CHF/km auf ÖV-Fahrten zwischen den Zonen mit einer grösseren Nachfrage in den Hauptverkehrszeiten im Vergleich zu den Nebenverkehrszeiten an.

entspricht einer Elastizität von -0,31.[18] Die Punktschätzungen für die Informations-Gruppe deuten nur darauf hin, dass es einen Informationseffekt ohne Preisgestaltung geben könnte, aber er ist schwächer und nicht statistisch signifikant.

Abbildung III – Behandlungseffekt auf die externen Kosten des Transports



Anmerkung: Die Abbildung zeigt den durchschnittlichen Behandlungseffekt für Reisen in der *Bepreisungsgruppe* und in der *Nur-Informationsgruppe*, relativ zur *Kontrollgruppe* (gestrichelte 0-Marke), sowie den Effekt der Hinzunahme einer Bepreisung zu bestehender Information. Die Balken bezeichnen 95%-Konfidenzintervalle.

Die Abbildung zeigt auch den differentiellen Effekt zwischen den beiden Interventionen, d.h. den kausalen Effekt der Hinzunahme von Bepreisung, zusätzlich bestehenden Informationen über die externen Kosten des Verkehrs (diese Interpretation ist möglich, da der Informationsgehalt in beiden Gruppen gleich war). Der Effekt ist statistisch signifikant für Stau, aber nicht für Gesundheits- und Klimakosten.

Der Effekt des Pigou-Bepreisungssystems ist in der Stichprobe relativ homogen in Bezug auf die wichtigsten soziodemografischen Merkmale wie Alter, Einkommen, Bildung etc. Wir fanden jedoch zwei Ausnahmen: Der Behandlungseffekt war für Männer stärker als für Frauen, und er war nicht statistisch signifikant für die französischsprachigen Teilnehmer. Es gilt allerdings zu berücksichtigen, dass es sich hierbei um latente Konstrukte handelt. Der Unterschied könnte durch unbeobachtete Variablen (z.B. Kinderbetreuung oder bestimmte Berufe) oder durch methodische Fragen, z.B. wie die Informationen in die verschiedenen Sprachen übersetzt wurden, verursacht worden sein.

Darüber hinaus fanden wir, dass der Effekt hauptsächlich von jenen Teilnehmern erzeugt wurde, die die Definition von “externe Transportkosten” korrekt verstanden. Diese Definition war den Teilnehmern zu Beginn der Behandlungsphase erklärt worden. Eine entsprechende Frage wurde in der abschliessenden Befragung eingefügt, um Unterschiede in Bezug auf das Lesen von Anweisungen oder Vorwissen zu erfassen. Diejenigen, die richtig antworteten, reagierten stark auf die Preisbehandlung, während diejenigen, die eine falsche Antwort wählten, überhaupt nicht auf die Preisbehandlung reagierten. Diese Erkenntnis deutet darauf hin, dass ein konzeptionelles Verständnis des Preisschemas bzw. dessen Rechtfertigung für dessen Funktionieren unerlässlich ist.

Obwohl wir keinen statistisch signifikanten Effekt der reinen Informationsbehandlung für die

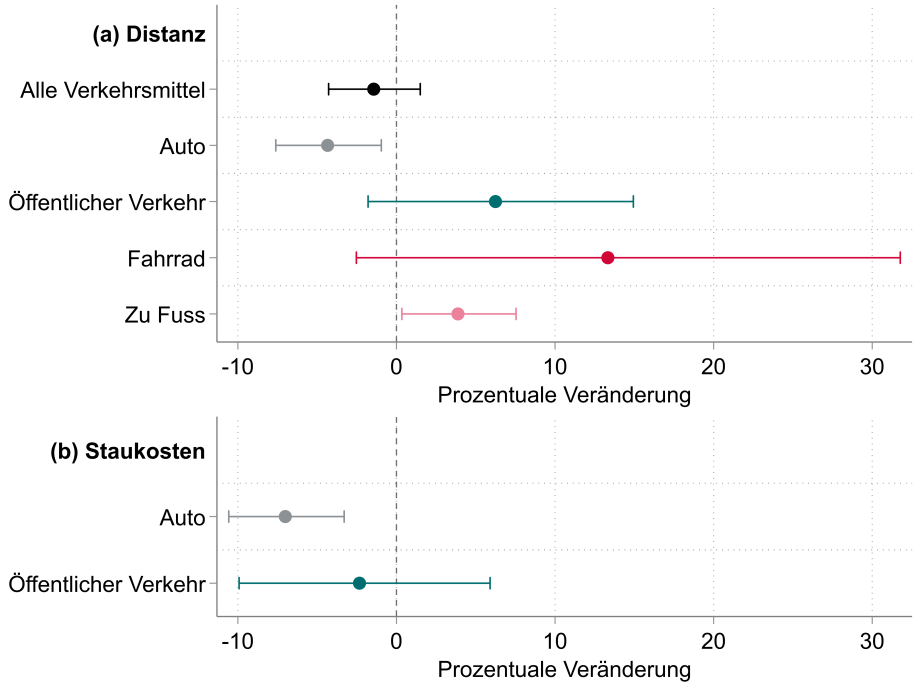
[18] Die Berücksichtigung der externen Kosten des Transports erhöht die Gesamtkosten um 16,4%, so dass die resultierende Elastizität (-5,1/16,4 =) -0,31 beträgt.

Gesamtstichprobe finden, reagierten einige Untergruppen auf die Informationsbehandlung (wenn auch in einem geringeren Ausmass als auf die Preisgestaltung). Zu diesen Untergruppen gehören Männer und Teilnehmer, die auf einer “altruistischen” Skala hohe Werte erreichten.[19] Dies impliziert, dass eine reine Informationsintervention zumindest für einen Teil der Bevölkerung einen Effekt haben würde.

Es gibt mehrere Möglichkeiten, wie Menschen ihre externen Kosten für den Verkehr reduzieren können. Die Preisgestaltung führte nicht zu einer signifikanten Verringerung der täglichen Gesamtdistanz, aber es gibt eine signifikante Reduktion der täglichen Distanz mit dem Auto, die durch eine Zunahme des öffentlichen Verkehrs sowie des Radfahrens und des Zufussgehens ausgeglichen wird (Abb. IVa). Der Effekt ist sowohl messbar für die durchschnittliche Reisedistanz an tatsächlichen Reisetagen (die sogenannte “intensive margin”) und für die Wahrscheinlichkeit, mit einem bestimmten Verkehrsmittel zu reisen (die “extensive margin”). Zum Beispiel ist der negative Effekt auf die durchschnittliche Entfernung mit dem Auto über alle Personen-Tage eine Kombination aus kürzerer zurückgelegter Entfernung für Autofahrer und einer geringeren Wahrscheinlichkeit, das Auto überhaupt zu benutzen.

Die Bepreisung reduzierte auch die Staukosten pro Pkw-Kilometer signifikant, was bedeutet, dass die Verkehrsmittelverlagerung nicht der einzige Mechanismus ist, der für die Reduzierung der externen Kosten verantwortlich ist (Abb. IVb). Wir haben eine signifikante Verschiebung der Abfahrtszeiten für Autofahrten in der morgendlichen Spitze beobachtet, aber nicht in den Abendstunden. Im Gegensatz dazu gab es keine Verringerung des Crowdings und keine Verschiebung der Abfahrtszeiten für öffentliche Verkehrsmittel.

Abbildung IV – Zugrundeliegende Mechanismen der Reduzierung der externen Kosten



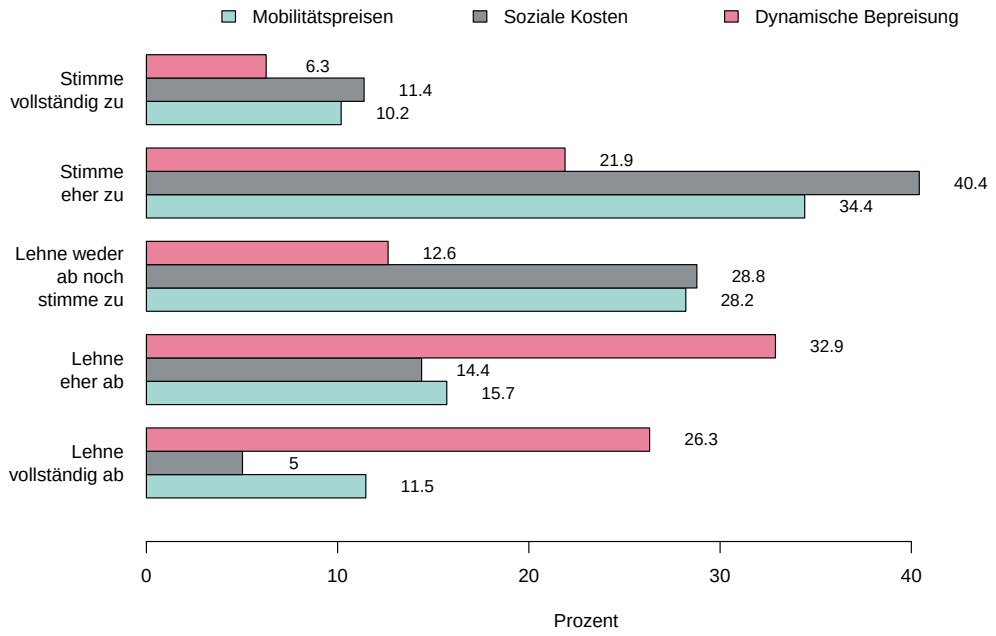
Anmerkung: Die Balken bezeichnen 95%-Konfidenzintervalle. Abb. (a) zeigt den durchschnittlichen Behandlungseffekt der Bepreisung auf die tägliche Entfernung, insgesamt und nach Modus. Abb. (b) zeigt den Effekt auf Stau und Crowding im privaten, bzw. öffentl. Verkehr.

[19] In der abschliessenden Umfrage, die nach Abschluss des Experiments durchgeführt wurde, wurde eine Reihe von Fragen gestellt, um die persönlichen Werte der Befragten zu eruieren.(Schwartz, 1992; De Groot and Steg, 2010). Mit dieser Methodik wurde den Befragten ein numerischer Wert entlang vier Dimensionen zugewiesen, die mit “altruistisch”, “egoistisch”, “hedonisch” und “biosphärisch” bezeichnet wurden. Es gab keine statistisch signifikanten Unterschiede entlang der anderen drei “Wertedimensionen”.

Selbst wenn der Nachweis, dass ein Pigou-Verkehrsbepreisungssystem funktioniert, erbracht ist, stellt dessen praktische Umsetzung eine Herausforderung dar, nicht nur in Bezug auf die Technologie und den Datenschutz, sondern auch in Bezug auf die soziale Akzeptanz. In der Einführungsumfrage haben wir drei Fragen gestellt, die die Präferenzen der Befragten hinsichtlich einer möglichen Einführung von Verkehrsbepreisung eruieren sollen. Um den Zweck des Experiments nicht zu verraten, waren diese Fragen Teil einer viel grösseren Batterie von Fragen. Die drei Fragen zielten auf das gleiche Konzept ab, waren aber unterschiedlich formuliert.

Eine Mehrheit der Befragten war entweder positiv oder neutral, wenn die Frage in Bezug auf die sozialen Kosten oder die Bepreisung von Externalitäten formuliert war (Abb. V. Wenn jedoch der Fokus auf die zeitlich variierende Natur dieser Bepreisung gelegt wurde (aber ohne Erwähnung sozialer Aspekte), war eine Mehrheit dagegen. Dies deutet darauf hin, dass die Bepreisung des Verkehrs prinzipiell eine politische Mehrheit finden könnte, dass es aber davon abhängt, wie über das Bepreisungssystem kommuniziert wird.

Abbildung V – Akzeptanz eines Transportpreissystems



Anmerkung: Die Abbildung zeigt den Zustimmungsgrad der Teilnehmer zu den folgenden Massnahmen, bzw. Aussagen: (i) Einführung von zeit- und streckenspezifischen Mobilitätspreisen, aufkommensneutral gestaltet durch Senkung anderer Steuern; (ii) der Preis für Mobilität sollte die sozialen Kosten widerspiegeln (z.B. Gesundheit, Umwelt, Stau); (iii) das Verkehrsnetz sollte durch Einführung von dynamischer Bepreisung effizienter genutzt werden.

Diskussion

Das MOBIS-Experiment untersuchte ein Verkehrsbepreisungssystem, das auf den sozialen Grenzkosten des Verkehrs basierte. Die externen Kosten waren am grössten für die Gesundheit, gefolgt von Stau- und Klimakosten. Die Bepreisung reduzierte alle Dimensionen der externen Kosten signifikant, aber sie war besonders effektiv bei der Reduzierung von Stau, sowohl in absoluten Zahlen als auch im Vergleich zur alleinigen Bereitstellung von Informationen. Die reine Informationsbehandlung hatte einen Effekt für Teilgruppen der Bevölkerung (z. B. Altruisten), war aber nicht statistisch signifikant für die Gesamtstichprobe. Die Verringerung der externen Kosten ist auf eine Kombination aus einer Verlagerung weg vom Auto hin zu anderen Verkehrsmitteln und hin zu Zeiten und möglicherweise Strecken mit geringerer Auslastung zurückzuführen. Der Effekt ist homogen über andere soziodemo-

graphische Merkmale wie Alter, Einkommen, Bildung oder Haushaltsgrösse, aber wir fanden einen signifikanten Unterschied zwischen den Geschlechtern und Sprachregionen. Die Elastizitätsschätzung ist vergleichbar mit Ergebnissen, die auf Mautpreisen basieren (Bain, 2019), aber niedriger als frühere Schätzungen, die auf Vorher-Nachher-Studien basieren (Leape, 2006; Nielsen, 2004). MOBIS ist die erste multimodale randomisierte kontrollierte Studie zur Bepreisung im Verkehrskontext und unterscheidet sich damit von unimodalen Ansätzen, bei denen das Fehlen von Preisen für alternative Verkehrsmittel zu einer Überschätzung der Effekte der Verkehrsverlagerung geführt haben könnte.

Autofahrer waren in dieser Studie überrepräsentiert. Da das Autofahren die grössten externen Kosten verursacht, kann die beobachtete kurzfristige Elastizität daher zu einer Überschätzung der Preiseffekte in der Allgemeinbevölkerung führen. Da das Bepreisungssystem im Experiment darin bestand, einem gegebenen Budget Geld zu entziehen, könnte ausserdem die Verlustaversion den Effekt im Vergleich zu einer Steuer erhöht haben (Tversky and Kahneman, 1991). Andererseits gibt es eine Reihe von Argumenten, die langfristig grössere Effekte erwarten lassen als in diesem 8-Wochen-Experiment. Bei einer dauerhaften Einführung von Verkehrsbepreisung würden zusätzliche Verhaltensanpassungen möglich, wie z.B. die Wahl des Arbeits- und Wohnortes, Änderungen der langfristigen Aktivitätsroutinen, der Besitz von Fahrzeugen/Abonnements oder Verhandlungen mit Arbeitgebern über Arbeitszeiten und -orte (z.B. Homeoffice). Darüber hinaus beschränkte sich die Verhaltensänderung auf Befragte, die das dem Experiment zugrunde liegende Konzept der externen Kosten verstanden haben. Während bei einer Kurzstudie zu erwarten ist, dass nicht jeder auf die “Regeln” achtet, würde eine allgemeine Einführung von Verkehrsbepreisung vermutlich eine grössere Resonanz haben.

Das MOBIS-Experiment zeigt, dass ein Pigou-Verkehrsbepreisungssystem in der Praxis funktioniert. Durch die multimodale Gestaltung ist das angewandte Bepreisungssystem nicht ausschliesslich eine Steuer für Autofahrer, wie manchmal argumentiert wird, sondern es bepreist die externen Kosten über alle Verkehrsträger hinweg in gleicher Weise.[20] Die erforderliche Technologie ist verfügbar, und eine Reihe von Ländern hat die externen Kosten des Verkehrs innerhalb ihrer Grenzen berechnet. Die COVID-19-Pandemie hat gezeigt, dass die Lebens-, Arbeits- und Reisemuster veränderbar sind. Es scheint gerechtfertigt zu erwarten, dass die Menschen auf die Preisanreize in ähnlicher, wenn auch weniger dramatischer Weise reagieren werden. Darüber hinaus ist eine Abkehr vom derzeitigen Finanzierungsmechanismus für den Verkehr, der sich hauptsächlich auf Treibstoffsteuern stützt, aufgrund von Verschiebungen bei den Verkehrsträgern, Treibstoffarten und Fahrzeugtechnologien unvermeidlich. Pigou-Verkehrsbepreisung ist ein alternativer Finanzierungsmechanismus, der auch mit einer grossen Elektrofahrzeugflotte implementiert werden kann.

Ein Pigou-Transportpreissystem, wie es im MOBIS-Experiment verwendet wurde, würde bei der praktischen Umsetzung vor einer Reihe von Herausforderungen stehen, darunter Bedenken hinsichtlich des Datenschutzes, der sozialen Akzeptanz und der technischen Beschränkungen bei der Erhebung des Preises auf Echtzeitbasis. Allerdings sollte sich auch ein vereinfachtes Preissystem an den externen Grenzkosten des Verkehrs orientieren, um die Effizienz des Verkehrssystems zu erhöhen. Eine zentrale Herausforderung wird darin bestehen, sich innerhalb des politischen Prozesses auf die Preisgestaltung (z.B. den Wert der Zeit oder die sozialen Kosten des Kohlenstoffs) zu einigen. Darüber hinaus ist bekannt, dass Kraftstoffsteuern regressiv sind, so dass die Verteilungsaspekte eines kostenbasierten Preissystems weiter untersucht werden sollten. Die Bemühungen, ein solches System voranzutreiben, müssen durch zusätzliche Massnahmen ergänzt werden, um negativen Verteilungsimplikationen entgegenzuwirken. Prinzipiell könnte jedoch eine Pigou-Bepreisung des Verkehrs zumindest in der Schweiz politisch umsetzbar sein.

Eine multimodale Bepreisung des Verkehrs auf der Basis der externen Kosten des Ver-

[20] Wir betonen, dass es sich bei dem System nicht um ein Durchschnittskostenpreissystem handelt, da es alle Fixkosten wie die Kosten für die Infrastruktur des öffentlichen Verkehrs (die in der Schweiz stark subventioniert werden) oder alle generalisierten Kosten des Strassennetzes, die nicht durch die Mineralölsteuer abgedeckt sind, ausschliesst. Während die Fixkosten für die Planung des Ausbaus des Verkehrsnetzes wichtig sind, sind sie für die Reiseentscheidung der einzelnen Nutzer zu einem bestimmten Zeitpunkt nicht relevant.

kehrs ist machbar und hat den gewünschten Effekt der Verlagerung von Verkehrsträgern, der Verschiebung von Abfahrtszeiten und der Änderung von Routen. Es führt somit zu einer effizienteren Nutzung des Verkehrssystems und zu einer Verringerung des Bedarfs am Netzausbau. Wenn es gerecht umgesetzt wird, könnte die Bepreisung des Verkehrs ein wichtiger Pfeiler einer nachhaltigen Verkehrspolitik werden.

Résumé exécutif – Français

Les systèmes de transport sont confrontés à de nombreux défis. En raison de la croissance démographique et de l'augmentation de la mobilité en général, les réseaux de transport atteignent leurs limites de capacité (ARE, 2016). Les embouteillages routiers qui en résultent entraînent des pertes de temps considérables pour les conducteurs : en 2017, les coûts du temps perdu dans les embouteillages en Suisse a été chiffré à 1 420 millions CHF (ARE, 2019). La Suisse a fortement investi dans son réseau routier et ferroviaire pour répondre à la demande croissante en matière de transport. Cependant, l'augmentation de la capacité des transports privés et publics est coûteuse et se heurte à des limites physiques. En outre, du fait qu'elle conduirait également à une augmentation de la demande, une croissance de la capacité du réseau routier n'aurait qu'un faible effet à long terme sur la congestion (Duranton and Turner, 2011).

Le secteur des transports est également l'un des principaux responsables de la pollution atmosphérique locale et des émissions de gaz à effet de serre. Alors que des progrès importants ont été réalisés dans les secteurs de l'industrie, des services et des ménages, les émissions du secteur des transports sont restées plus ou moins constantes, les gains d'efficacité ayant été neutralisés par une augmentation des distances parcourues (IEA, 2020). En Suisse, les émissions de CO_2 du secteur des transports étaient en 2019 au même niveau qu'en 1990.[21] Les coûts de santé liés à la pollution atmosphérique imputables au trafic routier s'élèvent à 2 200 millions CHF par an (Federal Office for Spatial Development, 2020).

Les embouteillages, les effets néfastes du changement climatique et des émissions polluantes sur la santé ont tous quelque chose en commun : ils représentent des externalités, c'est-à-dire des *coûts externes des transports*. Alors que l'utilisateur paie les coûts internes des transports, reflétés dans les prix du carburant, des titres de transport, de l'achat et de l'entretien des véhicules, entre autres, les coûts externes sont supportés par "les autres", c'est-à-dire par la société dans son ensemble. Ainsi, les coûts externes n'influencent généralement pas les décisions concernant le lieu, le moment et le mode de déplacement. Il en résulte une défaillance du marché nécessitant des interventions politiques, au-delà du cadre réglementaire existant.

Jusqu'à présent, des politiques de réglementation, telles que les limites de vitesse et d'émissions ou les inspections obligatoires de véhicules, ont été adoptées pour réduire les coûts externes des transports. Toutefois, une tarification des transports reflétant les coûts externes, ou "réels", constitue en théorie un moyen de régulation plus efficace, car elle permet aux individus de maintenir les déplacements à forte utilité tout en réduisant ceux qu'ils considèrent comme moins importants. Si le prix de chaque déplacement reflète l'intégralité des coûts et bénéfices marginaux et que les individus sont totalement rationnels et parfaitement informés, un niveau optimal en terme d'embouteillages et de pollution sera atteint.[22] Une tarification basée sur l'intégralité des coûts marginaux du transport favorise une utilisation plus efficace du système de transport existant et réduit donc, entre autres, la nécessité d'étendre le réseau.

Les taxes sur les carburants, les péages routiers et les droits d'immatriculation sont des exemples traditionnels de mesures tarifaires dans le secteur des transports. Cependant, ces mesures sont souvent motivées par le recouvrement des coûts de construction routière plutôt que par l'optimisation du comportement des voyageurs. Ainsi, ils ne reflètent généralement pas l'intégralité des coûts externes des transports (Parry and Small, 2005). Une exception est la redevance sur le trafic des poids lourds en Suisse, qui est explicitement motivée par l'internalisation des coûts externes du transport de marchandises, notamment en ce qui concerne les impacts sur l'écosystème alpin. Des systèmes de péage urbain ont

[21] Les émissions imputables au secteur des transports en Suisse (excluant l'aviation internationale) étaient de 14,9 et 15,0 millions de tonnes d'équivalents CO_2 en 1990 et 2019, respectivement. Voir `https://www.bfs.admin.ch/bfs/fr/home/statistiques/espace-environnement/indicateurs-lies-au-climat/influences-humaines.html`.

[22] Du point de vue de la société, le niveau optimal de pollution n'est généralement pas nul, mais plutôt défini par le niveau auquel le coût marginal de la réduction est égal aux bénéfices marginaux de cette réduction.

récemment été introduits dans un nombre croissant de villes autour du monde. Ces systèmes sont efficaces pour réduire les embouteillages et permettent d'internaliser, au moins partiellement, les coûts externes liés à la circulation automobile en milieu urbain (Small, 2008). Toutefois, étant donné que les prix sont fixes, ces systèmes ne tiennent pas compte des variations temporelles des embouteillages et ignorent les autres coûts externes associés à la conduite automobile et aux autres modes de transport.

En Suisse, les études antérieures sur la tarification des transports se limitent à des enquêtes et à des études de modélisation (par exemple, Vrtic *et al.*, 2010; INFRAS, 2019). Les études empiriques sur la tarification des transports, par exemple à Singapour (Agarwal and Koo, 2016), Londres (Leape, 2006) ou Stockholm (Eliasson *et al.*, 2009), calculent les effets globaux ou agrégés des systèmes de péage urbain. En revanche, les enquêtes de terrain se focalisant sur le comportement de déplacement individuel permettent de tenir compte des caractéristiques individuelles, ce qui permet des analyses plus détaillées et plus robustes.

Par exemple, dans le cadre d'études menées au Danemark et en Australie, des récepteurs GPS ont été installés dans des véhicules et les conducteurs ont ensuite été exposés à différents systèmes de tarification aux heures de pointe et aux heures creuses (Nielsen, 2004; Martin and Thornton, 2017b). Ces deux études font état d'une réduction du nombre de déplacements en voiture aux heures de pointe. À Singapour, les pendulaires ont réagi à une récompense financière en décalant leur heure de départ dans les transports publics (Pluntke and Prabhakar, 2013). Ces études antérieures étaient axées sur un seul mode de transport et ne pouvaient donc pas identifier les effets de la tarification sur le choix du mode de transport (c'est-à-dire les transferts modaux), bien que l'on s'attende à ce que la tarification affecte le comportement en matière de déplacement pour tous les modes (voiture, transports publics et modes non motorisés) (Tirachini and Hensher, 2012). Dans l'étude "Spitsmijden" menée aux Pays-Bas, les pendulaires ont réagi à des récompenses financières et à des avantages en nature en reportant l'heure de leur départ, en optant pour d'autres modes de transport et en travaillant à domicile (Ben-Elia and Ettema, 2011b). La seule étude antérieure à grande échelle menée dans le secteur des transports et comprenant un groupe de contrôle est un essai randomisé contrôlé qui n'a constaté aucun effet d'un traitement purement informationnel (c'est-à-dire sans incitatif financier) sur le comportement en matière de covoiturage et de déplacements pendulaires parmi les employés de cinq grands entreprises (Kristal and Whillans, 2020).

Ce résumé décrit les résultats du projet de recherche "Comportement en matière de mobilité en Suisse" (MOBIS), qui consiste en un essai randomisé contrôlé (ERC) simulant la tarification "pigovienne" des transports (également connu sous le nom de système "pollueur-payeur"), basée sur les coûts externes des transports.[23] Les coûts externes marginaux liés aux embouteillages, au changement climatique et à la santé ont été entièrement internalisés dans le système de tarification des transports utilisé dans le cadre de cette étude. Les déplacements des participants à l'étude ont été enregistrés au moyen d'une application smartphone et les coûts externes associés ont été calculés. La tarification des transports a été appliquée en fournissant un budget de transport à un tiers des participants, duquel ont été soustraits les coûts externes occasionnés par leurs déplacements. Afin de reproduire l'incitation financière de la tarification pigovienne des transports, les participants ont pu conserver les éventuelles économies résultant du changement de leur comportement de déplacement. Pour différencier l'effet du prix de celui de l'information pure, ou d'autres facteurs confondants, l'étude comprenait un deuxième groupe de traitement, dans lequel les participants recevaient les mêmes informations sur les coûts externes des transport que le groupe de tarification, mais sans devoir payer, ainsi qu'un groupe de contrôle. L'expérience a révélé une élasticité de -0,31 pour les coûts externes totaux associés au traitement par tarification. Autrement dit, une augmentation moyenne des coûts de transport de 10% due à l'introduction d'un système de tarification des transports basé sur les coûts externes en-

[23] Ce terme est dû à Arthur Pigou, qui a été le premier à formuler le concept d'internalisation des coûts externes associés à une activité en imposant le dommage social marginal sous forme de taxe corrective (Pigou, 1920). La taxe pigovienne est un concept standard en économie et est souvent appelée le principe du "pollueur-payeur".

traînerait une réduction des coûts externes des transports de 3,1%. L'étude MOBIS a été menée conjointement par des chercheurs de l'École polytechnique fédérale de Zurich, de l'Université de Bâle et de la Haute école des sciences appliquées de Zurich et a été soutenue par l'Office Fédéral des Routes (OFROU), l'Office Fédéral des Transports (OFT) et Innosuisse. À notre connaissance, l'étude MOBIS est le premier exemple d'un essai randomisé contrôlé multimodal d'une intervention de tarification pigovienne des transports.

L'étude MOBIS

L'étude MOBIS visait à évaluer l'efficacité de mesures d'information et de tarification des transports à changer le comportement d'invidus en faveur de modalités de déplacement plus optimisées et plus durables. L'échantillon de l'étude a été recruté parmi les habitants des agglomérations urbaines de Suisse alémanique et romande, dont les adresses ont été fournies par l'Office fédéral de la statistique, qui tient un registre complet des habitants, ainsi que par un vendeur privé.

21 800 participants ont répondu à l'enquête initiale de triage, qui contenait des questions sur le comportement de déplacement, les données sociodémographiques et un certain nombre de questions relatives à la politique des transports. Les participants éventuels à l'expérience devaient remplir un certain nombre de critères d'inclusion, tels que l'utilisation d'une voiture au moins deux jours par semaine et être âgés de 18 à 65 ans.

À partir de cette enquête initiale, plus de 4 000 participants ont été recrutés pour participer à l'expérience de tarification des transports, bien qu'au moment du recrutement, ni la nature de l'étude ni le fait qu'ils faisaient partie d'une expérience ne leur ont été révélés. Les participants à l'étude ont accepté de télécharger une application de suivi sur leur smartphone et de laisser suivre leurs déplacements quotidiens sur une période de 8 semaines. En échange de leur participation à l'ensemble de l'étude, ils ont reçu 100 CHF. 3 656 participants ont complété l'étude, et la quasi-totalité d'entre eux ont également répondu à l'enquête finale. L'échantillon de l'étude MOBIS diffère de celui de la population suisse en raison de la restriction d'âge et de l'accent mis sur les conducteurs automobiles, mais il reste assez similaire car l'échantillon de l'enquête initiale est tiré d'un groupe d'étude représentatif.

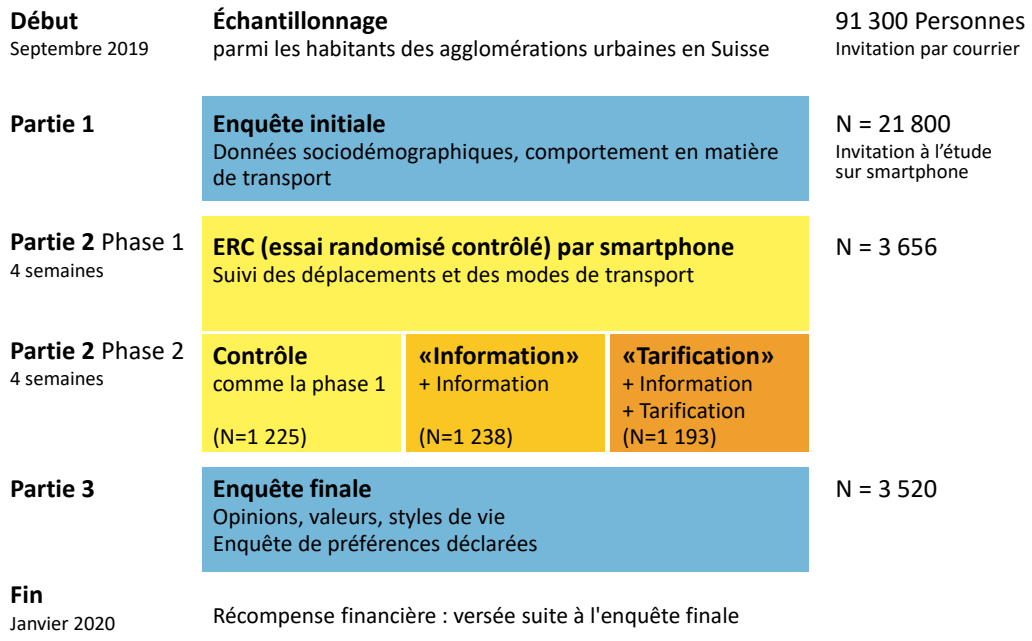
La figure I donne un aperçu du déroulement de l'étude. Le recrutement a eu lieu de manière continue entre août et novembre 2019. Une fois qu'un participant enregistrait un premier trajet, il était automatiquement intégré à l'échantillon. L'étude consistait en 4 semaines d'observation pour tous les participants, suivies de 4 autres semaines de traitement (ou d'observation continue pour le groupe de contrôle). L'affectation aux groupes a été effectuée de manière totalement aléatoire.

L'application a enregistré chaque déplacement et a attribué le mode de transport en fonction de l'itinéraire, de la vitesse et des profils d'accélération. La précision globale de la détection du mode de transport était de plus de 90%. Les participants ont pu revoir et corriger manuellement l'affectation des modes de transport. Pour chaque trajet, les coûts externes ont été calculés et chiffrés sur la base de coefficients de coût publiés par l'Office fédéral du développement territorial (ARE).

Pendant la période d'observation, les participants ont reçu un résumé hebdomadaire de leurs déplacements par mode de transport, comprenant la durée, la distance et le nombre de déplacements. Le groupe de contrôle a continué à recevoir uniquement ces informations jusqu'à la fin de l'étude.

Le 29^{e} jour de l'étude, les participants assignés au groupe d'information ont reçu un e-mail les informant des coûts externes des transport, de la manière dont ils sont calculés et monétisés, et de la façon dont ils peuvent être réduits. Une fois par semaine, ces participants ont reçu un résumé des coûts externes qu'ils avaient générés au cours de la semaine précédente. Les coûts externes étaient présentés par mode de transport et par catégorie de coûts, comme la santé, le climat et les embouteillages. Les participants affectés au groupe de tarification ont reçu les mêmes informations sur les coûts externes, mais ont en plus

FIGURE I – Aperçu de l'étude MOBIS



reçu un budget duquel étaient déduits leurs coûts externes de transport. Ces participants ont été informés qu'à partir de ce moment, ce budget serait utilisé pour payer les coûts externes causés par leurs déplacements, mais que tout montant restant sur leur compte à la fin de l'étude leur serait versé. Ces budgets individualisés ont été calculés sur la base des coûts externes de chaque participant pendant la période d'observation, plus une marge de 20%.[24] Ce traitement a donc simulé une tarification des transports basée sur les coûts externes marginaux.

L'effet de traitement moyen est calculé en comparant les participants des deux groupes de traitement avec les participants du groupe de contrôle qui ont commencé l'expérience le même jour. L'inclusion d'un groupe de contrôle a permis de contrôler les variations saisonnières et d'autres facteurs temporels qui pourraient influencer la génération des coûts externes des transport et ainsi biaiser les résultats. L'étude s'est achevée juste avant le début de la pandémie de Covid-19 en mars 2020. [25]

Calcul des coûts externes des transport

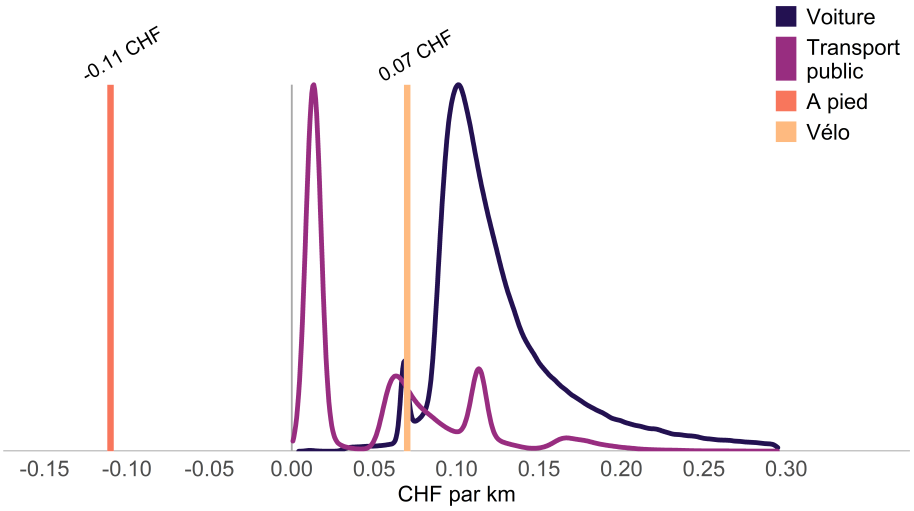
Les coûts externes des transport liés à la santé, aux émissions de CO_2 et aux embouteillages ont été calculés, pour les déplacements quotidiens enregistrés, à l'aide d'un processus de traitement des données automatisé. Pour calculer les coûts externes dus aux embouteillages et aux émissions, les données GPS ont été projetées sur le réseau routier suisse (Karich and Schröder, 2014) et traitées à l'aide de modules développés sur la base du modèle de transport MATSim (Horni *et al.*, 2016a). Les facteurs d'émissions de polluants atmosphériques utilisés dans le module d'émissions de MATSim proviennent de la version 3.3 du Handbook Emission Factors for Road Transport (HBEFA). Les pertes de

[24] Le budget moyen était de 144 CHF, mais dépassait 700 CHF pour certains participants.

[25] Environ un tiers des participants ont accepté de reprendre le suivi, dans le cadre d'un effort visant à étudier les comportements de mobilité en réponse aux politiques d'endiguement de la pandémie. Les résultats préliminaires de cette étude en cours sont présentés dans Molloy *et al.* (2020).

temps dues aux embouteillages ont été estimées à l'aide d'une méthodologie de coût marginal moyen tenant compte de la formation et propagation des embouteillages à travers le réseau routier (Kaddoura, 2015) et monétisées à l'aide de coefficients standards utilisés par le gouvernement suisse (Federal Roads Office - ASTRA, 2017).

FIGURE II – Distribution des coûts externes par personne-kilomètre utilisés dans l'étude MOBIS



Des valeurs standard par kilomètre ont été utilisées pour calculer les effets sur la santé des transports actifs (c'est-à-dire la marche et le vélo). Les effets sur la santé comprennent les coûts des accidents, dont la plupart sont externes aux personnes blessées en raison de la couverture par le système de santé suisse, mais aussi la partie externe des bienfaits pour la santé sous la forme d'une réduction des risques de mortalité et de morbidité résultant de l'activité physique. Alors que la marche à pied est associée à des bénéfices externes nets, les coûts externes des accidents l'emportent sur les bienfaits externes du vélo pour la santé selon les estimations actuelles. Par conséquent, le vélo a été associé à de faibles coûts externes nets dans le cadre de cette étude.[26]

Les coûts externes des transports publics (TP) ont été calculés sur la base de taux d'émissions polluantes par kilomètre. Les externalités liées au bruit n'ont pas été prises en compte car les valeurs de référence n'étaient pas disponibles. Afin d'estimer les coûts liés à une forte affluence dans les transports publics, un système de tarification par zone aux heures de pointe a été mis au point pour le réseau national de transports publics. Tout au long de l'expérience, les participants des deux groupes de traitement ont eu accès à une carte interactive qui leur indiquait où et quand la surtaxe pour les transports publics était appliquée.[27]

La figure II montre la distribution des coûts externes monétisés, par personne-kilomètre, pour chaque mode de transport. Alors que les valeurs par kilomètre pour les transports actifs sont fixes, les coûts externes liés auxs transports publics et à la conduite automobile dépendent respectivement du niveau d'affluence et des embouteillages et varient donc dans le temps et l'espace. Les distributions présentées sont celles qui ont été appliquées aux déplacements observés lors de l'expérience.

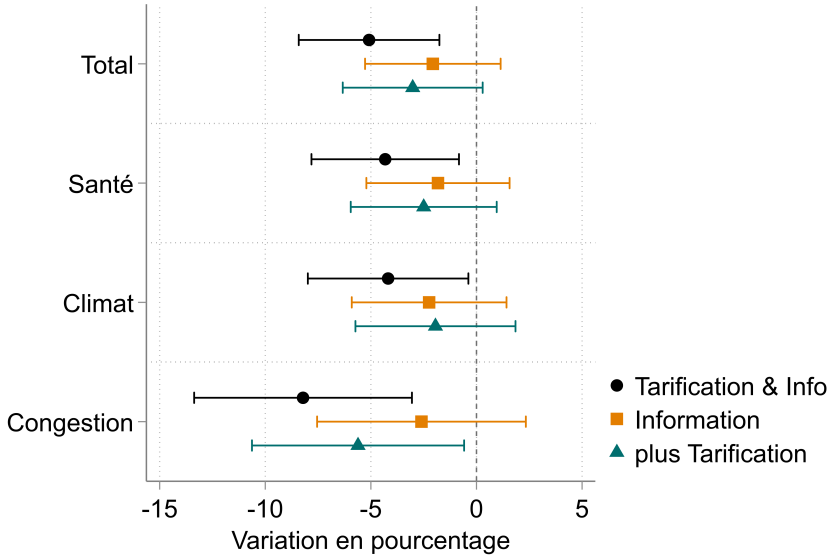
[26] La plupart des effets positifs sur la santé se traduisent par une diminution des risques de morbidité et de mortalité, qui sont des avantages privés (et donc non externes).

[27] Une surtaxe de 0,10 CHF/km a été appliqué aux trajets en transport public entre les zones où la demande est plus importante en heures de pointe qu'en heures creuses.

Résultats

La figure III montre l'effet de traitement moyen observé dans l'étude MOBIS. La tarification des transports, telle que mise en œuvre dans l'étude MOBIS (c'est-à-dire tarification + information), a réduit de manière significative les coûts externes des transport dans leur ensemble ainsi que pour chacune des trois catégories de coûts : santé, climat et congestion. Les participants appartenant au groupe de tarification ont réduit en moyenne leurs coûts externes de transport de 5,1 % par rapport au groupe de contrôle. Cet effet est statistiquement très significatif ($p<0,01$) et correspond à une élasticité de -0,31.[28] Les estimations ponctuelles pour le groupe d'information suggèrent seulement qu'il pourrait y avoir un effet d'information sans tarification, mais que celui-ci est plus faible et statistiquement non significatif.

FIGURE III – Effet du traitement sur les coûts externes des transport



Remarque : La figure montre l'effet de traitement moyen pour l'ensemble des déplacements dans le groupe de *tarification* et d'*information*, par rapport au groupe de *contrôle* (trait en pointillé au point 0). Les barres vertes indiquent l'effet de causalité de l'ajout de la tarification aux informations sur les coûts externes des transport. Les barres indiquent les intervalles de confiance à 95 %.

La figure montre également l'effet différentiel entre les deux traitements, qui est l'effet de causalité de l'ajout de la tarification aux informations sur les coûts externes des transport. Cette interprétation est possible car le contenu informationnel des deux traitements était le même. L'effet est statistiquement significatif pour la congestion, mais ne l'est pas pour les coûts climatiques et de santé.

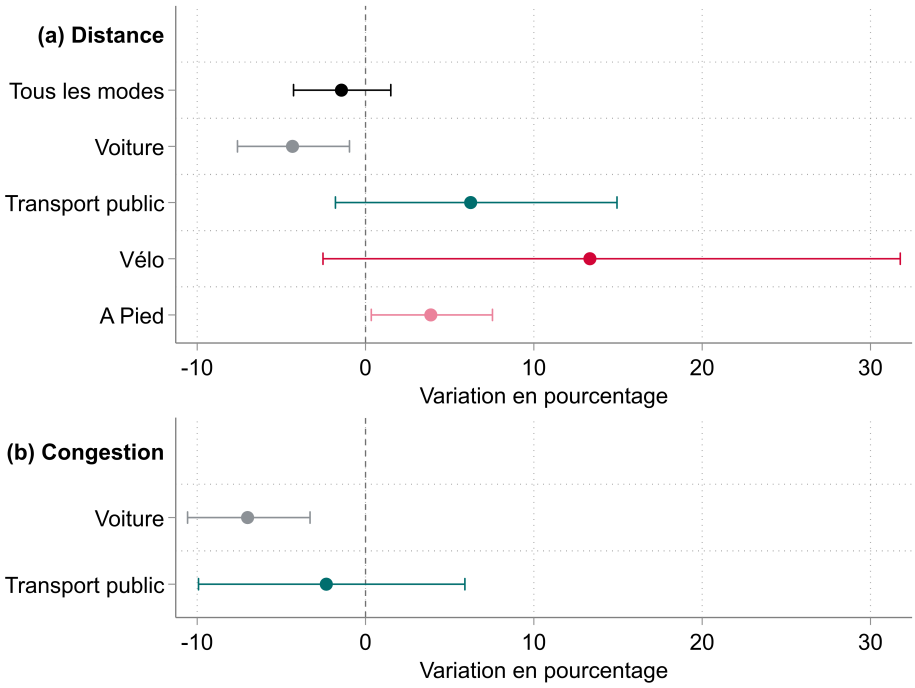
L'effet de la tarification pigovienne des transports est relativement homogène au sein de l'échantillon par rapport aux caractéristiques sociodémographiques les plus importantes telles que l'âge, le revenu, le niveau d'éducation, etc. Il existe deux exceptions : l'effet du traitement était plus fort pour les hommes que pour les femmes, et il n'était pas statistiquement significatif pour les participants francophones. Toutefois, il s'agit ici de variables latentes et ces différences pourraient donc être dues à des variables non observées (par exemple, le fait de s'occuper des enfants ou d'occuper certains emplois) ou à des considérations méthodologiques, par exemple la façon dont les informations ont été traduites dans les différentes langues.

En outre, nous constatons que l'effet est attribuable aux participants ayant correctement cerné la définition des *coûts externes des transport*. Cette définition leur avait été expliquée

[28] En tenant compte des coûts externes des transport, les coûts totaux augmentent de 16,4 %, de sorte que l'élasticité résultante est de (-5,1/16,4 =) -0,31.

au début de la phase de traitement. Une question à ce sujet leur a été posée dans l'enquête finale afin de tenir compte des différences en matière de lecture des consignes ou de connaissances préalables. Ceux qui ont répondu correctement ont réagi fortement au traitement par tarification, tandis que ceux ayant choisi une réponse incorrecte n'ont pas du tout réagi à la tarification. Cela indique qu'une compréhension conceptuelle du système de tarification, ou de sa justification, est essentielle pour son bon fonctionnement.

FIGURE IV – Mécanismes sous-jacents à la réduction des coûts externes



Remarque : Les barres indiquent les intervalles de confiance à 95 %. Le panneau (a) montre l'effet de traitement moyen de la tarification sur la distance quotidienne, globalement et par mode. Le panneau (b) montre l'effet sur la congestion, c'est-à-dire sur les embouteillages (voitures) et le niveau d'affluence (transports publics).

Bien que l'effet du traitement uniquement informatif ne soit pas statistiquement significatif pour l'ensemble de l'échantillon, certains sous-groupes ont répondu au traitement informatif, bien que dans une moindre mesure qu'au traitement par tarification. Ces sous-groupes comprennent les hommes et les participants qui ont obtenu un résultat élevé sur une échelle d'altruisme.[29] Cela implique qu'une intervention uniquement informative aurait un effet au moins pour une partie de la population.

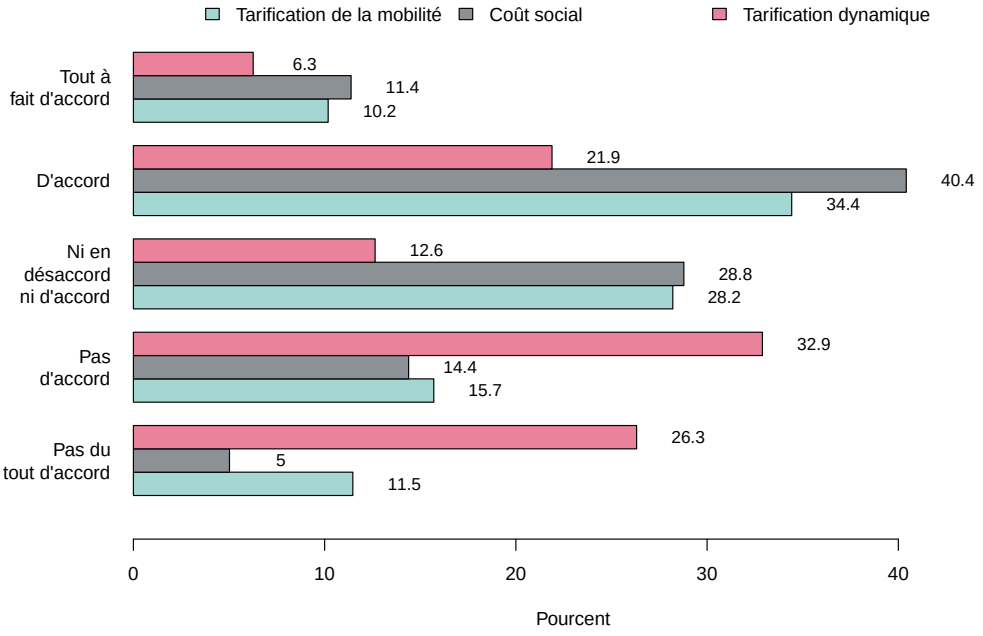
Plusieurs moyens permettent de réduire les coûts externes des transports. La tarification n'a pas réduit de manière significative les distances de déplacement journalières totales, mais on observe une réduction significative des distances journalières en voiture, contrebalancée par une augmentation des distance en transports publics, à vélo et à pied (Fig. IVa). Cet effet se manifeste à la fois sur la distance moyenne parcourue lors des jours où des déplacements ont effectivement eu lieu (marge intensive) ainsi que sur la probabilité de se déplacer (marge extensive). Par exemple, la réduction de la distance moyenne en voiture est une combinaison de distances parcourues plus courtes et d'une probabilité plus faible d'utiliser la voiture en premier lieu.

[29]Dans l'enquête finale réalisée à la fin de l'expérience, une série de questions a été posée afin de déterminer les valeurs personnelles des participants (Schwartz, 1992; De Groot and Steg, 2010). Grâce à cette méthodologie, les participants se sont vu attribuer une valeur numérique selon quatre dimensions : altruiste, égoïste, hédonique et biosphérique. Aucune différence statistiquement significative n'a été constatée pour les trois autres dimensions de valeur.

La tarification a également réduit de manière significative les coûts liés aux embouteillages par kilomètre parcouru en voiture, ce qui implique que le transfert modal n'est pas le seul mécanisme responsable de la réduction des coûts externes (Fig. IVb). Un décalage significatif des heures de départ pour les déplacements en voiture a été constaté à l'heure de pointe du matin, mais pas en soirée. En revanche, il n'y a pas eu de réduction de l'affluence ni de décalage des heures de départ pour les transports publics.

Même si la tarification pigovienne des transports fonctionne, sa mise en œuvre pourrait connaître des difficultés non seulement en termes de technologie et de confidentialité des données, mais aussi en termes d'acceptabilité sociale. Dans l'enquête initiale, trois questions ont été posées afin de connaître les opinions des participants sur une éventuelle introduction de la tarification des transports. Afin de ne pas révéler l'objectif de l'étude, elles faisaient partie d'un nombre beaucoup plus important de questions posées aux participants. Ces trois questions portaient sur le même concept mais étaient formulées différemment.

FIGURE V – Appui à la tarification des transports



Remarque : La figure montre le niveau de soutien des participants aux politiques et déclarations suivantes : (i) introduction d'une tarification de la mobilité en fonction du temps et de l'itinéraire, rendue neutre en termes de revenus en réduisant les autres taxes ; (ii) le prix de la mobilité devrait refléter le coût social (par exemple, la santé, l'environnement, la congestion) ; (iii) le réseau de transport devrait être utilisé plus efficacement en introduisant une tarification dynamique.

Lorsque la question était formulée en termes de coûts sociaux ou de tarification des externalités, une majorité de participants y était favorable ou neutre (Fig. V). Cependant, si l'accent était mis sur la variabilité temporelle de cette tarification (sans mention des aspects sociaux), une majorité y était opposée. La tarification des transports pourrait donc en principe trouver une majorité politique, mais cela dépendra de la manière dont le système de tarification est communiqué.

Discussion

L'étude MOBIS a mis en place un système de tarification des transports basé sur les coûts sociaux marginaux des transports. Les coûts externes étaient les plus élevés pour la santé, suivis des coûts de congestion et des coûts climatiques. La tarification a permis de réduire les coûts externes de chaque catégorie de manière significative, mais elle a été particulière-

ment efficace pour réduire la congestion, à la fois en valeur absolue et en comparaison avec l'information seule. Le traitement purement informatif a eu un effet sur des sous-groupes de la population (comme les altruistes), mais n'était pas statistiquement significatif à l'échelle de l'échantillon dans son ensemble. La réduction des coûts externes est due à une combinaison de l'abandon de la voiture au profit d'autres modes de transport et de l'adoption d'horaires et d'itinéraires moins congestionnés. L'effet est plutôt homogène en fonction des caractéristiques socio-démographiques telles que l'âge, le revenu, l'éducation ou la taille du ménage, mais une différence significative a été constatée entre les sexes et les régions linguistiques. La valeur estimée de l'élasticité est comparable aux résultats basés sur des péages routiers (Bain, 2019), mais inférieure aux estimations antérieures basées sur des études avant-après (Leape, 2006; Nielsen, 2004). L'étude MOBIS est le premier ERC multimodal sur la tarification dans un contexte de transport et diffère donc des systèmes de tarification unimodaux, où l'absence de tarification pour les modes alternatifs pourrait amplifier les effets de transfert modal.

À dessein, les conducteurs ont été surreprésentés dans cette étude. Étant donné que la conduite automobile engendre les coûts externes les plus importants, l'élasticité à court terme observée pourrait donc surestimer les effets de la tarification auprès de l'ensemble de la population. De plus, étant donné que le système de tarification utilisé dans l'expérience consistait à retirer de l'argent d'un budget donné plutôt qu'une taxe, l'effet observé pourrait être amplifié en raison de l'aversion à la perte (Tversky and Kahneman, 1991). Cela dit, plusieurs arguments portent à croire que les effets à long terme seront plus importants que ceux de cet essai de huit semaines. Avec l'introduction définitive d'un système de tarification des transports, des mesures de réaction supplémentaires seraient disponibles à la population, telles que le choix du lieu de travail et de domicile, les changements dans les habitudes de vie à long terme, la possession d'un véhicule ou d'un abonnement aux transports publics ou encore la négociation avec l'employeur des horaires et du lieu de travail. Par ailleurs, la réponse comportementale observée dans l'étude était limitée aux personnes ayant compris le concept de coûts externes sous-jacent à l'expérience. Alors qu'on peut s'attendre à ce que certains ne prêtent pas attention aux "règles" dans le cadre d'une étude de courte durée, une introduction de la tarification des transports à grande échelle aurait vraisemblablement un impact plus important.

L'étude MOBIS montre que la tarification pigovienne des transports fonctionne en pratique. Par son caractère multimodal, le système de tarification appliqué ne vise pas exclusivement les conducteurs, comme parfois avancé, mais tarifie équitablement les coûts externes pour tous les modes de transport.[30] La technologie nécessaire est disponible, et plusieurs pays ont déjà chiffré les coûts externes des transports à l'intérieur de leurs frontières. La pandémie de Covid-19 a démontré que les habitudes de vie, de travail et de déplacement sont susceptibles de changer et il semble légitime de s'attendre à ce que les gens réagissent aux incitations tarifaires de la même manière, bien que de façon moins spectaculaire. En outre, le passage du mécanisme actuel de financement des transports, qui repose principalement sur les taxes sur les carburants, à un autre mécanisme alternatif est inévitable en raison de l'évolution des modes de transport, des types de carburants et des technologies des véhicules. La tarification pigovienne des transports est un mécanisme de financement alternatif qui peut également être mis en œuvre en présence d'un parc de véhicules électriques important.

Un système de tarification pigovienne des transports tel qu'utilisé dans l'étude MOBIS se heurterait à un certain nombre de difficultés lors de sa mise en œuvre pratique, notamment des problèmes de confidentialité, d'acceptabilité sociale et des contraintes techniques liées au calcul de la taxe en temps réel (Verhoef, 2000). Cela dit, même un système de tarification simplifié devrait être guidé par les coûts externes marginaux du transport afin d'accroître l'efficacité du système de transport. L'un des principaux défis consistera à s'entendre sur

[30] Nous insistons sur le fait qu'il ne s'agit pas d'un système de tarification des coûts moyens, car tous les coûts fixes, tels que les coûts d'infrastructure des transports publics (qui sont fortement subventionnés en Suisse) ou les coûts généralisés du réseau routier non couverts par la taxe sur les carburants, sont exclus. Alors que les coûts fixes sont importants pour planifier l'expansion du réseau de transport, ils ne sont pas pertinents pour les décisions de déplacement ponctuelles des individus dans le temps.

les prix à fixer (par exemple, la valeur du temps ou le coût social du carbone) dans le cadre du processus politique. En outre, il est bien connu que les taxes sur les carburants sont régressives (Eidgenössisches Finanzdepartement (EFD), 2013; ECOPLAN, 2012; ECOPLAN, EPFL & FHNW, 2019), et les aspects de répartition d'un système de tarification basé sur les coûts externes méritent donc d'être étudiés davantage. Les efforts déployés pour faire progresser un tel système devront donc être complétés par des mesures auxiliaires visant à contrecarrer les conséquences négatives sur la répartition des richesses. En principe, nous pensons toutefois que la tarification pigovienne des transports pourrait être politiquement réalisable, du moins en Suisse.

La tarification multimodale du transport basée sur les coûts externes est réalisable et entraîne les effets souhaités quant au transfert modal, au décalage des heures de départ et le changement des itinéraires, menant ainsi à une utilisation plus efficace du système de transport et à une réduction de la nécessité d'étendre les réseaux. Appliquée de manière équitable, la tarification des transports pourrait devenir un pilier essentiel de la politique de transport durable.

1 Introduction

Transportation systems face tremendous challenges going forward. Road congestion and capacity limits of public transportation, especially during rush hour in major agglomerations, are common concerns in many countries worldwide. Climate change calls for a reduction in transportation-related carbon emissions. Transportation funding, heavily dependent on gasoline tax, will need to be reshaped due to shifts in fuel types and vehicle technologies.

Various transport policies aim to address these and other problems related to urban transport through change in mobility behavior (in contrast to e.g. capacity increases). Economic incentives (e.g. road pricing or congestion fees) and information-based measures (e.g. feedback, or educational campaigns) are two distinct approaches to induce behavioral change.

Information-based measures target the knowledge and motivation of consumers. On the one hand, they aim to educate them about better choices (e.g. alternative routes) or undesired consequences (e.g. environmental impacts) and on the other, they try to persuade or nudge them towards making better choices. Thereby they may appeal to both selfish and altruistic notions. However, there are concerns that such “soft” measures will not yield sufficient, lasting effects on key aspects of today’s most pressing urban transport issues, such as for example congestion or greenhouse gas emissions.

In contrast, economic incentives increase the cost of undesirable behavior (e.g. driving during rush hour) and thus directly appeal to consumers’ financial considerations. In the context of transportation, such financial incentives are generally referred to as transport pricing. If this pricing is based on the full social marginal costs, it is efficient in a “Pigovian” sense. Even if transport pricing departs from the first-best level, it is nevertheless a highly flexible instrument as prices can be adjusted according to scarcity (i.e., the level of congestion) or some desired effect on demand (e.g., carbon emission reduction goals).

The technical feasibility of transport pricing, and in particular the idea of dynamic pricing dependent of time and location, has made great strides thanks to technical progress, high penetration of mobile devices and advances in the collection and handling of location data (e.g. GPS tracking data). For these reasons, transport pricing has attracted the interest of policy makers as a potential solution to problems as diverse as congestion and related capacity limits of transport infrastructure; achieving sustainability goals through shifts to cleaner fuels and more sustainable transport modes; as well as reshaping the transportation funding system threatened by declining gasoline tax revenues. At the same time, transport pricing has stirred political headwinds out of opposition to "increasing taxes on drivers" and concerns about data confidentiality and equity, among others.

1.1 The MOBIS study

The main aim of the Mobility Behavior in Switzerland (MOBIS)[31] study was to investigate the effectiveness of Pigovian transport pricing (i.e., time- and location-based pricing based on the social marginal costs of transport) with regards to changing mobility behavior in large Swiss agglomerations. The effectiveness of transport pricing was investigated as part of a randomized experiment and compared to an information-based treatment as well as a business-as-usual control group.

MOBIS is, to the best of our knowledge, the first large-scale implementation of a dynamic, time and location-based, multimodal transport pricing system. As such, MOBIS aimed to identify and address numerous challenges related to the feasibility and technical implementation of such a scheme, both within a research context and with regards to a possible

[31] The original name of this project is “Empirical analysis of mobility behavior in the context of dynamic pricing”. However, to avoid that the study participants would pick up on the purpose of the experiment, which could have biased their behavior, the project was referred to as "Mobility Behavior In Switzerland (MOBIS)" in all communications with study participants. From here on we refer to the study using the acronym “MOBIS”.

up-scaling to a national policy level. The MOBIS study aimed to simulate a possible future implementation of a dynamic transport pricing scheme in Switzerland. The pricing scheme was designed to cover all main travel modes, to allocate dynamic prizes dependent on travel time and route, and to set prizes based on external costs associated with travel.

MOBIS conducted a Pigovian transport pricing experiment from July 2019 to March 2020 in the German and French speaking cantons of Switzerland. The experiment consisted of a four-week observation phase (baseline), followed by a four-week intervention (or treatment) phase. In total, almost 3,700 participants successfully completed the tracking study. Their mobility behavior was recorded using a GPS tracking app and additional information was collected using an introduction survey and a final survey.

After four weeks of tracking, the participants were randomly assigned to one of two treatment or a control group. The members of the "information" group were exposed to information about the external costs of travel they themselves generated during the previous week, by means of regular e-mails. The members of the "pricing" group received the exact same information about their external costs as the information group, but additionally they had to pay for these costs (more precisely, as discussed below, these costs were subtracted from a budget). The goal of the field experiment was to measure the effect of these two treatments, relative to the control group that continued to be observed.

Conducting a pricing-based and an information-based intervention within the same study framework provided the opportunity to assess, to what extent the effects of transport pricing could be achieved by soft measures instead. This is of interest from a policy perspective as both approaches attract opposition and support, albeit for varying reasons.

The MOBIS study found that economic incentives, i.e. Pigovian transport pricing, lead to a significant reduction of the external costs of transport. The reduction was due to a combination of mode shift (away from driving and towards public and active transport) and a change in departure times, which is important for congestion. In contrast, information-based incentives resulted in statistically significant changes only for subgroups, but not for the sample overall.

1.2 Travel behavior data

A main challenge in MOBIS was the collection of travel behavior data suited for the evaluation of the anticipated policy effects. Traditional survey methods such as travel diaries have been standard practice for decades to collect mobility data. However, in light of new big data techniques their limitations are increasingly becoming apparent. Passive collection of mobility traces, mainly using GPS or GSM technologies for mobile tracking apps, offers new possibilities in transport survey methods by collecting continuous and detailed records of individual mobility data over long periods of time. This additionally allows for more elaborate study designs such as incorporating near real-time feedback to the participants.

These moving parts do come with potential issues. The use of passive collection of mobility traces, mainly using GPS or GSM technologies, has already been shown to mitigate some of the key challenges in traditional survey methods, including response burdens, dropout rates and trip reporting accuracy Axhausen *et al.* (2002); Schmid *et al.* (2019a); Madre *et al.* (2007); Wolf *et al.* (2003); Danalet and Nicole (2017). However, passive data collection has fundamental issues, namely the difficulty in recruiting representative samples (i.e. selection bias), the lack of individual level socio-economic attributes and data quality and consistency Bricka (2008). Since a representative sample with proper individual-level data is essential when analysing the economic and societal impact of policy measures such as transport pricing, passive big data alone does not suffice, and needs to be paired with traditional survey methods.

Tracking methodologies also face the dual challenges of privacy and data security. Care needs to be taken that data is securely stored, transferred and processed at different stages of the project. The relevant laws and regulations need to be abided by, which are particularly strong for passively collected data such as GSM data. The explicit consent of the participant

is required for the collection of their data through either the network operator or a GPS tracking App. Participants in the study also need to have the right and possibly to have their data deleted if they wish to prematurely exit the study.

1.3 Information-based treatments

Information-based incentives, also called "soft measures", involve information provision and persuasive techniques in order to induce voluntary behavior change (Gärling and Fujii 2009; Jones and Sloman 2003; Rose and Ampt 2003; Taniguchi *et al.* 2007; Taylor 2007; Taylor and Ampt 2003). They are often put in contrast to the so called "hard (transportation policy) measures", which involve improvement of infrastructure, legal instruments with command-and-control character as well as changes in price structures (Bamberg *et al.* 2011; Möser and Bamberg 2008). Traditionally, transportation policy in most countries was primarily based on hard measures. Recently, there has been an increased interest in alternatives because it has been recognized that hard measures are associated with political feasibility and acceptance problems (Gärling and Schuitema 2007; Jones 2003) and are not able alone to sufficiently reduce car use (Stopher 2004). Some soft transport policy measures have been shown to be effective (Brög *et al.* 2009; Cairns *et al.* 2008; Fujii *et al.* 2009; Möser and Bamberg 2008; Richter *et al.* 2010; Taylor 2007), associated with low costs (Brög *et al.* 2009; Loukopoulos 2007; Richter *et al.* 2011) and scalable (Parker *et al.* 2007). A more detailed review of the scientific literature is provided in section 2.

The rapid development of Information and Communication Technologies (ICT) in the last decades and the corresponding evolution of so called "persuasive technologies" (Fogg 2002) has spurred a new wave of soft transport policy measures, as summarised by Anagnostopoulou *et al.* (2016) and Sunio and Schmöcker (2017) in their reviews. They usually combine traditional persuasive techniques with new ICT tools, such as smartphone apps, which increasingly deploy gamification elements (Cellina *et al.* 2019).

While there are a number of pilot projects combining different persuasive technology features in different geographical contexts, systematic and statistically robust evaluations of the corresponding behavioral effects including sufficiently large sample sizes and control groups are still missing (Sunio and Schmöcker 2017). MOBIS contributes to filling this gap by applying a randomized controlled trial with a sufficient sample size to detect even modest behavioral responses.

1.4 Transport pricing

Road pricing, or road user charges, are broad terms for direct fees placed on road use with the goal to either create direct revenue streams to recoup large infrastructure investments (e.g. bridges, tunnels), to manage demand (e.g. peak use), to gain revenue to mitigate road use impacts (e.g. public transportation investments), to internalize costs of road use related impacts (e.g. emissions), or any combination thereof. Examples include toll roads or bridges, congestion fees applied to specific, congestion-prone zones, or fees applied to different classes of vehicles, among others. Modern versions of road pricing optimize their effects through time and location dependent (i.e. dynamic) fee structures. A successful example from Switzerland is the performance-related heavy vehicle charge. It is a federal charge that depends on the total weight, emission level and kilometers driven and is applied to all vehicles heavier than 3.5 tonnes using the Swiss road network.

Transport pricing, in the sense of this study, is the mode-neutral generalization of such concepts and may include public transport use. The transport pricing scheme implemented in MOBIS is “Pigovian” in the sense that it is based on the social marginal damage of transport and thus fully internalizes the marginal external costs in the user price (for a further discussion, see Section 2.1). It is, however, not an average full cost pricing scheme, as it does not reflect any fixed costs. These include, for example, the costs of infrastructure in public transport (which is a natural monopoly and thus heavily subsidized) and any generalized costs of the road network not covered by the fuel excise tax. For a recent discussion of the definition of the external costs of transport, see CE Delft (2019).

Last, we point out that the term "mobility pricing" as used by the Swiss Federal government in the past (Rapp *et al*., 2007; Swiss Federal Council, 2016; INFRAS, 2019) is a more narrow concept than the Pigovian transport pricing implemented in this study and only focuses on congestion, while abstracting from other externalities. For this reason, and to avoid any possible confusion, we use the term “Pigovian transport pricing” in this report.

2 State of the art

This section reviews the scientific literature on on transport pricing (i.e. economic incentives to change travel behavior), information-based treatments to change travel behavior, and GPS tracking in transport research.

2.1 Transport pricing theory

The cost of travel in transport can be divided into three categories: (i) individual, or private costs - i.e. those payed by the traveler; (ii) the costs of travel borne by other individuals, known as external costs; and (iii) infrastructure costs, which are fixed costs that can be paid by users or through subsidies. In transport, external cost categories commonly include congestion, environmental effects, health effects, and accidents. (Verhoef, 2000).

The theoretical foundations for road pricing were laid by Pigou (1920) in his work on the internalization of the external costs in a market. He used the example of two roads to suggest that differential taxes can be useful in increasing the overall utility in the simple network where congestion is present. Knight (1924) explored this further, but suggested that a government intervention would be required, and tolls should be set by private operators.

Vickrey (1963) used a bottleneck model to demonstrate how road pricing could influence travelers' choice of route and transport mode. Vickrey demonstrated that in perfect congestion pricing, tolls must match the severity of congestion, and vary by time of day, location, type of vehicle and current conditions. It then follows that transport users should be charged their marginal external costs - costs which would otherwise be absorbed by other transport users and society (Button and Verhoef, 1998).

The methods for road pricing can be categorized by their level of optimally internalizing the external costs. In first-best pricing, the marginal external cost is charged to the the user. In this case, both the charging mechanism and the amount charged need to be optimal Verhoef (2000). In second-best pricing, the pricing mechanism is guided by the principle of marginal external costs, but the implemented scheme is simplified (Small *et al.*, 2007).

Most of the early work on the pricing of externalities focused on the different transport networks in isolation - the congestion on the road network was not considered in the context of public transport or non-motorized modes. Multiple researchers have identified how this is insufficient. Small (2008) argued that a road congestion charge can act as an effective way to financially support public transport, by raising the cost of car travel, which has been traditionally cheap as the numerous external costs are not paid by the driver. Tirachini and Hensher (2012) also examined the intricate relationship of pricing between car travel, public transport and non-motorized modes, in both a first-best and second-best context. As is acknowledged in the literature, there exist limitations to implementing first-best pricing. Verhoef (2000) identified both general issues such as the "limited social and political acceptability and the technical feasibility of marginal external cost pricing" and the unlikelihood that the assumptions required for effective Pigovian taxes apply.

2.2 Transport pricing in research and practice

Although the theoretical challenges of efficiently internalizing external costs in transport have been discussed for decades, it is only more recently that solutions have been implemented for personal vehicle travel, either experimentally or in reality. Schemes for freight traffic are already widespread, with Germany being one example (Link, 2008). A number of studies have examined the effect of the introduction of real world congestion pricing schemes.

The London congestion charge is one of the most well known real world implementations (Leape, 2006). First applied in 2003, it has seen numerous extensions since, including additional charges for heavily polluting vehicles and discounts for electric cars. According to Leape (2006), the London congestion charge resulted in a decrease in car trips of 34%,

which, with a GBP 5 congestion charge, running costs of GBP 0.45 per mile, and an average return journey of 34km (as in Börjesson and Kristoffersson (2018) below), results in an elasticity of -0.72.

In Stockholm, road pricing has also been implemented in the form of a congestion charge (Eliasson *et al.*, 2009). In both cities, cars entering a cordon around the central business district have to pay a charge during certain times. These second-best schemes only include road travel, and are relatively blunt instruments. An analysis by Karlström and Franklin (2009) showed that drivers crossing the toll cordon boundaries in Stockholm were 15% more likely to switch to public transport. Börjesson and Kristoffersson (2018) analyze the Stockholm congestion charge, as well as the very similar scheme in Gothenburg. These authors find peak travel time elasticities of -0.49 and -0.53 for each of the cities, respectively. For the off peak travel times, the elasticities increased in absolute terms to -1.13 and -0.93, respectively.

Over the years, a variety of road pricing schemes have been implemented in Singapore, starting in 1975 with a paper-based peak-hour permit scheme (Chin, 2005). In 1994, the system was revised to cover two levels of licensing. Starting in 1997, the ERP (Electronic Road Pricing) was introduced, where vehicles are charged each time they pass through a gantry (Agarwal and Koo, 2016). The charges are regularly adjusted to maintain a certain level of service. In 2023, a satellite (GPS) based system will be introduced (Tan, 2020). Olszewski (2007) note that these measures help to keep the roads free from major congestion, maintain car share of work trips below 25%, and incentivize the use of public transport.

Several field experiments empirically evaluated the impact of dynamic pricing on mobility behavior. For a review of studies that applied economic incentives in the transport context, see Dixit *et al.* (2017). Their analyses emphasizes the importance of proper study designs to achieve internal and external validity and to obtain generalizable results, i.e. applicable to real world contexts.

In the Danish AKTA study (Nielsen, 2004), 500 drivers around Copenhagen had a GPS receiver installed in their vehicle (before the widespread availability of GPS-enabled mobile devices). After a control period, they were exposed to different peak and off-peak road pricing schemes over 8-12 weeks, with the charges calculated based on the data from the GPS receiver. Based on the difference between participants' behavior before and after the introduction of the pricing, the study found relatively small behavioral responses (Nielsen, 2004)). Worth noting, however, is the large elasticity of -1.95 for the high km-based toll, where an increase in cost of 4% resulted in a decrease in trips of 7.8%

The Melbourne road pricing experiment also investigated the feasibility of a road pricing scheme for a sample of customers for an Australian tollway operator in metropolitan Melbourne (Transurban, 2016). It was conducted over 17 months with 1,635 participants, and a range of charging schemes. The results showed that such a system could act as a significant funding source for new transport investment, and help manage demand in congested areas and peak hours. In (Martin and Thornton, 2017a), they observed a price elasticity of -0.13 to per kilometer charges. They also found that low-income participants (who were found to drive less) responded more. Here, as in the AKTA study, a GPS device was installed in the participants' cars for the duration of the study.

Ben-Elia and Ettema (2011a,b) conducted a field experiment in the Netherlands that provided a financial incentive for commuters to switch their departure times and/or transport modes and reported a significant response to prices between 3 and 7 Euro per avoided rush-hour car trip. Additionally the rewards increased the weekly shares of driving earlier and later as well as of 'not driving' compared to both pre- and post-test levels. Their results also suggest that men tended to change behavior more often than women.

In Singapore, commuters responded to congestion pricing by shifting departure times (Pluntke and Prabhakar, 2013). In the USA Andersen *et al.* (2014) combined a field and laboratory experiment in Orlando and in Atlanta and found that drivers respond to toll prices and

changes in the time of travel.

None of these studies involved a control group, such that the effects can be ascribed to the pricing regime only under the rather restrictive assumption that nothing else changed between the observation and treatment periods. Real world congestion pricing affects everyone, thus there is no untreated control group against which the effect could be measured. In MOBIS, we avoid this problem by assigning a third of the participants to a control group that never receives any informational or pricing treatment.

To our knowledge, there have been very few RCTs in the context of mobility that involved incentives. Two are exploratory in nature as they are based on a very small sample size (Flüchter and Wortmann, 2014; Wemyss *et al.*, 2019). The only RCT that we are aware of with a large sample size is by Rosenfield *et al.* (2020), who carry out an experiment involving 2,000 employees at the Massachussetts Institute of Technology. They use a control group and three treatment groups, one of which was provided incentives to increase commuting by public transport (as opposed to driving). None of the treatment arms led to statistically significant effects.

2.3 Information-based treatments

Möser and Bamberg (2008) focus on a group of five types of "soft" transportation policy measures considered most mature[32]: Workplace travel plans [33], school travel plans[34], personalized travel planning, travel awareness campaigns and public transport marketing.[35] Among the 141 studies that they considered, none employs a randomized control trial due to the absence of a proper control group (for more details about the importance of a control group, see below). The most common setup was a before-after analysis of one of the above types of soft interventions. The authors report a statistically significant random-effects pooled effect size of 0.15 associated with the above-named "soft" transportation policy measures, which is comparable with an increase of no-car use proportion from 39 to 46%.

Kristal and Whillans (2020) carry out a series of RCTs involving almost 70,000 employees of a large organization. The participants were exposed to different informational treatments (such as nudges, travel plans and personalized recommendations) with the aim of increasing the share of carpooling, but there were no statistically significant effect.

Jariyasunant *et al.* (2015) evaluate an effect of the QT app, which aims at changing mode or trip choice by automatically collecting trip data, converting them into a travel diary and giving a quantitative feedback (time and money spent, calories burned and CO_2 emitted) to the traveler. In a before-after study (without a control group) involving 135 test persons over the 3-week period in San Francisco Bay (USA), the authors find a significant negative effect of the app features on the distance traveled and a significant effect on various psychological determinants of travel behavior, such as awareness of the environmental consequences of transport modes, attitudes towards sustainable mobility, social norms in favor of sustainable mode choices, perceived behavioral control regarding the travel behavior change as well as the intention to choose more sustainable transport modes.

Bothos *et al.* (2014) evaluate an effect of the Peacox app, nudging the users to consider the environmental friendliness of travel modes and routes while planning a trip. The app

[32] Less mature measures being car clubs, car sharing schemes, teleworking, teleconferencing, and home shopping. For a more comprehensive overview see Cairns *et al.* (2008)

[33] (Möser and Bamberg, 2008, p. 12) describe them as "a bundle of measures put in place by an employer to encourage more sustainable travel, particularly less single occupancy car use". Possible elements of workplace travel plans include new public bus or rail services linking to the site, dedicated shuttle buses between the site and the town center, giving all staff public transport information etc.

[34] According to Möser and Bamberg (2008), typical elements of school travel plans include special walking or cycling promotion days, pedestrian and cycle training programs for children, cycle parking etc.

[35] (Möser and Bamberg, 2008, p. 12) describe personalized travel planning, travel awareness campaigns, and public transport marketing as "marketing techniques providing travel advice and information to people based on an understanding of their personal trip patterns". Typical measures from this group include pocket sized public transport timetables for the main routes into town, a timetable for the nearest bus stop, a personalized journey plan for a trip made on a regular basis etc.

shows CO_2 emissions visualizations and deploys personal and collaborative challenges to motivate users to reduce the emissions caused by their mobility choices. In a before-after study without a control group involving 24 test persons over the 8-week period, the authors do not find a significant effect of the app treatment on neither on the mode choice nor on the environmental concern. However, the authors find a significant positive effect on the attitudes toward sustainable mode choices.

Carreras *et al.* (2012) evaluate the effect of the SUPERHUB app and open-source platform, which motivates users to make more sustainable mobility choices using a combination of goal-setting, self-monitoring, rewards and sharing features. The study was conducted as a before-after comparison without a control group in Helsinki (Finland) and involved 471 test persons over the 8-week period. The authors do not find a significant effect of using the app neither on the travel behavior nor on the environmental attitudes.

Maerivoet *et al.* (2012) investigated within a before-after trial with 35 test persons from the city of Leuven and its surroundings (Belgium) the effect of the hypothetical road pricing scheme communicated in real-time through an on-board display as a cost per kilometer depending on location, time and vehicle type. The field experiment consisted of three phases. The first phase was the baseline phase and lasted 2 months. In the second phase, which lasted another 2 months, the real-time communication of the road pricing scheme was triggered and accompanied by the competition to achieve the largest behavior change. In addition the data of the first month of this phase were analyzed and served as a basis of personalized tips how to further improve the behavior. The third phase, which lasted 1 month, was the post-treatment phase and served to analyze the persistence of the effect. The authors find that the test persons jointly drove 5% less on secondary and local roads during the peak hours in the competition phase. However 3 out of 4 test persons fell back into their previous behavioral pattern in the post-treatment phase.

In a recent study, Cellina *et al.* (2019) evaluate the effect of the GoEco! app involving automatic mobility tracking, eco-feedback, social comparison and gamification elements on CO_2 emissions and energy consumption per kilometer in the Swiss cantons of Zurich and Ticino. In contrast to the three above-named studies, Cellina *et al.* (2019) apply randomized control trial – design with higher internal validity – and are thus in a better position to investigate causality between the app treatment and the travel behavior of their test persons. However, due to the high attrition of their initial sample, they were able to test their hypotheses on only 52 test persons for all routes (treatment group Ticino: 21, control group Ticino: 10, treatment group Zurich: 13, control group Zurich: 8) and 45 test persons for regularly traveled routes only (treatment group Ticino: 15, control group Ticino: 7, treatment group Zurich: 14, control group Zurich: 9). They find that the GoEco! app lead to a significant reduction in both CO_2 emissions and energy consumption per kilometer, however only in Ticino and only for regularly traveled. In contrast, in the canton of Zurich, no significant effect of the GoEco! app was found.

Few studies have used an explicit control group for similar experiments. No statistically significant effects could be measured in Flüchter *et al.* (2014) and Cellina *et al.* (2016) due to their small samples.

The feedback effect on consumption has been extensively studied in the energy field as well. In the most comprehensive meta-analysis known to the authors of this report, Delmas *et al.* (2013) analyze the evidence from 156 studies and quantify the energy savings from information-based strategies. They find an average reduction effect of 7.4%. The authors also find that a comparatively stronger effect of individualized energy audits and consulting than the effect of energy consumption feedback and find that the overall effect declines with the rigor of the study. Having a stronger focus on energy consumption feedback, Karlin *et al.* (2015) conduct a meta-analysis of 42 studies and find a significant overall feedback effect on pro-environmental behavior of 7.1%, however with a very large range. The relationship between the feedback and the consumption reduction was found to be moderated by feedback frequency, medium, comparison message, duration, and the combination with other interventions, such as goal setting or financial incentive. McKerracher and Torriti (2013)

focus on real-time feedback on electricity consumption provided through in-home displays and conduct a meta analysis of 27 recent studies. Paying special attention in the selection of the studies on sufficiently large sample sizes as well as representative samples and recruitment methods they find a more modest conservation effect of the real-time feedback of 3-5%. A very recent field trial in Italy on real-time electricity consumption feedback resulted in even smaller consumption reduction between 0.5 and 1.9% (Marangoni and Tavoni 2021). An effect of a similar order of magnitude was documented by Allcott (2011) in probably the most prominent study dealing with the information-based measures to reduce energy consumption. In a randomized natural field experiment with around 600'000 US households, the author finds an average reduction effect of 2% associated with the Home Energy Reports, ranging from 0.3% in the lowest to 6.3% in the highest decile. Much more supportive evidence regarding the effect of the feedback on energy consumption provides a series of works based on the Amphiro display providing real-time water and energy consumption feedback under the shower (Tiefenbeck *et al.* 2018, 2016, 2019). The authors find over 20% energy savings in a randomized control trial with over 5'000 customers of a Swiss energy provider (Tiefenbeck *et al.* 2018). The effect does not decline significantly after one year (Tiefenbeck *et al.* 2016). A smaller, yet still substantial effect (11.4%) was observed when the trail was conducted with almost 20'000 hotel guests, who on the contrary to the customers of an energy provider didn't opt in to participate in the study and hence are probably a more representative sample (Tiefenbeck *et al.* 2019).

2.4 GPS tracking in transport behavior research

Data collected from mobile devices first started to play a role in transport research in the 2000's, starting with Asakura and Hato (2004), who used call detail records (CDR) to investigate the feasibility of using mobile network data to study metropolitan scale travel behavior. At this stage, the first iPhone was still a prototype, and it would not be until 2008 that the first iPhone with integrated GPS was released (Apple Inc., 2008). Further work using aggregated mobile network data continued (Gonzalez *et al.*, 2008; Ahas *et al.*, 2010; Anda *et al.*, 2018). However, the benefits of passive mobile network data - namely the non-existent response burden and sample size come with trade offs which need to be acknowledged. Privacy laws normally ensure that the traces must remain anonymous, meaning that minimal, if any, demographics are available. Secondly, particularly in Europe, tracking of participants over consecutive days is rarely allowed without their explicit permission (Cik *et al.*, 2020).

While cellular network data is collected passively by the network operator, the collection of GPS data requires the installation of an app on the device. However, the spatial and temporal accuracy of the data is very good, rarely exceeding 30m in outdoor settings (Zandbergen and Barbeau, 2011). In contrast, the accuracy of cellular network positioning is not comparable to that of GPS data (Widhalm *et al.*, 2015). On mobile phones, the data from the GPS receiver is often augmented with other available sources, such as WiFi, cell tower triangulation and accelerometers to improve accuracy, which are collectively known as *location services*. For the purpose of this project these location services will be referred to as GPS, as is common in the literature. GPS data can either be collected anonymously through aggregation services at a large scale (Buck *et al.*, 2014), or through the recruitment of participants, who are asked to install and use a specific app. For studies where a representative sample is required, or behavioral models with socio-demographic variables are to be developed, the recruitment of participants is naturally the preferred option.

Over the last 20 years, GPS has been increasingly used both in the collection of travel diaries and the understanding of daily patterns (Wolf and Guensler, 2000). Many of these studies have been of short duration, i.e. a couple of days Allström *et al.* (2017); Greene *et al.* (2012), due to the acknowledged response burden and resulting attrition observed in these studies (Kohla and Meschik, 2013). As Widhalm *et al.* (2015) note, the sample size and observation period of most GPS studies is still limited. A selection of recent GPS-based travel surveys is presented in Table 1.

In addition, continuous methodological advancements have been made in the processing of collected GPS data. The process is normally divided into stages: filtering, trip segmen-

tation, transport mode detection and where necessary, map matching to a network. For an overview of the various methods and advances, see Shen and Stopher (2014) and Zheng (2015). Graphhopper (Karich and Schröder, 2014) provides an open-source framework for map-matching GPS traces to an OpenStreetMap (Haklay and Weber, 2008) network using the Hidden Markov Model approach developed by Newson and Krumm (2009).

Table 1 – Response rates in various tracking studies

Project name	MOBIS	SPOT (1)	IN-THE-MOMENT (2)	ATLAS (3)	AKTA (4)	Cincinnati (5)	Atlanta (6)	Reno (7)	Tel Aviv HTS (8)
Tracker	MotionTag	MEILI	rMove	SITSS	Device	Device	Device	Device/App	App
Country	Switzerland	Sweden	USA	NZ	Denmark	USA	USA	USA	Israel
Year	2019	2015	2015	2014	2001-2003	2010	2011	2015-2016	2016-2017
Tracking days	56	7	7	3	112	3	7	7	2
Min. incentive (USD)	$100		$25		variable	$25	$25	$25	
Validation/annotation	Optional	Yes	Yes	yes	no	yes	yes	yes	yes
Invited persons (N)	90,909	130,000	1,427	186	25,000	11,118	16,374	25,817	67,199
Intro survey (N)	21,571								
% of invited	23.73%								
Qualified (N)	6895	1159	478						38,500
% of invited	7.58%	0.89%	33.50%						57.29%
% of intro completed	31.96%								
Registered (N)	5375	495	295	77	500	4656	1938	602	27,415
% of invited	5.91%	0.38%	20.67%	41.40%			11.84%		40.80%
% of qualified	77.96%	42.71%	61.72%						71.21%
Started tracking (N)	4218	293	295	73	500	4656		602	25,201
% of invited	4.64%	0.23%	20.67%	39.25%	2.00%	41.88%			37.50%
% of qualified	61.17%	25.28%	61.72%						65.46%
Completed tracking (N)	3690	51	240	65	500	3849	1061	312	23,240
% of invited	4.06%	0.04%	16.82%	34.95%	2.00%	34.62%	6.48%	1.21%	34.58%
% of qualified	53.52%	4.40%	50.21%						60.36%
% of registered	68.65%	10.30%	81.36%	84.42%	100.00%	82.67%	54.75%	51.83%	84.77%

1. Allström *et al.* (2017), 2.Greene *et al.* (2012), 3.Safi *et al.* (2015), 4.Nielsen (2004),
5.Wargelin *et al.* (2012), 6.Livingston (2011), 7.Stopher *et al.* (2018), 8.Nahmias-Biran *et al.* (2018)

3 Methods

3.1 Overview of the study

The main research question of the MOBIS study is: What are the effects of economic incentives and information on individual mobility behavior? To answer this question, the study was designed as follows (see also Figure I in the executive summary).

From an initial survey of 21,800 participants randomly selected across major Swiss agglomerations, a panel of 3,700 participants was recruited for the tracking study, of which 3,656 successfully completed the study. Addresses were randomly selected and provided by the Swiss Federal Statistical Office, which maintains a comprehensive registry of inhabitants.

The initial survey contained questions about travel behavior, socio-demographics and a number of transport policy issues. It further served as a screening mechanisms to identify subjects suited for the transport pricing experiment. Potential participants had to fulfill a number of inclusion criteria, in particular, a minimum of car-use on two days per week.

To take part in the tracking study, the participants agreed to download a tracking app on their smartphones and to have their daily travel tracked over a period of 8 weeks. They further had to consent to the use of their data for research purposes. In return for their participation in the complete study, the participants were offered CHF 100, which were paid at the study's end.

The 8-week GPS tracking study consisted of two consecutive 4-week phases, an observation and a treatment phase respectively, book-ended by an introduction and a final survey. During the observation phase, all study participants were treated equally, receiving weekly reports of their mobility behavior by email, which included tracked distance by transport mode. During the treatment phase, the study participants received additional "treatments" beyond the weekly reports of the observation phase, depending on their randomly assigned group (pricing, information or control).

For the pricing group, a pricing scheme was implemented and each participant received a virtual mobility budget corresponding to the external costs of their travel estimated during the observation phase, calculated based on time loss due to congestion, health effects and CO_2 emissions. This mobility budget was used to pay for pricing group participants' external travel costs during the treatment phase. To create a financial incentive mimicking the effect of a real world transport pricing scheme, with the implicit goal to reduce external costs associated with travel, participants were told that they could keep any amount left on their mobility budget at the end of the study.

The information group was presented the same calculation of external costs as the pricing group, but their travel did not come with any financial implications or incentives. Both the pricing and information groups were presented with estimated external costs by transport mode and type of external costs, as well as an explanation of the concept of external costs.

There may be unobserved determinants of transport behavior (e.g. general traffic volume, road repairs, weather), which may have changed during the same time as we applied the pricing and information treatments. To assess such bias, the MOBIS study used a control group without any treatments which was observed simultaneously to the pricing and information groups. The control group obtained the same information about their travel as during the observation phase, i.e. a breakdown of distances traveled by mode, but without any information about associated costs.

3.2 The MOBIS study: Step by step

In this section, we describe the study in more detail, starting with the pilot study and ending with the user support that took place throughout the experiment.

3.2.1 Pilot study

The pilot study had multiple goals:

- to determine the best recruitment method between sending up to three invitation letters and sending only one letter followed by a phone call
- to estimate the number of addresses required for the main study based on the participation rates observed in the pilot study
- to test the resilience of the planned recruitment and data collection system, including surveys, tracking app, and participant help-desk, among others

The pilot study took place between April and the end of July 2019.

We invited 1,500 persons to the pilot study by mail, using a sample of addresses and phone numbers purchased from a private vendor, Schober Information Group AG (in 2020 renamed KünzlerBachmann Directmarketing SIG AG). Half the addresses (750) were used for the 3-letter method and the other half for the 1-letter method. Two weeks after the first invitation letter, if the invited persons did not respond (i.e. completing the introduction survey), a reminder was sent out. People assigned to the 3-letter group received up to two additional invitation letters and a phone call to kindly remind them to participate in the study. In contrast, addressees in the 1-letter group only received a phone call. The pilot study found that the 3-letter method was more effective for the recruitment.

Specifically, 28% of the 3-letter group completed the introduction survey, while only 15% of the 1-letter group did so. The recruitment rate of the letters slightly decreased over time. The first letter recruited on average around 11% of the recipients (9% in the 3-letter group and 12% in the 1-letter group), while the second letter recruited around 10% and the third one around 8%. The phone call contributed on average 2% of the called persons (around 3% in the 1-letter group and 1% in the 3-letter group). Based on these findings, the 3-letter approach without phone calls was chosen to be used in the main study.

On average, 3.4% of the invited people (3.2% in the 1-letter group and 3.4% in the 3-letter group) completed the study, i.e., they filled out the introductory survey, they qualified and registered for the field experiment, they were tracked during 8 weeks and they filled out the final survey.

For the pilot study we used the app ETH-IVT Travel Diary (developed for the IVT) to track the participants. While the app itself functioned well for collecting raw tracking data from the participants, the performance of the segmentation and mode detection was discovered to be lacking in real world application, despite promising results during earlier testing. Due to the tight time-frame on the project, it was clear that wasn't enough time to improve the machine learning algorithms before the necessary start of the main study. Hence, we decided to use an alternative app “Catch My Day" (developed by Motion Tag for a previous mobility study on car-sharing of the IVT) for the main study. A further lesson learned was that an efficient help-desk per email and phone was required for the main study. The high number of queries in the pilot study showed that we needed a help-desk management tool (we used Freshdesk) and templates to manage queries from the participants.

3.2.2 Sample size

In order to determine the appropriate sample size of the experiment, we carried out a series of power calculations by means of simulation. In panel data, autocorrelation is a design feature, which we also observe in our data (i.e., a particular respondent makes similar travel choices over time). The presence of autocorrelation implies that the standard formulae for power calculations, e.g. as in Duflo *et al.* (2007), are biased (Burlig *et al.*, 2020). Computing the power of an experiment based on simulations addresses this problem as it uses the empirical correlation structure in the data.

We based our power calculations on data from two earlier transport studies carried out by

ETH-IVT.[36] We imposed a significance level of p=0.05, a power of 0.8 and an effect size of 5%. Given these settings, the power calculations indicated that we needed a sample size of around 1,100 for each group (treatment and control). Given that we have two treatment groups, this led to a target sample size of 3,300 for our study. To ensure that this sample size was attained even after removing respondents who did not participate on a sufficient number of days or who had to be excluded for other reasons, we set a recruitment goal of 3,600 people. Once we attained this number, recruitment was stopped.

3.2.3 Invitation

Assuming a participation rate in the main study similar to the one observed in the pilot study (i.e. 3.4%), approximately 100,000 addresses were expected to be required to achieve the goal of 3,400 participants. Ultimately, 90,909 persons were invited to participate in the MOBIS study. They received the invitation letter per post. The invitation letters were sent in two waves.

- The first wave started in August 2019. 60,409 persons were contacted using home addresses provided by the Swiss Federal Statistical Office (BFS in German). Only persons aged 18 to 65 in 2018 and living in an agglomeration of the German- and French-speaking Swiss cantons were invited. The persons who did not react after the first invitation letter received up to two reminders (a second and third invitation letter). The time lag between the invitation letter and the reminders was between 3 and 4 weeks.

- The second wave was invited in October 2019. 30,500 additional persons were contacted using home addresses purchased from the private vendor Schober Information Group AG. The persons of the second wave only received a single invitation letter, i.e., no reminder was sent. 56 persons in the second wave accidentally received a duplicated participant ID which had already been allocated to participants in the first wave. These persons were informed that despite the invitation, they could not participate in the study.

The invitation letter was written in German, French and English. The front side of the invitation showed the German or the French version, while the back side always showed the English version. The language of the front side was assigned based on the communication language, which was provided in the list of addresses. In case of Italian speaking persons, the main speaking language of their home canton was assigned.
The content of the invitation was the same for all languages. The letter explained the background of the study (rationale, participating universities and supporting institutions) and provided instructions for completing the online introduction survey and registration. The participant ID (a five-letter code) was provided in these instructions. This ID enabled the access to the introduction survey, registration and final survey. Finally, the letter informed about the financial reward for complete participation and about the data privacy policy. The full invitation letters in all languages can be found in Appendix B.1.

3.2.4 Introduction survey

The invited persons who were willing to participate in the MOBIS study firstly had to fill out an online introduction survey. This survey had two goals: First, to collect transport-related opinion from the general population, and second, to identify subjects who qualified for the main study based on the following inclusion criteria:

- To be the recipient of the personal invitation letter (the invitation was not transferable to other persons)

- To live in a metropolitan area in the German- or French-speaking part of Switzerland (the lists of addresses included only people living in these areas but the survey double-checked the post code)

- To be between 18 and 65 years old in 2018 (the list of addresses provided by the BFS

[36] The 6-week MOBIDrive (Axhausen *et al.*, 2002) and the 6-week Thurgau survey (Axhausen *et al.*, 2007).

was pre-filtered by age at this year)

- To travel by car at least two weekdays per week (including their own car, car-sharing as a driver, or with a taxi and App-based services such as Uber as passenger)
- To use of a smartphone that can install the tracking app
- To be able to walk 200 meter without assistance (to ensure that participants have free mode choice)
- To not work as a professional driver (to ensure that participants have free mode choice)

People meeting the above listed inclusion criteria were were invited to register for the field experiment of the MOBIS study by clicking on a web link embedded at the end of the introduction survey survey. Beyond the questions related to the aforementioned inclusion criteria, the introduction survey contained questions related to the following topics.

- Socio-economic background: education, nationality (for the 2nd wave because this information was not included in the list of addresses), household size and household income.
- Employment background: employment status (e.g. student, employed, retired), workload, postcode of the working place.
- Mobility behavior: vehicle ownership, travel frequency for each transport mode, car fuel, year of production of the car, car size, engine size, type of bicycle type, type of public transport pass.
- Transport-related opinions: evaluation of potential problems commonly associated with transport and factors influenced by transport policy as well as agreement with specific transport policies.

The introduction survey was accessible online through the survey platform Qualtrics. The full content of the MOBIS introduction survey in English is shown in Appendix B.2.

3.2.5 Registration

People who completed the introduction survey, met the inclusion criteria and accepted to participate in the tracking study were sent forward to the registration (survey), which was also accessible online through Qualtrics. The registration had as a goal to confirm the acceptance of the conditions and terms of the field experiment and to collect the emails of the participants for sending interventions (incentives) and information. The full content of the MOBIS registration in English is shown in Appendix B.3.

3.2.6 Tracking

All eligible participants willing to participate were given a registration code and directions to install the Catch-my-Day app (see Section 3.3). A flat incentive of CHF 100 (approx. USD 100) was offered to all participants, conditional on completing the entire study (including both the introduction and final surveys) and payable at the study end.

Participants could start tracking at any time, and the 8 weeks would start from the first complete tracking day. To remain eligible for the CHF 100 compensation, participants were informed that they needed to track at least half the time for the duration of the study. Participants identified as not tracking for a certain number of consecutive days (initially 2, later 3) were notified by email, with the aim of increasing the quality of the tracking data and reducing the dropout rate. A minimum number of days between reminders was set, initially to 2 days, and later increased to 4 days, to avoid burdening the participants.

In the first 4 weeks, i.e., the observation phase, participants received a weekly email summarizing their kilometers traveled on each transport mode. Participants who did not gener-

ate tracking data on more than 12 days in the first 4 weeks were not allowed to participate in the treatment phase, and did not receive compensation.

At the end of the 4-week observation phase, each participant was randomly assigned to either one of two treatment groups (*information* or *pricing*), or the control group. Those in the treatment groups were informed by email that the conditions of the study were changing, and received an explanation of the external costs of transport along the three dimensions health, climate and congestion. During the next 4 weeks, i.e., the treatment phase, the participants in both treatment groups received weekly supplemental information on their external costs from the previous week. In addition, participants in the pricing group were provided with a virtual mobility budget, equal to 120% of their external costs estimated during the observation phase,[37] and from which their external costs in the treatment phase would be subtracted. The status of this mobility budget was made available to them in each weekly report, and any amount remaining was additionally transferred to them at the end of the study as an incentive to reduce their externalities. Due to the rolling start of the experiment, participants received these reports on different days of the week. As such, a pipeline was developed to download the tracking data, calculate the corresponding external costs and email the reports. Participants in the control group continued to received a weekly email with their kilometers traveled per mode throughout the treatment phase.

The weekly reports were comprised of modular panels, as shown in Figure 1. The introduction and distance by mode panels were presented to all participants in both study phases (top and bottom part of left panel). The external cost and chart explanation panels (right panel) were shown to the information and pricing groups in the treatment phase, and the remaining budget information only to the pricing group during the treatment phase. The panel combinations are summarized in Table 2.

Table 2 – Experiment layout by treatment group

Treatment	Control		Information		Pricing	
Phase	1	2	1	2	1	2
Intro	x	x	x	x	x	x
Distance summary	x	x	x	x	x	x
Explanation				x		x
External costs				x		x
Budget						x

Note: 1=observation phase, 2=treatment phase.

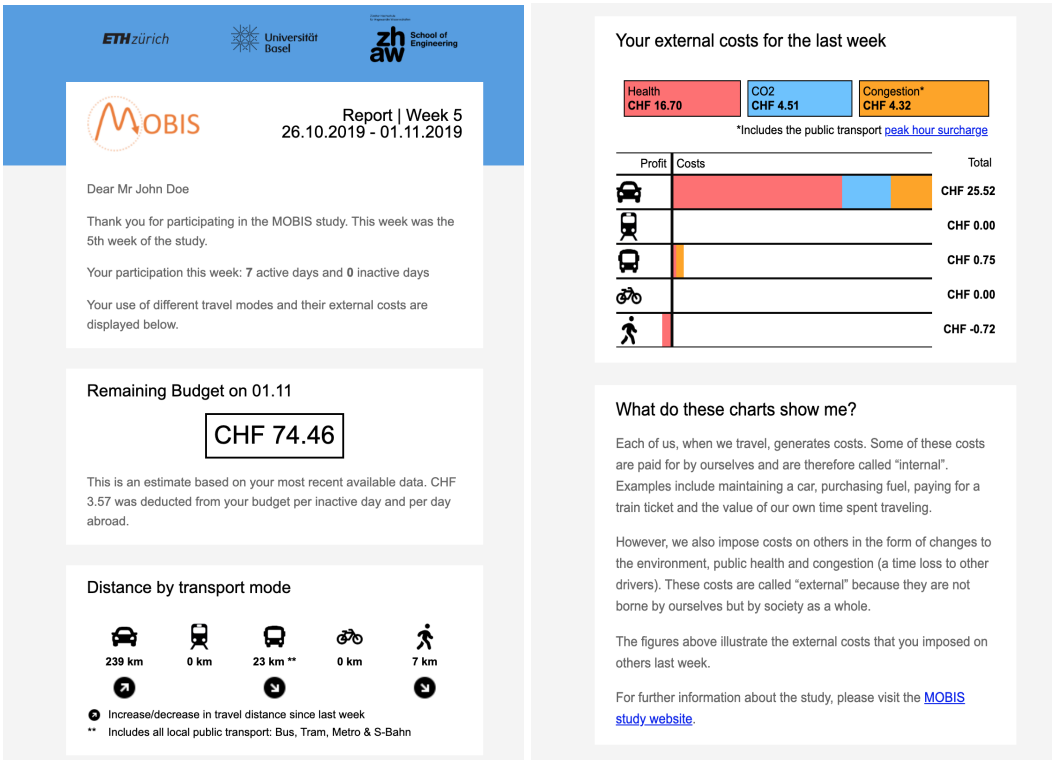
3.2.7 Final survey

Upon completing the tracking study, participants received an email with a link to the final survey. The final survey contained questions related to the following topics.

- Socio-economic background: self-reported absences during the field experiment.
- Employment background: same questions as in introduction survey to check changes during the experiment and flexibility in working conditions regarding home office and work schedule.
- Transport-related opinions: short list of the subtopics asked in the introduction survey.
- Car attitudes
- Motivation and impact of the MOBIS study
- Awareness and evaluation of the interventions

[37] The additional 20% were added to account for the possibility of participants increasing their external costs due to changes in their home or work location. Participants that completely exhausted their budget were kept in the sample, but their tracks for the days after which the budget was exhausted were not used for analysis.

Figure 1 – Weekly reports as shown to participants



Note: Left panel (top and bottom): Shown to all participants for the duration of the study; right panel: shown to information and pricing groups during treatment phase; left panel (middle): shown to pricing group during treatment phase.

- Stated choice experiment
- Opinion regarding the use of the revenues of transport pricing
- Lifestyles and values
- Health-related questions
- Bank data for the payment

The complete final survey can be found in Appendix B.4.

3.2.8 Compensation

All participants who completed the final survey received CHF 100 for their full participation, except those who did not generate tracking data on more than 12 days during the treatment phase, who instead received CHF 50 for partial participation (this partial compensation was not discussed ex-ante). Participants who did not generate enough tracking data in the observation phase were removed from the study, and thus did not receive any compensation. In addition, participants in the pricing group received any positive amount remaining on their virtual mobility budget.

Importantly, all participants were informed about the compensation of CHF 100 upon completion of the study. The possibility of a partial compensation was not mentioned and introduced at the end mainly as a gesture of appreciation towards people that delivered some tracks (but not enough to be included in the study). Likewise, the possibility of earning money during the pricing treatment was only communicated to the pricing group, and only on day 29 of participation.

A form was provided at the end of the final survey in which the participants could enter their bank account details, and all payments were processed by the ETH finance department. Table 3 shows a summary of the allocated virtual budgets, remaining balances paid out to the participants as well as the incurred costs. Only the 1,147 participants who completed the pricing treatment and received compensation are included. Remaining balances (i.e., exhausted budget) are capped to zero, as this is the amount that was actually paid out. This was the case for 202 participants.

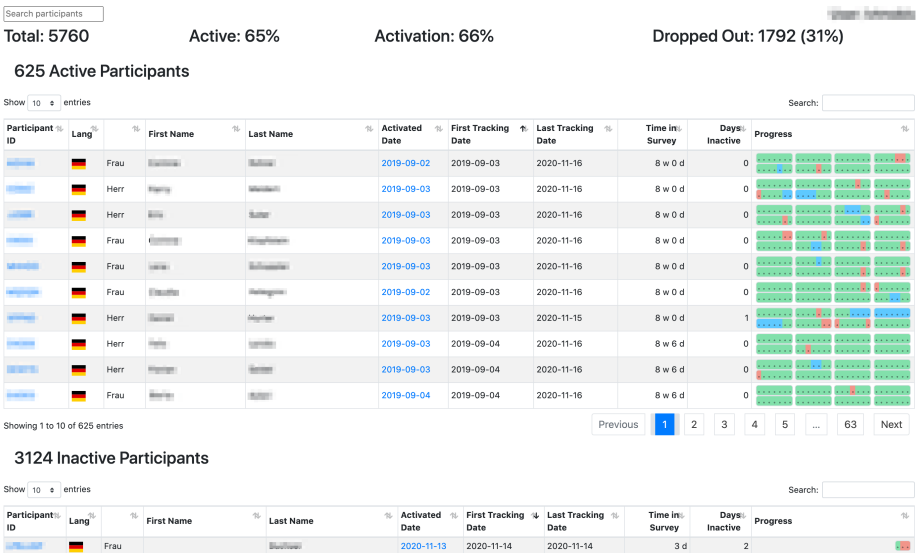
Table 3 – Summary statistics of virtual budgets, remaining balances and incurred costs (all in CHF).

	Virtual budget	Remaining balance	Incurred costs
Mean	173.82	45.45	132.89
Std. dev.	101.63	48.53	81.66
Min	50.00	0.00	0.00
25%	100.00	7.00	75.72
50%	150.00	31.44	115.37
75%	230.00	68.53	172.72
Max	745.00	432.68	616.08

3.2.9 Study monitoring

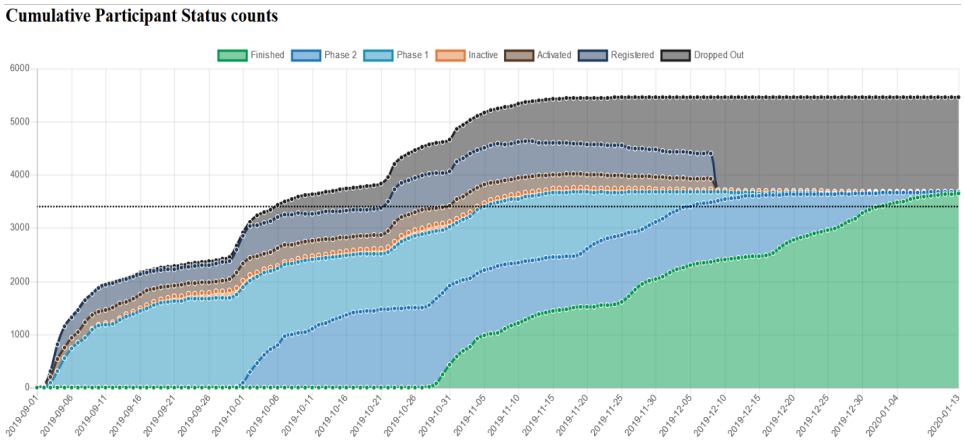
Two dashboards were developed for the monitoring of both the participants and the participation rate (see Figures 2 and 3 respectively). The first dashboard was essential for troubleshooting with participants, as it gave a visual overview of their participation by week, including when they track abroad. The second gave an overall view of the response rate. This helped identify that a second invitation wave was required to meet the target number of participants. In one instance, the observed increase in the share of inactive participants helped detect the impact of an iOS upgrade on participation.

Figure 2 – The overview page of participants



Note: This screenshot was taken after the conclusion of the study, and the participants counts do not reflect the real status during the study.

Figure 3 – Screenshot of the MOBIS response rates dashboard



3.2.10 User support

A project website[38] was created to support people invited to the MOBIS study. The website contained links to the introduction survey and the tracking study registration (in case people lost the invitation letter or stopped the registration process at some point), a project description, information for study participants (including a general information sheet, instructions for the tracking app, data privacy policy and consent) as well a Frequently-Asked-Questions section. The website was available in English, German and French.

Additionally, a help-desk service was set up to allow participants to ask questions and communicate any issues they might have had during the study. The communication with the help-desk was possible via phone call or email. The phone help-desk was open 10 hours per week, from 17:00 to 19:00 from Monday to Friday and from 10:00 to 12:00 on Saturday. The online help-desk received 5,218 emails during the study, of which nearly 50% came during the on-boarding process. A summary of the tickets received and processed by the online help-desk is provided in Appendix C.2.

3.3 Tracking app

To track the movements of the study participants, we used the Catch-My-Day app. This is a location tracker for iOS and Android, which uses the location services of the respective operating system. GPS tracks are stored on the phone and uploaded to the Motiontag analytics platform, where trip stages (Etappen in German), travel modes and activities are imputed. The concept of a stage is important, as a trip between two activities can consist of multiple stages (e.g., a trip by public transport may consist of five stages: a walk to the bus, the bus to the train station, walk to the platform, a rail journey, and finally the walk to the destination). The splitting of a day into stages and activities is called *segmentation*. This is performed by the Motiontag app using machine learning, rather than specific thresholds such as a minimum duration between stages.

The stages in the MOBIS study and the Swiss Mobility and Transport Microcensus (MTMC) follow the same definition, except for the minimum length restriction, which is not applied. The MTMC is a representative travel diary survey of the Swiss population undertaken by the Swiss Federal Statistical Office and the Swiss Federal Office for Spatial Development (2017). A trip in the MTMC is defined as:

> Each trip consists of one or more stages. A stage is part of a trip that is covered by the same means of transport, where walking is considered as one means of transport. A new stage begins with each change of means of transport, as well as with a change between two means of transport of the same type. The

[38] https://www.ivtmobis.ethz.ch/mobis/

> minimum length of a stage is 25 meters in public space.

The MTMC defines the following trip purposes:

> Individual stages, but also stages aggregated to trips, are undertaken for a specific purpose. The MTMC distinguishes the following purposes: Work, education, shopping/errands, business, providing services, leisure, service trip, accompaniment of another, and transferring/changing modes. For leisure travel, the purposes are further differentiated.

Motiontag does not provide the capability to assign a purpose to a trip or stage. Hence the trip purpose is determined from the purpose of the activity following the trip, if that activity occurred within 1 hour of that trip. No stage purpose is imputed. The activity categories available in Motiontag are home, coworking, assistance, education, errand, home office, leisure, shopping, waiting and work.

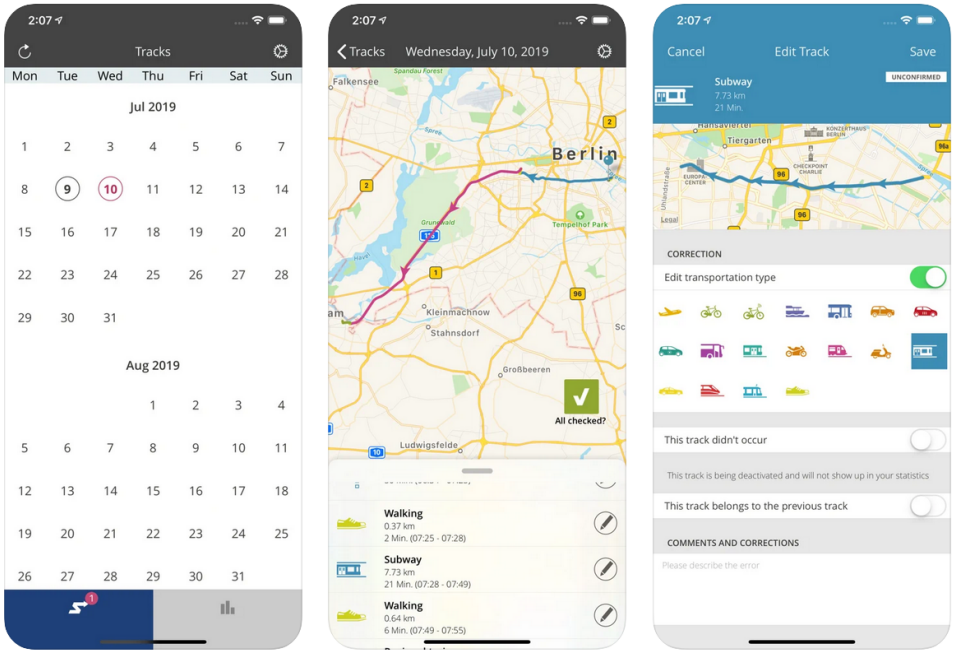
The Motiontag SDK segments collected GPS data for an individual into stages and activities. However, for some analyses, aggregation to the trip level is required. A trip was defined as the chain of consecutive stages between two activities, where the gap between them was 15 minutes or less. This definition is slightly different to that used in the MTMC, as GPS allows for a much more precise determination of the departure and arrival times.

The activity purpose was labeled by participants for approximately 45% of the activities. The remaining activity purposes were imputed using a random forest approach, trained on the labeled activities. For the specifics of this approach, see Gao *et al.* (2020).

3.3.1 Assignment of transport modes

Catch-my-Day app gives a best guess of the travel mode for each stage. The participants could then confirm this detected mode, or correct it. This confirm-correct procedure was also optional, as with the activity confirmation. Around 29% of stages were confirmed by the participants. The topic of corrections is discussed more in 4.6.2. The following modes are detected the by Catch-my-Day app:

Figure 4 – The Catch-my-Day interface. From left to right: 1) Calendar home page. 2) Daily view showing recorded trips. 3) Editing the mode of a selected trip.



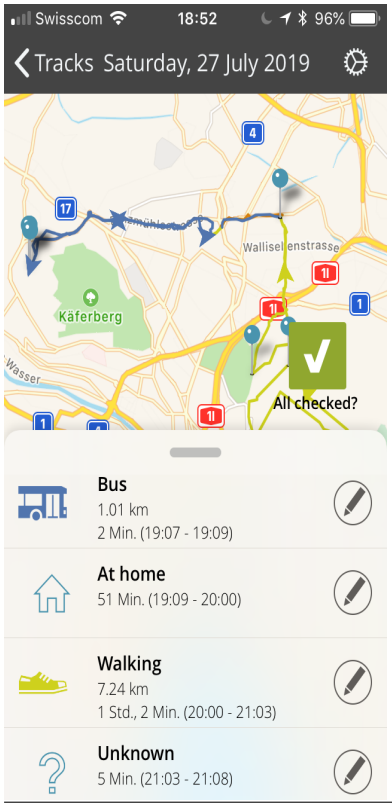
- Airplane
- Bicycle
- Bus
- Car
- Ferry
- S-Bahn (Local train)
- Regional train
- Subway
- Train (other)
- Tram
- Walk
- Boat*
- Carsharing*
- Motorbike/Scooter*
- Taxi/Uber*

Those marked with an asterisk are not automatically detected, but selectable by the user as a correction. E-bikes and E-Scooters were not detectable or selectable during the experiment.

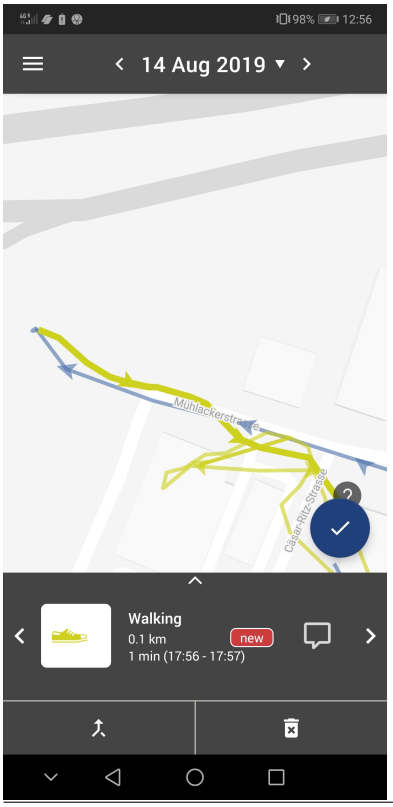
Users can view their daily travel patterns on their phone in the form of a logbook, validate the travel mode and activity purpose or indicate if a stage or activity did not take place. The database stores both their correction and the original algorithmic imputation. There are some user-interface differences between the iOS and Android versions, which are most noticeable in the validation interface.

Figure 5 presents the validation interface of the app for the respective operating systems.

Figure 5 – Trip/validation interface



(a) iPhone



(b) Android

Users were required to activate the app by creating an account, which requires the provision of an email address and the choice of a password, along with the unique registration code provided. Participants are not required to validate their trips and activities, but were informed that this was possible and would be appreciated.

To increase the retention rate, automated reminder emails were sent to participants when

they had not activated the app, or no data was recorded in the last 3 days. These reminders were sent every 4 days until the participant started tracking again or dropped out. A help-desk was set up for participants experiencing difficulties. User-guides on correctly configure one's smartphone for the app were provided.

3.3.2 Accuracy of mode detection

In recent years, state-of-the-art machine learning algorithms for mode and activity detection have achieved accuracy rates of over 90%, depending on the approach (Wu *et al.*, 2016; Nikolic and Bierlaire, 2017). Hence, we made validation of the trip purpose and mode optional for participants, in order to not increase the response burden excessively over the 8 weeks. 85.7% of participants confirmed at least 1 of their trips; however, of those who did use the validation functionality, 20.4% of iPhone users and 44.1% of Android users did not make a single correction over the 8 weeks, respectively. Even with state-of-the-art accuracy rates, such a validation behavior is extremely unlikely. As such, we can assume that these participants did not use or understand the validation interface correctly, and these participants are therefore removed from the following analysis on the mode detection performance. The difference between the two operating systems also indicates that the iPhone validation interface was much more intuitive.

The mode detection provided by the tracking app was a key component of the MOBIS study. As far as the authors aware, this is the first study to incentivize changes in mobility behavior based on the output of a mode detection algorithm. As seen in Table 4, the algorithm worked exceptionally well on location data from both operating systems. There is small difference in accuracy between iOS and Android, with iOS being on average slightly better (92.23% vs 92.10%) with a p-value of 0.01, test of equal proportions). However, the differences in accuracy are more observable at the categorical level. The iOS performs better on car, local rail, regional rail, tram and walk. However, the differences are only 1-3% in accuracy. Note that 'Rail' groups all rail modes together for conciseness. It is also worth noting that while the accuracy of some individual rail modes is quite low, the overall rail accuracy is very good. The main confusion was between different rail mode types.

Table 4 – Comparison of the mode detection performance bewteen iOS and Android

	% Correct			
Mode	Android		iOS	
Airplane	99.48%		98.86%	
Bicycle	81.59%		79.14%	
Bus	66.98%		66.82%	
Car	92.98%		93.15%	
Rail	89.50%		91.05%	
Local train		88.67%		90.18%
Regional train		71.35%		73.40%
Subway		93.56%		92.53%
Train		63.13%		63.78%
Tram	95.01%		96.64%	
Walk	95.56%		97.21%	

Table 5 presents the confusion matrix between the modes. Here we can see that the algorithm often mis-detected car travel as bus travel. For conciseness, the category 'Other *' includes those modes which could be manually selected by the participant, but which were not automatically detected. These included: Carsharing, Taxi/Uber, Motorbike/Mopeds, and Gondolas. Most of these were detected as car travel, and the 1,500 'Bicycle' trips which were corrected to 'Other' were predominately trips by motorbike or moped.

These mode detection results confirmed the indications of our pretest that the automatic detection could indeed be used to calculate the external costs of travel with sufficient accuracy and determine the phase 2 budget and deductions based on these. If the accuracy had been too low, more participants would have dropped out of the study, seeing it as 'unfair' if

the budget and deductions did not match their travel behavior.

Table 5 – Confusion matrix of mode detection accuracy

	Confirmed mode									
	Airplane	Bicycle	Boat	Bus	Car	Rail	Tram	Walk	Other	**Total**
Predicted										
Airplane	**2,113**	-	-	-	22	-	-	-	-	**2,135**
Bicycle	4	**26,201**	136	438	1,499	177	149	2,771	1,500	**32,875**
Bus	1	435	2	**35,713**	15,085	140	280	889	865	**53,410**
Car	372	2,495	741	8,028	**366,649**	3,314	1,950	2,834	7,433	**393,816**
Rail	64	56	85	1,748	7,298	**60,270**	691	258	298	**70,768**
Tram	-	49	2	128	396	60	**20,174**	149	16	**20,974**
Walk	80	3,807	456	1,224	9,960	868	868	**514,944**	638	**532,845**
	2,634	**33,043**	**1,422**	**47,279**	**400,909**	**64,829**	**24,112**	**521,845**	**10,750**	**1,106,823**

3.4 Computation of external costs

The health, emissions, noise and congestion costs of the mobility behavior are imputed on the recorded daily trips using an automated data pipeline. Additionally, data collected from the online introduction survey was incorporated into the data processing pipeline to improve the imputation.

3.4.1 External costs from driving

For the calculation of external costs in private road transport, GPS Tracks are aligned to the road network using Graphhopper (Karich and Schröder, 2014) and processed using modules developed on top of the MATSim framework to calculate the external costs of congestion and emissions. The emissions factors are taken from the HBEFA database (version 3.3), and applied using the MATSim emissions module (Hülsmann *et al.*, 2011; Kickhöfer *et al.*, 2013). For congestion, an average marginal cost approach incorporating spillback effects and flow congestion was applied, based on the work of Kaddoura (2015). These modules returned quantities of the externalities in grams (for emissions) and seconds of caused delay (for congestion) for road transport, which were then converted to monetary costs using the values in Table 6.

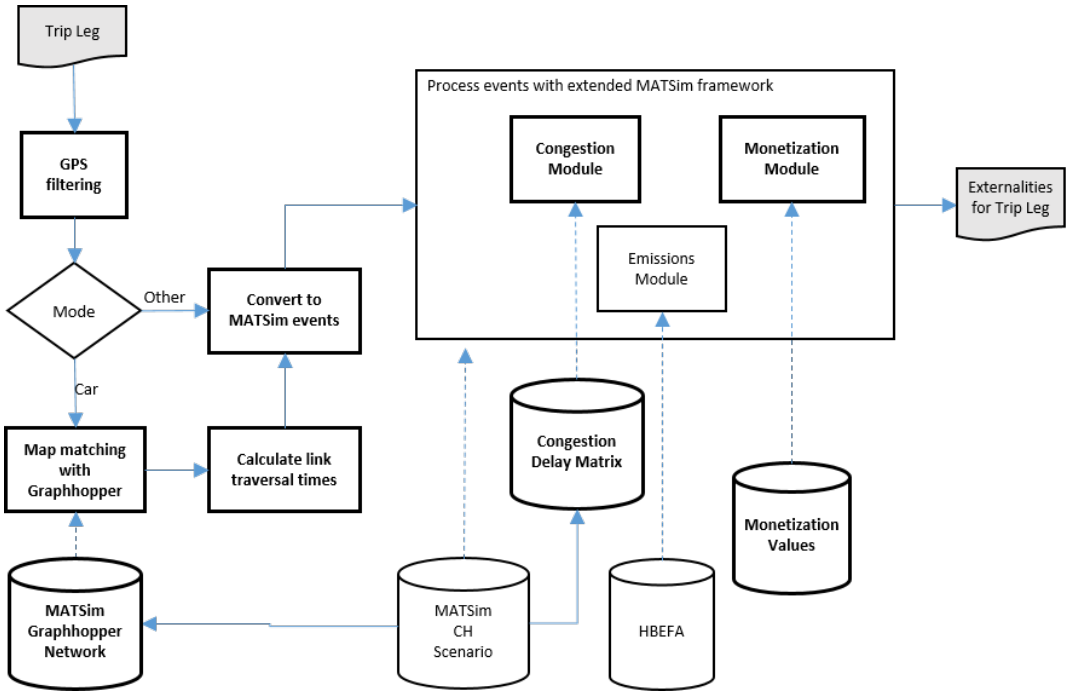
Table 6 – Monetization of externalities

Emission	Aspect	Value	Unit
Scenario year		2019	
CO_2	Climate Costs	136.08	CHF/ton [a b]
PM_{10} Costs (Healthcare)	Rural	515,497	CHF/ton [a b]
	Urban	1,358,461	CHF/ton [a b]
NO_x	Regional	7,109	CHF/ton [a b]
VTTS		25.77	CHF/h [c]

[a] Federal Roads Office - ASTRA (2017) - updated for 2019,
[b] metric tons, [c] scaled nominal wage rate from [a]

Figure 6 illustrates how data flows through the externalities pipeline. The objects in bold are those developed as part of this project. Dotted lines indicate data inputs from static sources, and solid lines are the flow of the GPS-based trip data through the model. The lack of flows inside the MATSim framework is intentional, as those modules are built on top of the MATSim event framework (Horni *et al.*, 2016b). The pipeline is described in more detail in Appendix E.

Figure 6 – MATSim-based externalities pipeline



3.4.2 External costs from public and active transport

For modes other than driving, per-Km values were applied to the recorded length of the trip. These are presented in Table 7. Note that the total health cost of the active modes is the sum of the accident costs and health benefits. This results in cycling having an external cost rather than benefit, in alignment with the Swiss norms.[39]

Table 7 – Per-km monetary costs used in the MOBIS experiment.

Mode	CO_2	PM_{10}	NO_x	Accidents	Noise	Health
Train	0.000066	0.0140	-	0.00066	0.0087	-
Bus	0.0144	0.0437	0.5440	0.0141	0.0257	-
Tram	-	-	-	0.0126	0.0075	-
Bicycle	-	-	-	0.257	-	-0.1870
Walk	-	-	-	0.075	-	-0.1863

Note: Negative values indicate an external benefit.

Table 8 illustrates the mean values for the various external costs are illustrated, grouped into the categories CO_2, congestion and health that the participants saw in the weekly reports. For a more detailed analysis of the road congestion costs - where the NISTRA methodology was not applied see Appendix E, where the external costs are also compared to the Swiss normative values. The costs are presented per stage, kilometer and minute respectively.

3.4.3 Peak hour pricing model for public transport

In contrast to private car travel, the marginal social cost of public transport (in terms of pollution and noise) decreases as the occupancy rate increases. On the other hand, crowding affects willingness to pay and can be seen as a form of congestion in public transport, and delay in some circumstances (Tirachini *et al.*, 2013). However,crowding effects are extremely heterogeneous, both spatially and temporally. Even in peak hour, crowding can

[39] As no pollution values were provided by NISTRA, a value of zero was used for the tram mode. This has a very small effect on the study results, as they would be similar to Train (which are low).

Table 8 – Average external costs - CHF/Km

	CO_2	Congestion	Health	Total
Car	0.326	0.330	1.014	1.670
Bus	0.040	0.033	0.148	0.221
Tram	0.000	0.048	0.034	0.082
Train	0.002	0.322	0.296	0.621
Bike	0.000	0.000	0.296	0.296
Walk	0.000	0.000	-0.069	-0.069

Table 9 – Average external costs - CHF/Stage

	CO_2	Congestion	Health	Total
Car	0.026	0.033	0.078	0.138
Bus	0.014	0.014	0.071	0.100
Tram	0.000	0.022	0.015	0.037
Train	0.000	0.014	0.012	0.025
Bike	0.000	0.000	0.070	0.070
Walk	0.000	0.000	-0.111	-0.111

Table 10 – Average external costs - CHF/Minute

	CO_2	Congestion	Health	Total
Car	0.017	0.018	0.053	0.089
Bus	0.006	0.005	0.027	0.038
Tram	0.000	0.006	0.004	0.010
Train	0.000	0.013	0.011	0.024
Bike	0.000	0.000	0.024	0.024
Walk	0.000	0.000	-0.017	-0.017

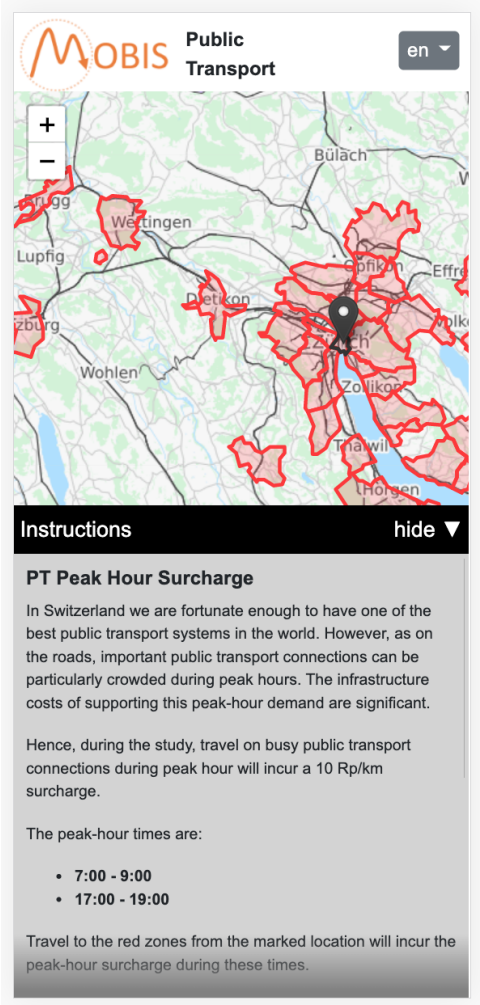
be restricted to particular transit lines during very short periods (Zurich Public Transport, 2017). As such, it would be unreasonable to distribute the crowding effects in an aggregate measure across peak hour travelers in a specific public transit region. Additionally, for each public transport operator, data would have to be collected separately and collated as it is not available on a national level. As an alternative solution, a zonal peak-hour surcharge pricing scheme was developed for the national public transport network, as a form of second-best pricing. Throughout the experiment, participants had access to a interactive map which showed them where and when the pricing scheme applied (see Fig. 7. The peak-hour pricing surcharge applied a 10 Rp/km surcharge on public transport trips between those zones with a larger demand in peak hours compared to the off-peak.

The zoning system was based on the *gemeinde*[40], with large urban municipalities such as Zurich being split into their *kreise*[41]. The surcharge was applied to transit stages between any two zones which experience peak hour demand. The peak hour windows and the affected zone-pairs were determined using the output of the MATSim scenario for Switzerland (Bösch *et al.*, 2016). The peak windows were set as 7am-9am and 5pm to 7pm, and not adapted for regional variations in working patterns. Municipality pairs were priced if the maximum hourly transit trip count during peak hour was greater than three times the average hourly transit trip count during the daily off-peak (9am - 5pm) for that pair. A municipality could also be paired with itself if the the above criteria was met, and the direction of the peak hour flow is not considered. If the trip was partially in both the peak and off-peak periods, only the proportion of the travel duration that overlaps with the peak period was

[40] A *gemeinde* in Switzerland is roughly translatable as a municipality.
[41] A *kreise* in Switzerland is roughly translatable as a municipal district

charged.

Figure 7 – The PT surcharge guide as viewed on a mobile device. The red areas indicate destination zones which would be charged during peak-hour from the black zone. The map is movable and zoomable by the user.



3.5 Data preparation

The identifying information of the participants was combined with the tracking data collected from the Catch-my-Day app, and stored on an ETH PostgreSQL database. This was also connected with answers on vehicle ownership from the introduction survey that was necessary for the estimation of the external costs. This database also stored the output of the external cost imputation, and the record of communications with the participants. The details of every communication were stored, and tracking pixels included in the email to capture the participants interaction with the communications. The interactions captured included both the opening of the email, and the hyperlinks in the email that were clicked. If actions were performed multiple times, these were also recorded, including the timestamp.

3.5.1 Weather data

As weather is an important predictor of travel mode choice, in particular for active modes and public transport, the tracking data was linked with precipitation and temperature data from MeteoSwiss. Precipitation data was available from a spatial model that combines rain gauge precipitation measurements with rain radar, resulting in a 1km grid of hourly

precipitation estimates.[42] These were linked to trip origin locations and start times. Daily precipitation[43] as well as mean, minimum and maximum temperature[44] was also available as a 1-km grid, and was also linked to each trip.

3.5.2 Non-chosen alternatives

For the analysis of mode choice under treatment conditions using the discrete choice methods, the attributes of the non-chosen alternatives which would have been available to the traveler are required. For more background on discrete choice modeling, please see Train (2009) or Ben-Akiva and Lerman (2018). For this purpose, a software module was developed on top of MATSim to calculate the attributes of all the available alternatives for a trip, given the start and end coordinates and arrival and departure time.

The mode alternatives considered were walking, cycling, private car and public transport. Car trips were routed on the Swiss road network, as generated for the MATSim Switzerland scenario (Bösch *et al.*, 2016; Hörl, 2017), under calibrated typical congested conditions in the scenario. This scenario is the same on as used for the externalities calculation. The walking and cycling alternatives were also routed on the respective networks, based on the start and end points of the original trip, using fixed speeds of 5km/h and 15km/h respectively. Road gradients were not taken into account.

For public transport, not only are the travel distance and duration required for the modeling framework, but also the ticket cost, trip frequency, egress/ingress distance and number of transfers in the trip. The identification of the main mode of a multimodal public transport trip is also important, as it is acknowledged that different public transport modes have varying VTTS values (Schmid *et al.*, 2019b). To capture this information, the pt-pricing software module (Hörl and Molloy, 2019) was used to route the public transport trips on the same MATSim network as the other modes. The necessary transit schedule was taken from the openly data timetables (Business office of Customer Information System Tasks (SBB CFF FFS), 2019) and for ease of application, the timetable from the 24.09.2019 was taken, using the timetables issued on 2019-09-28, under the assumption that the timetable is generally consistent across weekdays and the MOBIS study period. The frequency of the route is calculated as the number of connections between the start and end point within a 2 hour window around the start time of the trip and scaled to trips/hour. The egress and ingress distance are calculated using beeline distance multiplied by 1.4, between the start of the trip and the initial public transport stop, and the last stop and the destination, respectively.

3.5.3 Data cleaning

Before using the data for analysis, it was cleaned using some routine procedures that check for plausibility and remove obviously problematic data. In addition, we removed the data if one of the following was true:

- Average daily speed for car and PT above 100 km/h, above 40 km/h for bicycling and above 20 km/h for walking
- More than 500 km/day for car and PT, and more than 20 km/day for walking

In order to not bias the data by selectively removing particular trips that were mis-measured or mis-assigned and thus reducing the daily average, we removed all data for that person and that day.

3.6 Data analysis

The data analysis can be separated into two types: A series of regression analyses based on continuous variables, used to estimate the treatment effects from the experiment; and

[42] https://www.meteoschweiz.admin.ch/content/dam/meteoswiss/de/service-und-publikationen/produkt/raeumliche-daten-combiprecip/doc/ProdDoc_CombiPrecip.pdf

[43] https://www.meteosuisse.admin.ch/content/dam/meteoswiss/de/service-und-publikationen/produkt/raeumliche-daten-niederschlag/doc/ProdDoc_RhiresD.pdf

[44] https://www.meteoschweiz.admin.ch/content/dam/meteoswiss/de/service-und-publikationen/produkt/raeumliche-daten-temperatur/doc/ProdDoc_TabsD.pdf

discrete-choice models to investigate travel behavior based on observed data ("revealed preferences" or RP) and based on the stated choice experiment ("stated preferences or SP). These very different modeling approaches are described in different subsections.

3.6.1 Estimating causal treatment effects

The main analysis investigates the effects of the experiment on the overall external costs associated with participants' travel.

Given that we randomize the treatment, the econometrics involved in estimating the average treatment effect (ATE) are straightforward, as there are no self-selection or endogeneity issues that need to be addressed. The randomized treatment creates an exogenous variation that can be directly used to identify the effect, without further adjustments, and, importantly, without relying on parametric assumptions. The nonparametric nature of this approach differentiates it from the discrete-choice modeling, which has a different objective and is discussed in the next subsection.

To estimate the effect of the treatment, we aggregate the data to the person-day level. The ATE can be estimated by

$$Y_{its} = c_0 + \alpha^P \cdot DiD^P_{its} + \alpha^I \cdot DiD^I_{its} + \mu_i + \mu_t + \mu_s + \epsilon_{its} \tag{1}$$

The dependent variable is the outcome of interest for person $i \in (1, ..., N)$ on calendar day $t \in (1, ..., T)$ and day of study $s \in (1, ..., 56)$. This can be the total quantity of external costs, the external costs along a particular dimension (health, climate and congestion), distance traveled in total or by mode, the mode share, or additional outcomes as specified in the results section.

The two difference-in-differences terms DiD^P_{its} and DiD^I_{its} are the products of treatment group and treatment period dummies, and are equal to one if the pricing (P) and the information treatment (I), respectively, are active for person i on a particular day, and zero otherwise. The treatment starts on the 29th day of the experiment. Due to the rolling recruitment, the beginning of the experiment (and thus also the beginning of the treatment period) varies by person, which is the reason for why we need to control for both t and s. To control for unobserved heterogeneity, we include fixed effects on the person (μ_i), day-of-calendar (μ_t) and day-of-study (μ_s) level. For example, people who tend to produce a high level of external costs of transport (regardless of the treatment) will have a high value for (μ_i). The day of calendar fixed effects capture common shocks that affect travel (and thus the associated external costs) for everyone in Switzerland, e.g., due to a national holiday or a sports event. The day-of-sample fixed effects account for the possibility that respondents may respond differently to the treatment over time. In fact, we find a high variation on the first day (presumably due to technical issues and learning by participants) and on day 29 (the first day of the treatment). We remove these two days from the analysis.

Finally, the error term ϵ_{its} has an expected mean of zero and a variance of σ. We allow for a correlation of the error within participants and day of calendar.

Due to the random assignment, we do not need to control for any covariates as they will, in expectation, affect the treatment and control groups equally. This leads to a fully nonparametric regression in which we compare simple means. However, because weather information is an important predictor for mobility, especially for leisure activities and for active transport modes, we enrich our tracking data with temperature and precipitation data from MeteoSwiss[45]. This could reduce the noise in the regression and thus increase the precision of our estimates.

The weather variables are assigned separately for each recorded trip in the data based on a 1 $\times$ 1 km grid. To allow for a nonlinear effect of temperature on travel choices, we define

[45] See `www.meteoswiss.admin.ch`

heat and cold for an observed trip j on day t as follows:

$$Heat_{jt} \equiv \max\{tmaxd_{jt} - 25,\, 0\} \tag{2}$$
$$Cold_{jt} \equiv \max\{10 - tmind_{jt},\, 0\} \tag{3}$$

The variables $tmaxd_{jt}$ and $tmind_{jt}$ refer to the daily maximum and minimum temperature, respectively, recorded in degrees Celsius at the grid point closest to the departure location for trip j.

This type of nonlinearity in temperature is often used to explain energy use, with “heat” typically recorded in the form of “cooling degree days" (when air conditioning is running) and cold as "heating degree days" (when buildings are heated). The aim of this method is to reflect the fact that it can be too hot or too cold, which cannot be reflected if temperature were included as a linear variable. The cut-off values of 25 and 10 degrees are based on widely perceived conceptions of what constitutes a hot day (temperature above 25 degrees Celsius) and a cold day (temperature below 10 degrees Celsius). However, the results are robust to different threshold values.

The precipitation data is provided on a daily basis for the dame grid. To compute the values per person and day, we take the average of the heat, cold and precipitation values across all trips taken by person i on day t. Precipitation, heat and cold are then added as linear control variables to (1) in some regressions.

The ATE of pricing plus information is given by the coefficient estimate α^P; the ATE for information only is given by α^I; and the ATE for pricing *per se* (conditional on having been informed) is their difference, $\alpha^P - \alpha^I$.

To investigate potential differences of the treatment effect along major socio-economic variables, we interact the DiD terms in (1) with dummy variables. For example, to investigate a potential effect heterogeneity between the genders, we estimate

$$\begin{aligned} Y_{its} = c_0 + \alpha^P \cdot DiD^P_{its} + \gamma^P \cdot DiD^P_{its} \cdot male_i + \alpha^I \cdot DiD^I_{its} + \gamma^I \cdot DiD^I_{its} \cdot male_i \\ + \mu_i + \mu_t + \mu_s + \epsilon_{its}\,, \end{aligned} \tag{4}$$

where $male_i$ is a dummy variable that is equal to one for men and zero otherwise. The pricing-related ATE for women is given by α^P, whereas that for men is given by $\alpha^P + \gamma^P$. The same logic applies to the effect of the information treatment and any other interaction dummies.

For the regressions that use external costs as the dependent variable, we estimate (1) in levels by using Stata’s `reghdfe` command. The estimation in levels (rather than logs) is necessary as the external costs associated with walking are negative, and there are many person-days with overall negative values. We then compute the proportional response by dividing the coefficients (which are in CHF) the external costs generated during the observation period.

For regressions in which the dependent variable is non-negative, we estimate proportional effects directly by using a Poisson Pseudo-Maximum Likelihood (PPML) model. We prefer this approach to taking logarithms due to the possible presence of heteroskedasticity, which can lead to a bias in log regressions, and the presence of zeroes in the data. For a discussion of the advantages of using a Poisson model in the presence of zeroes and heteroskedasticity, see Santos Silva and Tenreyro (2006). We use Stata’s `ppmlhdfe` command that was developed by Correia *et al.* (2019) and Correia *et al.* (2020).

3.6.2 Stated choice experiment

This section describes the MOBIS stated choice experiment (SCE), which formed part of the final survey of the MOBIS study. The MOBIS field experiment was subject to constraints with regard to the intensity of the pricing treatment, which we relaxed in the SCE. The main aim of the SCE was to provide more information on the elasticity of the demand response

to transport pricing by multiplying the Pigovian rate by different factors (0.5, 2, 4, and 8), thus providing more points on the demand curve for mobility at different levels of transport pricing.

Since the focus of the MOBIS study is on the impact of externalities on mobility behavior for regular car users, the natural reference point for the SCE was a typical observed car trip for each participant. We selected a regular car trip for each user that took place within the observation phase of the MOBIS study and was associated with the highest potential external costs.[46] We split the SCE into three parts, each presenting an alternative mode (public transport or bicycle) or time of departure (before or after peak rush hour) compared to the reference car trip. We denote the three SCE types as Car-PT, Car-Bike, and Car-Alt, respectively.

SCE design The starting point of the SCE design was a D-efficient pivot design with ten blocks. Table 11 presents the attributes and their respective levels for each SCE. In the current setting, however, we adjusted certain attributes ex post to better mimic the MOBIS field experiment.[47] For example, we constrained the private cost of each alternative to be the same across all choice sets. In particular, the private cost for the baseline car trip and the alternative car trip in the Car-Alt SCE were set at 0.70 CHF/km. The private (ticket) costs for the public transport alternatives were adjusted depending on the subscription status of the respondent. Those holding a half fare subscription were presented with half the actual ticket cost. For those respondents with a regional pass or GA (full fare reduction), we applied the half-fare price multiplied by a "savings" factor depending on in which region the alternative trip takes place. These factors capture the reduction in ticket prices when holding a regional subscription compared to purchasing the full-price ticket on a daily basis[48]. The private costs for the Car-Bike SCE were set at zero for bicycles (since the long run average costs of maintaining a bicycle are essentially zero) and at 0.07 CHF/km for e-bikes, which captures the energy costs of recharging the battery. In the Car-Alt SCE, we additionally constrained the climate and health externalities to be the same for each choice set, since the effect of departure time on these externalities should be minimal.

The departure time shifts for the Car-Alt SCE were changed from the original design if the suggested shift would move the alternative trip into rush hour. As such, some respondents only saw choice sets where the departure time shifts were either all earlier or all later than the observed trip. For the Car-PT SCE, the public transport option was calculated using the Google Maps API. For the Car-Bike SCE, travel times were calculated based on travel speeds of 15 km/h and 20 km/h for bicycles and e-bikes, respectively. We constrained the travel times for the bicycle alternative to 80 minutes, since longer travel times would almost certainly not be considered as a viable alternative to the observed trip.

We prepared respondents for the SCE with the introductory text in Figure 8. Next, we provided respondents with a map and a description the specific observed trip on which the SCE choice sets were based (see Figure 9). Once informed about the baseline trip, respondents were presented with four choice sets for each SCE type, resulting in a total of 12 choice sets overall. The choice sets were presented either in blocks of four for each SCE type or in random order. The alternatives were also randomly presented as either Option 1 or Option 2, to counter any potential left-right bias. Figures 10, 11, and 12 provide examples of the choice sets as seen by the respondents. In the cases where, for example, no viable PT alternative was found, respondents received additional departure time choice sets. The same is true for respondents where the bicycle alternative would have taken more than 80 minutes.

[46] This would typically be a trip that takes place in the morning or evening rush hour. In this case, the morning rush hour peak is 7:30 and the evening rush hour peak is 17:30, as calculated by MATSim (Axhausen *et al.*, 2016).

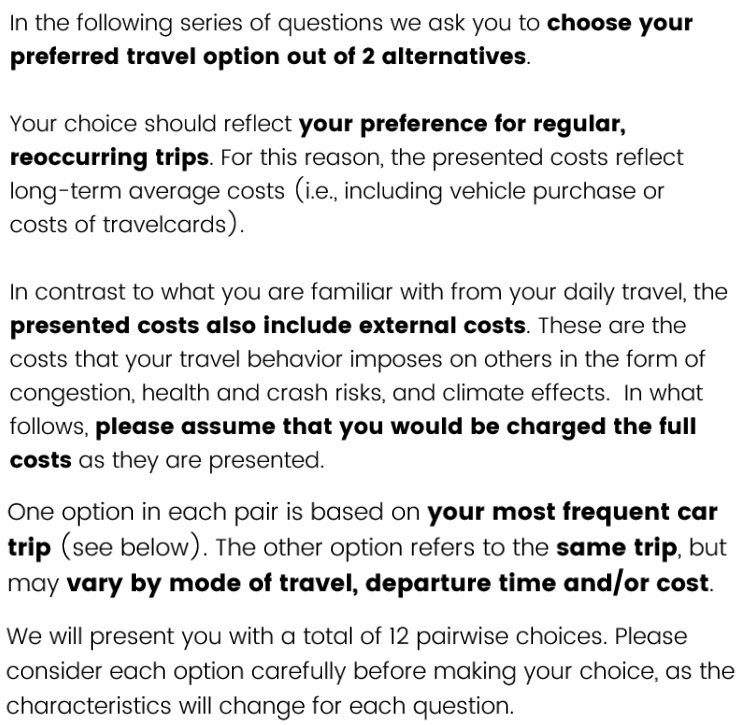
[47] This comes at the cost of not being able to uncover stable willingness to pay estimates in the same order of magnitude as other Swiss studies.

[48] There is large heterogeneity in these factors, which range from a 24% reduction in Geneva to a 76% reduction in Basel

Table 11 – SCE Attributes

Attribute	Mode				Levels
	Car	Alt	PT	Bicycle	
Departure	✓	✓	✓	✓	
Arrival	✓	✓	✓	✓	
Duration	✓	✓	✓	✓	Alt: (50%, 60%, 70%, 80%, 90%, 95%) $\times$ Car Duration
Access/Egress			✓		
In-vehicle time			✓		
Departure time shift		✓			- 60 min, - 30 min, + 30 min, + 60 min
Reliability (delay $>$ 10 min every)	✓	✓	✓		Car and PT: every 5 trips, every 10 trips, every 20 trips, never Alt: every 20 trips, never
Weather			✓	✓	cold and wet, cold and dry, warm and wet, warm and dry
Mode			✓	✓	PT: bus, tram, subway, train Bicycle: standard, e-bike
Occupancy			✓		low, medium, high
Frequency			✓		every 10 min, every 20 min, every 30 min
Changes			✓		1, 2, 3, 4, 5, 6
Health benefit				✓	low, medium, high
Bicycle lane				✓	main road w/o bicycle lane main road with bicycle lane, residential street or bicycle path
Total Cost	✓	✓	✓	✓	
Private Cost	✓	✓	✓	✓	
External Cost	✓	✓	✓	✓	
Congestion Cost	✓	✓	✓		Alt: (20%, 40%, 60%, 80%) $\times$ Car Congestion Cost
Health Cost	✓	✓	✓	✓	
CO_2 Cost	✓	✓	✓		

Figure 8 – SCE introduction



SCE methodology The first part of the analysis of the SCE is based on a discrete choice approach within a random utility model framework (see Train (2009); Hensher *et al.* (2015). The starting point is the standard multinomial logit (MNL). Utility U of alternative j for observation n is

$$U_{jn} = V_{jn} + \varepsilon_{jn},$$

where V_{jn} is the systematic or observed part and ε_{jn} is an iid, mean zero EV1 error term, which captures individual preferences and the influence of non-included variables and potential measurement error. V_{jn} is a combination (usually linear) of k attributes and their associated marginal utilities (the parameters to be estimated):

$$V_{jn} = \sum_{k=1}^{K} \beta_k x_{jnk}.$$

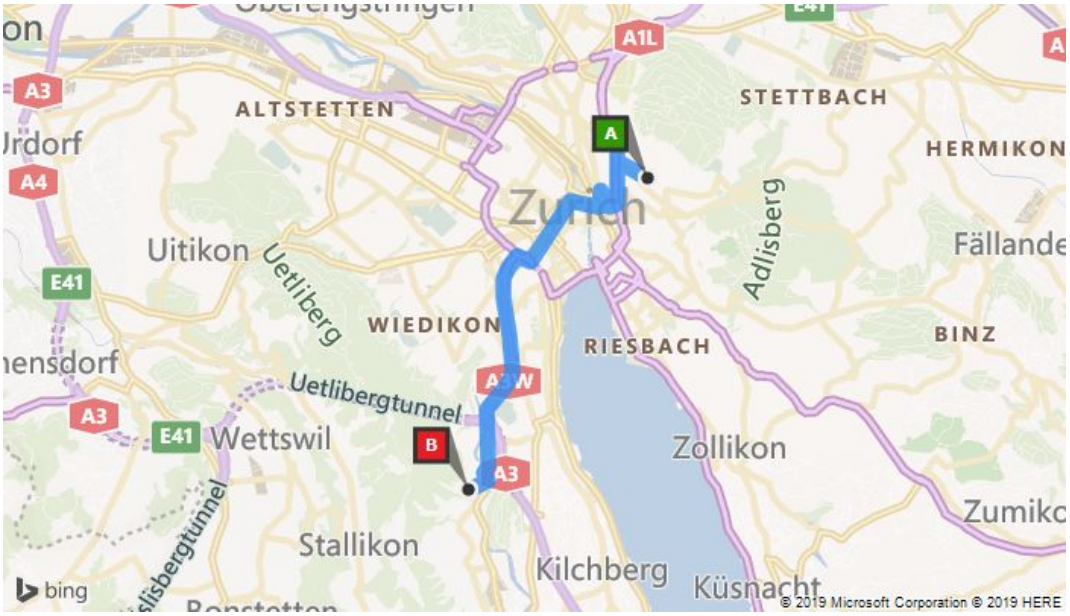
Following the theory of utility maximization, observation n selects the alternative j, which provides the highest utility U, with probability

$$\begin{aligned} P_{jn} &= P(U_{jn} > U_{in} \qquad \forall j \neq i) \\ &= P(\varepsilon_{in} - \varepsilon_{jn} < V_{jn} - V_{in} \qquad \forall j \neq i) \\ &= \int f(\varepsilon) d\varepsilon, \end{aligned}$$

where $f(\varepsilon)$ is probability density function of the joint (logistic) distribution of the error terms. The probability of person n choosing alternative j is then

Figure 9 – Observed trip information and map

On **12.12.** at **17:09** you drove from **Zurich, Zurich** to **Zurich, Zurich** by car. The trip took about **39 min** and resulted in private costs of **5,70** CHF. Below you see a visual depiction of the route you took.



$$P_{jn} = \frac{e^{V_{jn}}}{\sum_i e^{V_{in}}}.$$

The parameters are estimated by way of maximum likelihood, where the log-likelihood function takes the following form:

$$\ln L = \sum_{n=1}^{N} c_{jn} \cdot \ln P_{jn},$$

where N is the number of observations and c_{jn} is equal to one if j is chosen and zero otherwise. P_{jn} is the probability calculated with the estimated parameters.

The standard MNL model is able to incorporate heterogeneity between respondents by interacting attributes with respondent characteristics. A common formulation exploits respondents' sensitivity to cost and travel times as a function of income and distance. Specifically, the cost parameter is defined as

$$\beta_{n,cost,elasticity} = \beta_{cost} \cdot \left(\frac{income_n}{\overline{income}} \right)^{\lambda_{income,cost}} \cdot cost_n,$$

where $\overline{income}$ is the mean income within the sample and $\lambda_{income,cost}$ is the income elasticity of cost.

For travel time, a further interaction is added, which captures the sensitivity of travel time to trip distance:

$$\beta_{n,time,elasticity} = \beta_{time} \cdot \left(\frac{income_n}{\overline{income}} \right)^{\lambda_{income,time}} \cdot \left(\frac{distance_n}{\overline{distance}} \right)^{\lambda_{income,time}} \cdot time_n,$$

Figure 10 – Car-Alt

	Option 1: Car	Option 2: Car
Departure	17:09	16:39
Arrival	17:48	17:02
Duration	39 min	23 min
Change in departure time		-30 min
→ Delay >10 min	every 5 trips	every 20 trips
Total price	7,35 CHF	6,60 CHF
private share	5,70 CHF	5,70 CHF
external share	1,65 CHF	0,90 CHF
→ Congestion caused	1,25 CHF	0,50 CHF
→ Health/accident costs	0,30 CHF	0,30 CHF
→ Climate damages	0,10 CHF	0,10 CHF

where $\overline{distance}$ is the mean distance within the sample. $\lambda_{income,time}$ is the income elasticity and $\lambda_{distance,time}$ is the distance elasticity of travel time, respectively.

Due to the additional statistical power gains from larger sample sizes, joint estimation of the three SCEs is a useful approach. In this case, the utilities of two of the three SCEs are multiplied by a scaling factor (one being the reference set at unity). This provides an indication of the scale differences between the respective experiments and facilitates the interpretation of the parameters between the SCEs.

A final input into the model is the multiplication factors with which we randomly multiplied the observed external costs for each choice set in the SCE. Both alternatives received the same multiplication factor within each choice set. In order to test whether these factors had a significant effect on the choice probabilities, we include each of the five factors as dummies within the utility function of the non-reference alternative. The parameter estimates for these dummies replace the standard alternative specific constants and provide a pseudo "treatment effect" for that specific factor. Using only these factors dummies would recover the choice probabilities for each subset as defined by the multiplication factor, however these do not tell us whether certain attributes or respondent characteristics have a significant influence on these choice probabilities, given a multiplication factor. In other words, we may be omitting important explanatory variables in the model. To combat this, we include a rich set of individual-specific demographics and characteristics based on responses to both the introduction and final surveys.

With the above refinements, the utility specification for the analysis takes the following form:

$$V_{jn} = Scale_{SCE} \cdot \left(\sum_{f=1}^{F} ASC_f Factor_{jnf} + \sum_{k=1}^{K} \beta_k x_{jnk} + \sum_{c=1}^{C} \beta_c x_c \right), \tag{5}$$

where $Scale_{SCE}$ is the estimated scale parameter, ASC_f is the estimated parameter on the multiplication factor f, β_k is the estimated parameter on attribute k, and β_c is the estimated parameter on respondent-specific characteristic c.

3.6.3 Values and lifestyles

For the analysis of the effect of values on the choice of a transportation mode, we used the scale originally developed by Schwartz (1992) shortened by De Groot and Steg (2010) and further adapted by Steg *et al.* (2014). It identifies 4 meta-values particularly relevant for

Figure 11 – Car-PT

	Option 1: Car	Option 2: Public Transport
Departure	17:09	17:04
Arrival	17:48	17:45
Duration	39 min	41 min
→ Travel time		31 min
→ Access and egress time		10 min
Main mode		Rail
Changes		1
Occupancy		low
Frequency		every 30 min
Delay >10 min	every 5 trips	never
Weather		warm, dry
Total price	7,35 CHF	2,10 CHF
private share	5,70 CHF	1,90 CHF
external share	1,65 CHF	0,20 CHF
→ Congestion caused	1,25 CHF	0,10 CHF
→ Health/accident costs	0,30 CHF	0,10 CHF
→ Climate damages	0,10 CHF	0,00 CHF

explaining environmentally relevant behavior - egoistic, altruistic, hedonic and biospheric, based on 16 value items.[49] The meta-values are constructed as a mean of 3 to 5 items originally stated on a 9-point Likert scale, simplified in our study to a 5-point Likert scale as for example in the Swiss Household Energy Demand Survey (Weber *et al.* 2017). In particular, the respondents were ask to what extent they consider the 16 value items as *guiding principle in their lives* (Schwartz 1992).

To analyze the lifestyle effect on the choice of a transportation mode we applied the Otte lifestyle typology. Otte (2008) distinguishes 2 lifestyle-defining dimensions: (1) modernity and biographical perspective[50] and (2) endowment level (including both material and cultural wealth)[51]. In contrast to the related socio-demographic variables - age and income - both lifestyle dimensions are expressed in subjective rather than objective terms. The two dimensions are constructed based on 5 items measured on a 4-point scale. The answer categories are labeled either as the level of agreement to a statement or the level of frequency of performing an activity. The question regarding the restaurant expenditure is

[49] These values are based on the following items: Egoistic: social power (control over others, dominance), wealth (material possessions, money), authority (the right to lead or command), influential (having an impact on people and events) and ambitious (hard-working, aspiring). Altruistic: equality (equal opportunity for all), a world at peace (free of war and conflict), social justice (correcting justice, care for the weak) and helpful (working for the welfare of others). Hedonic: pleasure (joy, gratification of desires), enjoying life (enjoying food, sex, leisure etc.) and self-indulgent (doing pleasant things). Biospheric: respecting the earth (harmony with other species), unity with nature (fitting into nature), protecting the environment (preserving nature) and preventing pollution (protecting natural resources).

[50] This dimension is measured based on the following 5 items: (1) I enjoy my life to the full, (2) I live according to the religious principles, (3) I hold on my family's old traditions, (4) I go out often.

[51] This dimension is measure based on the following 5 items: (1) I cultivate an upscale standard of life, (2) Restaurant expenditures, (3) Visiting art exhibitions and galleries, (4) Reading books, (5) Reading a nationwide newspapers, such as NZZ.

Figure 12 – Car-Bike

	Option 1: Car	Option 2: Bicycle
Departure	17:09	17:16
Arrival	17:48	17:48
Duration	39 min	32 min
Delay >10 min	never	
Bicycle route		Residential/ Bicycle street
Weather		warm, dry
Health benefit		high
Total price	12,35 CHF	1,15 CHF
private share	5,70 CHF	0,00 CHF
external share	6,65 CHF	1,15 CHF
→ Congestion caused	4,90 CHF	
→ Health/accident costs	1,25 CHF	1,15 CHF
→ Climate damages	0,50 CHF	

an exception in that regard, since it is phrased as an open-end question. The answers to that question are recoded in a 4-point scale according to the guidelines of Otte (2010) and adapted to the Swiss context by Tomic *et al.* (2021). Simple means of the 5 items per dimension are then calculated to construct the dimension indices, which are by construction also expressed on a 4-point scale. The dimensions are then trichotomized taking the values 2 and 3 as the threshold values and defining the levels of modernity and biographical perspective as traditional (dimension index 1 to 2), semi-modern (dimension level 2 to 3) and modern (dimension level 3 to 4) and the levels of endowment as low (dimension index 1 to 2), middle (dimension index 2 to 3) and high (dimension index 3 to 4). The 9 Otte lifestyle types result from the pairs of dimension levels: (1) traditional workers (traditional, low endowment), (2) home-centered (semi-modern, low endowment), (3) entertainment-oriented (modern, low endowment), (4) conventionalists (traditional, middle endowment), (5) advancement-oriented (semi-modern, middle endowment), (6) hedonists (modern, middle endowment), (7) conservatives (traditional, high endowment), (8) liberals (semi-modern, high endowment), (9) reflexives (modern, high endowment).

4 Results

This section is structured as follows: We start by presenting the participation and retention rates during the study and then provide some descriptive statistics from the surveys and the tracking study. In section 4.3 we show the average treatment effects of the experiment and investigate the effect heterogeneity and potential underlying mechanisms. Section 4.4 describes the results from the discrete-choice modeling based on revealed preferences and section 4.5 presents the outcome of the stated choice experiment. In section 4.6, we discuss potential challenges to our identification strategy.

4.1 Participation

4.1.1 Participation rates

As Table 12 shows, out of the about 91,000 persons who were invited to participate in the MOBIS study, 3,519 (around 4%) completed the full study, including introduction survey, tracking with smartphone and final survey. Out of the invited people, around 24% of the invited people completed the introduction survey, 8% fully qualified for the study, 6% registered for the study and 4% completed the tracking period. About 32% of people completing the introduction survey met the inclusion criteria (6,895/21,571).

Table 12 – Participation rate by study stage

Stage	N	Percent
Invited persons	90,909	100%
Starting of the introduction survey	22,148	24.4%
Completing the introduction survey	21,571	23.7%
Partly qualified[1]	11,266	12.4%
Interest to participate in the study	7,444	8.2%
Fully qualified[2]	6,895	7.6%
Completing the registration	5,460	6%
Accepting the terms and conditions of the registration	5,375	5.9%
Activating the app	4,622	5.1%
Starting the tracking	4,218	4.6%
Completing the tracking	3,690	4.1%
Completing the final survey	3,519	3.9%

[1] Meeting the 1st group of criteria, i.e., car use, age and home postcode.

[2] Meeting the 2nd group of criteria, i.e. smartphone, capable to walk and professional driver.

Table 13 shows that the car use was the most restrictive inclusion criteria. Only about 54% of people who completed the introduction survey used the car on at least two weekdays per week. Almost 100% lived in a Swiss agglomeration (excluding the Canton of Ticino[52]) and around 98% were between 18 and 66 years old (addresses were pre-selected based on location and age). Out of 7,433 persons fulfilling the three above mentioned criteria and indicating interest in participating in the MOBIS study, almost 100% used a smartphone, about 91% were non-professional drivers and almost 100% were capable to walk without help.

The recruitment of the MOBIS participants comprised two waves (see Section 3). We sent up to three invitation letters to people who belonged to the first wave and only one letter to people from the second wave. Table 14 shows that the number of persons completing the introduction survey decreased after each additional invitation letter. Around 45% of people completed the introduction survey after the first invitation, while around 35% and 20% did it after the reminder of the second and the third invitation, respectively. A similar pattern was

[52] Ticino was excluded because it is quite different to the rest of Switzerland in terms of topography and availability of public transport, and because we would not have had sufficient statistical power to conduct a subsample analysis of Ticino anyway as this canton includes less than 5% of the Swiss population.

Table 13 – Number and percent of people meeting the MOBIS inclusion criteria.

	Criteria	N	Percent
1st criteria	Using the car at least 2 days per week[1]	11,648	54.00%
(N = 21,571)	Living in a Swiss agglomeration	21,472	99.54%
	Between 18 and 66 years old	21,094	97.79%
2nd criteria	Using a smartphone	7,418	99.65%
(N = 7,444)	Non-professional drivers	6,750	90.68%
	Capable to walk without help	7,427	99.77%

[1] As car driver or passenger excluding car-pooling.

observed for the registration (85%, 10% and 5%).

Table 14 – Effect of the invitation letters on the participation on the MOBIS study

Wave	Letter	N	% of Wave
1	1	8,423	14.0%
1	2	6,103	10.1%
1	3	4,442	7.38%
1	No Response	41,224	68.5%
2	1	2,963	9.71%
2	No Response	27,537	90.29%

4.1.2 Retention

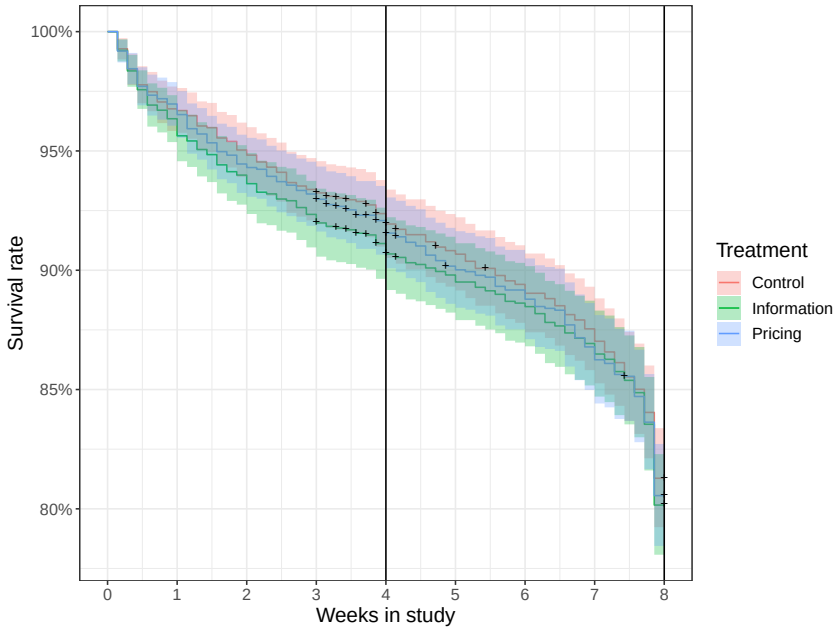
To explore the retention rate of participants in the tracking phase, we performed a survival analysis on the duration of tracking in the study. First, a Kaplan-Meier approach (see Figure 13) shows the impact of the treatment on the length of time which participants would track. Participants who were automatically dropped out after phase 1 due to poor tracking compliance but were still tracking at the end of phase 1 were censored (marked by a cross). There is no significant difference between the three treatment groups in their survival curves. A sharp decrease in survival is evident in the last study week. As participants were informed at the end of the study that they could delete the app, the last few days of tracking were sometimes not collected before the app was deleted.

Given the participation goal of 8 weeks, one would expect that the attrition rate would be highest early on in the study and flatten out as participants neared the 8-week goal, after which they would receive the incentive. However, the survival curve is almost linear. Furthermore, Figure 13) shows that the treatment didn't affect the attrition rate in the second phase.

A time-variant Cox proportional hazards model is to investigate the impact of different factors on the participation duration (see Table 15 for the model results). To account for time-dependent effects, the study period was stratified into fortnightly windows. Those in high-income brackets (more than 12,000 CHF/year) were more likely to stop tracking. Conversely, those from larger households and those with tertiary education were more likely to track for longer. A significant gender-based difference was only observed in the final fortnight, where females were more likely to remain in the study.

Contrary to expectations, there was no significant effect of age on the hazard rate. This suggests that common concern about the feasibility of tracking studies for older age groups is unfounded, at least up to the age of 65, the age limit in this study. The coefficient on employment is time-dependent, implying that those in the workforce (i.e. excluding students, homeworkers and retirees) were more likely to remain in the study throughout the first fortnight.

Figure 13 – Kaplan-Meier survival curve by treatment group. The cross indicates censoring of participants



The participant's mobile device played a much larger role. Having an Android phone of any model increased the hazard drastically. However, this effect was strongest in the first week. The effects were even larger for Huawei models. The incompatibility of GPS loggers with Android (and particularly Huawei devices) is already well known; however, here the effect is quantified, and seen to be dramatic. The effect was also time-dependent, with the most significant hazard in the first fortnight. At the end of the second fortnight, participants who tracked insufficiently were removed from the study - this explains the reduction in the Android hazard coefficient for the third fortnight, when many of them could have been expected to stop tracking, had they not been removed from the study.

At the end of the tracking study, participants were told that they could delete the app, but were also encouraged to continue using it if they wished. Figure 14 shows the dropout rate for the whole study, including the post-study period. The majority of the participants dropped out soon after the study, but even 6 months after the study was completed, around 5% of participants continued to use the app. Anecdotal reports from participants indicated that they enjoyed having an overview of their travel, and that it even continued to inform their travel decisions. The impacts of the mobile operating system continued even after the study, with the post-study retention rate falling faster for Android users.

4.1.3 Participant engagement

Participants in the information and pricing groups were effectively treated through information provided in a weekly email detailing their externalities and the costs incurred. Interactions with the emails were recorded using standard email tacking techniques. Emails that remained unopened were effectively missed treatments. Table 16 presents a overview of the engagement with the email communications. The open rate did not change drastically over the duration of the study. Participants in the pricing group viewed their emails much more often than the control or information groups. The information group also opened their emails repeatedly in the first two weeks of phase two, before returning to a pattern similar to the control group, whereas the pricing group continued to repeatedly open their emails.

Participants in the treatment groups likely repeatedly reopened the emails to check their externalities and remaining budget. We suggest that this 'repeat opening' behavior is a useful indicator to measure the level of engagement with the treatment.

Table 15 – Cox porportional-hazard model

	Beta (SE)	HR (95% CI)	p
Income $>$ 12,000 CHF	0.28 (0.09)	1.32 (1.10, 1.58)	0.003 **
Household size	-0.07 (0.03)	0.93 (0.87, 1.00)	0.038 *
Age (decades)	0.00 (0.03)	1.00 (0.95, 1.06)	0.883
Tertiary education	-0.19 (0.08)	0.83 (0.70, 0.97)	0.022 *
German speaking	0.03 (0.09)	1.03 (0.87, 1.22)	0.752
Female			
fortnight=1	0.02 (0.15)	1.02 (0.77, 1.35)	0.895
fortnight=2	-0.07 (0.20)	0.93 (0.62, 1.39)	0.721
fortnight=3	-0.04 (0.22)	0.96 (0.62, 1.48)	0.841
fortnight=4	-0.28 (0.12)	0.76 (0.60, 0.96)	0.022 *
Android			
fortnight=1	0.87 (0.16)	2.38 (1.73, 3.26)	0.000 ***
fortnight=2	0.46 (0.22)	1.58 (1.02, 2.45)	0.040 *
fortnight=3	-0.01 (0.25)	0.99 (0.60, 1.62)	0.960
fortnight=4	0.41 (0.13)	1.51 (1.17, 1.94)	0.002 **
Huawei			
fortnight=1	0.38 (0.20)	1.47 (0.99, 2.18)	0.057 .
fortnight=2	0.37 (0.32)	1.45 (0.78, 2.70)	0.239
fortnight=3	0.29 (0.41)	1.33 (0.59, 2.98)	0.487
fortnight=4	0.15 (0.21)	1.16 (0.77, 1.75)	0.465
Employed			
fortnight=1	-0.33 (0.16)	0.72 (0.53, 0.97)	0.033 *
fortnight=2	-0.07 (0.23)	0.94 (0.60, 1.47)	0.775
fortnight=3	0.24 (0.27)	1.27 (0.75, 2.15)	0.369
fortnight=4	0.05 (0.14)	1.05 (0.80, 1.38)	0.718
AIC		10484.33	
Coordance		0.602	
Num. events		655	
PH test		0.76	
Note:		$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$	

Figure 14 – Post-study participation survival curve

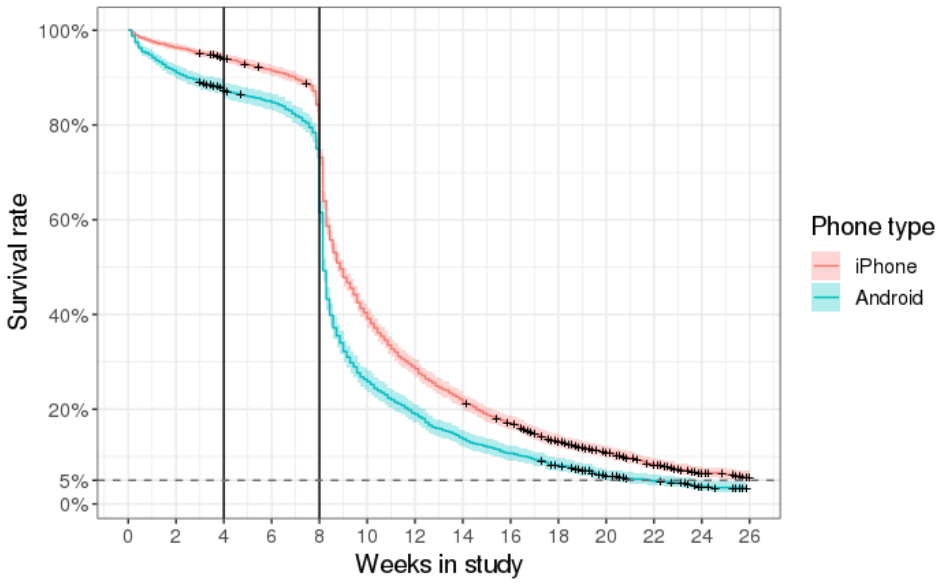


Table 16 – Engagement with various emails through the study

Email & Treatment	n	% Opened	Times opened (mean)	Time to open (h) median (IQR)	
Welcome					
-	5475	82.36	2.78	8.50	(2.88 - 20.33)
Report 1					
	4168	84.88	2.13	7.37	(2.53 - 19.22)
Report 2					
	4132	81.03	1.87	6.66	(2.59 - 18.37)
Report 3					
	4105	78.59	1.83	6.19	(2.51 - 17.85)
Report 4					
Control	1247	79.23	1.62	5.40	(2.30 - 14.65)
Info	1262	83.68	1.99	5.40	(2.40 - 16.83)
Pricing	1222	82.90	2.64	6.06	(2.35 - 17.57)
Halfway					
Control	1250	76.80	1.60	5.60	(2.41 - 15.54)
Info	1263	83.29	1.72	5.50	(2.53 - 17.35)
Pricing	1222	80.93	2.17	5.51	(2.24 - 17.15)
Report 5					
Control	1243	76.43	1.55	5.96	(2.42 - 15.37)
Info	1255	80.80	1.90	6.28	(2.42 - 17.29)
Pricing	1213	80.54	2.24	6.94	(2.66 - 19.82)
Report 6					
Control	1238	77.06	1.87	5.78	(2.35 - 16.89)
Info	1252	78.12	1.87	5.87	(2.57 - 17.32)
Pricing	1208	79.22	2.09	6.24	(2.41 - 17.87)
Report 7					
Control	1235	74.98	1.61	5.83	(2.35 - 15.83)
Info	1248	77.64	1.66	6.08	(2.44 - 18.16)
Pricing	1205	80.25	2.02	6.07	(2.33 - 17.49)
Report 8					
Control	1231	79.69	1.50	6.11	(2.55 - 17.01)
Info	1246	78.33	1.46	6.41	(2.49 - 18.85)
Pricing	1200	81.50	2.01	6.55	(2.49 - 18.80)

4.2 Descriptive statistics

4.2.1 Surveys

Table 17 shows the socio-demographic characteristics of our participants of the introduction survey and the tracking study and compares them to the transport Mikrocensus, which is a representative survey of the Swiss population.

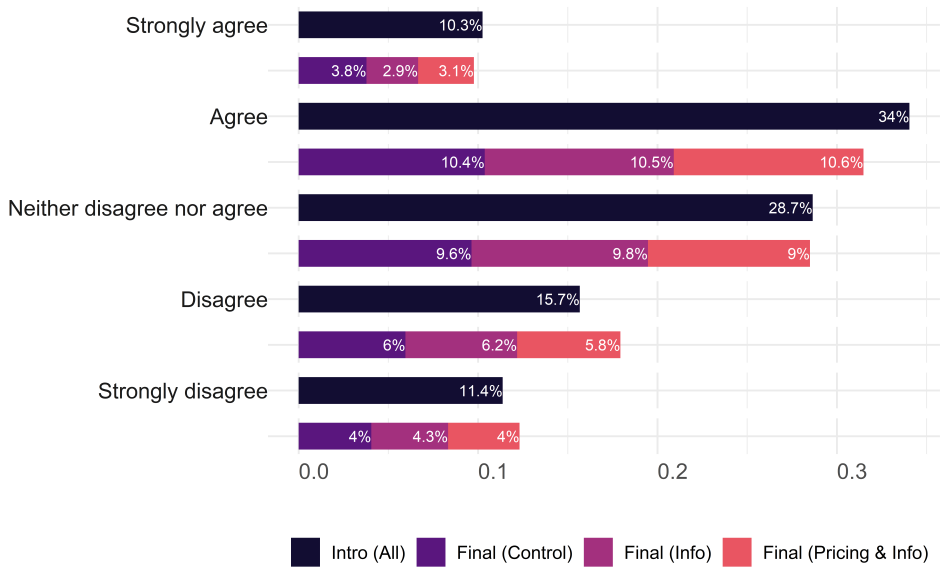
The MOBIS tracking study imposed an eligibility criterion related to car use, among others. The respondents of the MOBIS introduction survey differ from the Microcensus population in terms of the age distribution, as we limited the study to ages 18-65, and in terms of the regional coverage (only urban agglomerations and no Ticino canton). The MOBIS sample also has higher levels of education, employment and income.

The tracking sample differs from the introduction survey sample in terms of employment, household size income, and access to car, probably due to the eligibility requirement of traveling by car on at least two days per week. This condition is correlated with working away from home, which in turn drives the differences in the other variables. The cantons Vaud (19% of the tracking sample) and Geneva (9%) account for the vast majority of the French-speaking participants, whereas the German-speaking participants mostly come from Zurich (38%), Basel (2% city and 10% region), Aargau (5%) and Bern (12%).

In addition to socio-demographic information and variables required to assess eligibility for the tracking study, the introductory survey also asked participants about opinions and attitudes related to transport policies. Some of these questions were repeated in the final survey of the tracking study, to assess whether the transport pricing experiment changed some participants' opinions.

For the comparisons in the graphs below, the Introduction sample (all) can be regarded as a fairly representative sample of working-age adults in major Swiss agglomerations, whereas the tracking study participants (i.e. Tracking, Control, Information, Pricing) present a sample which skews towards driving.

Figure 15 – Support for transport pricing in the introductory survey and among participants of the tracking study.



Notes : Based on question "Indicate whether you agree or disagree with each policy: Time- and route-specific mobility pricing, made revenue-neutral by lowering other taxes".

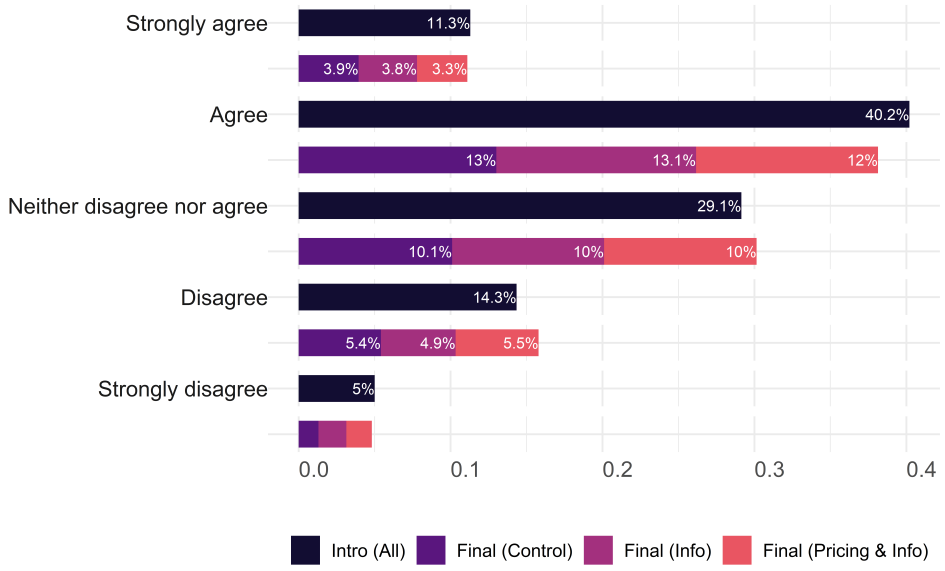
Figure 15 shows that 43% of respondents to the introductory survey favored the implementation of a time- and route-specific, revenue-neutral transport pricing scheme, whereas

Table 17 – Demographic information for the MOBIS sample

Variable	Level	Mobis Intro Full	Mobis Tracking	Micro-census
Age	Under 18	0	0	13.2
	[18, 25]	19.4	19.3	9
	(25, 35]	18.7	17.8	14.2
	(35, 45]	19.2	22.3	15.4
	(45, 55]	20.8	22.8	16.7
	(55, 65]	18.3	16.6	12.9
	66 and older	3.6	1.2	18.5
Education	Mandatory	9.1	6.6	19.3
	Secondary	43.6	48.5	49.5
	Higher	47.3	44.9	31.2
Employment	Employed	66.4	71.3	48.2
	Self-employed	7.4	6.3	7.2
	Apprentice	1.8	1.7	2.6
	Unemployed	4.3	3.9	2.5
	Student	9	7.9	3.7
	Retired	3.3	3.2	19.3
	Other	7.7	5.6	16.5
Gender	Female	50.6	50.2	50.7
	Male	49.4	49.8	49.3
Household size	1	15.8	11.7	34
	2	33	30.2	35.4
	3	20	21.5	13
	4	22.8	27.4	12.5
	5 or more	8.3	9.2	5.1
Income	4 000 CHF or less	12.1	7.4	17.8
	4 001 - 8 000 CHF	29.9	29.6	32.8
	8 001 - 12 000 CHF	24.4	29	17.4
	12 001 - 16 000 CHF	11.9	14.6	6.8
	More than 16 000 CHF	7.9	9.9	4.5
	Prefer not to say	13.8	9.5	20.7
Language	German	63.1	66.1	68.4
	French	28.5	26.1	25.3
	Italian	0	0	6.3
	English	8.5	7.8	
Nationality	Switzerland	98.2	98.1	75.9
	Other	1.8	1.9	24.1
Access to car	Yes	61.5	87.7	75.8
	Sometimes	15.1	11.1	18.1
	No	23.4	1.2	6.2
Full PT subscription	Yes	15.8	8.05	9.5
	No	84.2	92.0	90.5
Half fare PT subscription	Yes	47.7	48.9	32.8
	No	52.3	51.1	67.2
No PT subscription	Yes	24.4	33.5	43.5
	No	75.6	66.5	56.5
Access to bicycle	Yes	68.1	71.4	65.2
	Sometimes	4.0	4.6	8.88
	No	27.8	24.0	23.7

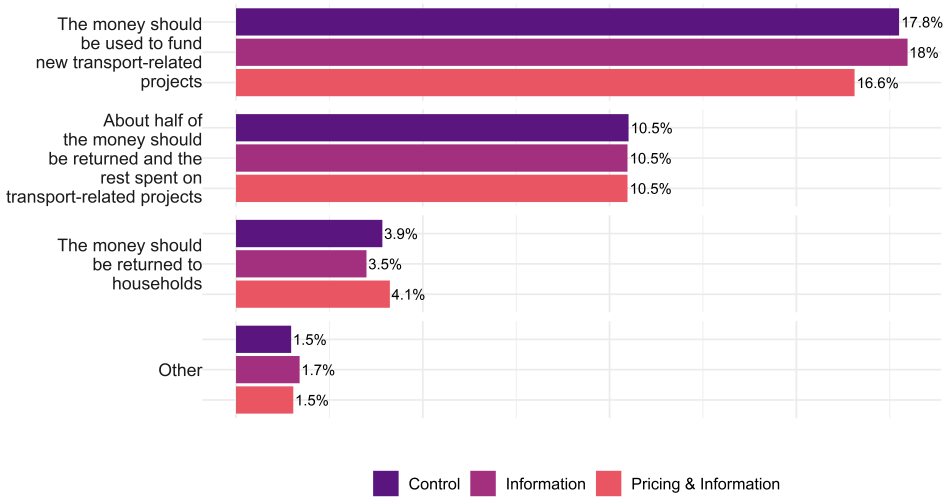
29% were undecided, and 27% were opposed. Acceptance was slightly lower among those who finished the tracking experiment. A majority of participants agreed that such pricing should reflect social costs of mobility (Fig. 16). However, these results depend on the exact wording. Support was substantially lower (29-31%) when the question was rephrased and included "higher prices during rush hour" as an example (Fig. A.1 in the Appendix).

Figure 16 – Support for price of transport reflecting the social costs of mobility.



Answers provided to the following question: “Please indicate your level of agreement or disagreement with the following statements: The price for mobility should reflect the social cost (e.g., health, environment, congestion)”.

Figure 17 – How revenue from Pigovian transport pricing should be used.

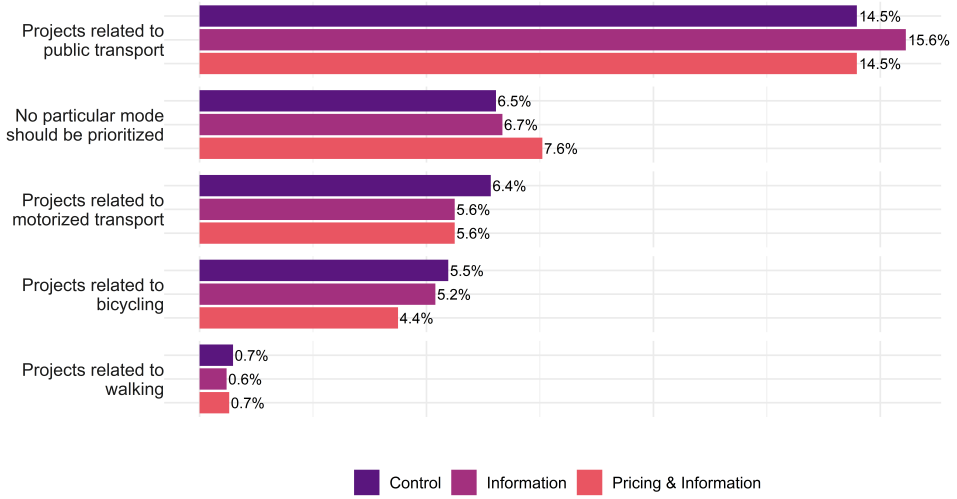


Answers provided to the following question: “If dynamic mobility pricing (i.e., prices depending on mode, route and time) were introduced, what should be done with the revenue?”.

How the revenue from a transport pricing scheme should should used was further explored in the final survey (Fig. 17). About half the participants supported investing the revenue in new-transport related projects and only about 10% supported the concept to return the revenue to households in its entirety (e.g., by lowering other taxes). About one third of participants supported a combination of both. If the revenue were to be used for transport

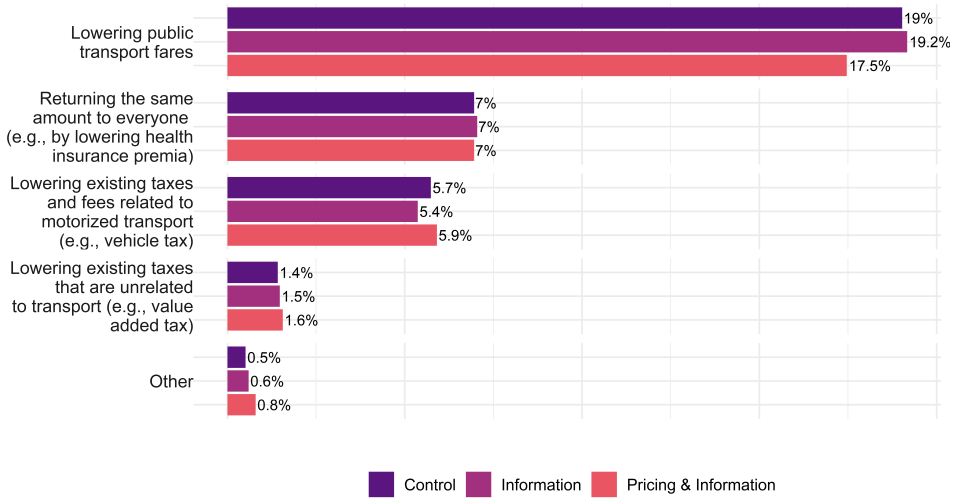
projects, support was strongest for public transport projects, more than twice as high than any other mode (45%). Support for no particular mode preference (21%) was similar to support for investments in motorized transport (18%) or bicycling (15%), whereas investments in walking were unpopular (2%) (Fig. 18). If, however, the revenue were to be returned to households, the preferred mechanism was through lowering public transport fares (56%), whereas returns through lower health insurance premiums (same amount to everyone), transport related taxes (e.g. vehicle tax), or transport-unrelated taxes (e.g. added-value tax) were much less popular (Fig. 19).

Figure 18 – Types of projects for which revenue from transport pricing should be invested.



Answers provided to the following question: “If the money were used to fund transport projects, how should it be prioritized?”

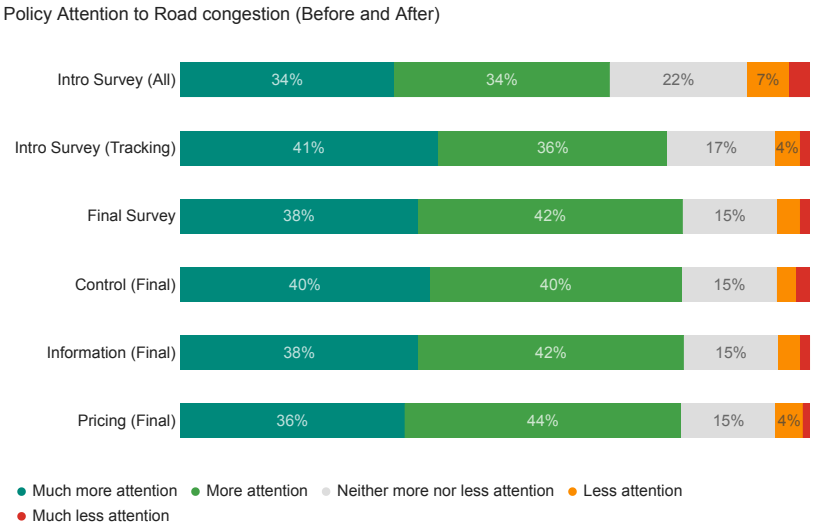
Figure 19 – How revenue from transport pricing should be returned to households.



Answers provided to the following question: “If the money were returned to households, which option would you prefer?”

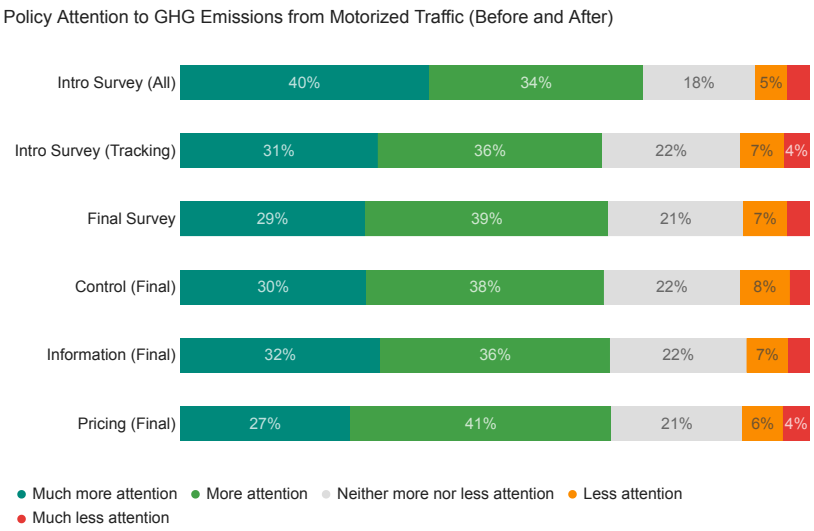
Besides transport pricing, we also asked the participants about their opinion of other transport policies. Compared to the introductory survey sample (68%), participants in the tracking study expressed somewhat stronger support for policies addressing congestion (77%), which grew slightly during the pricing study (80-82%) (Fig. 20).

Figure 20 – Support for increased policy efforts to address congestion.



Answers provided to the following question: Please indicate for each problem whether it should receive more or less attention from policy makers, compared to how much attention it currently receives: Road congestion.

Figure 21 – Support for increased policy efforts to address greenhouse gas emissions from transport.

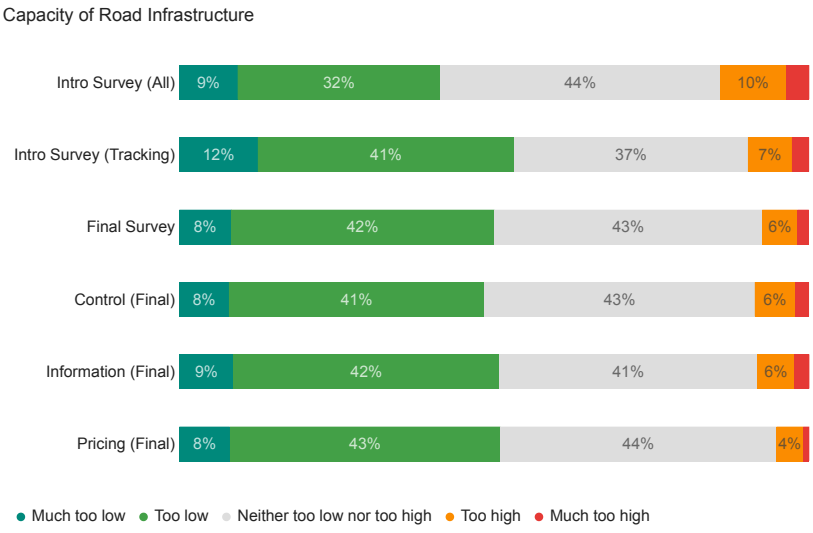


Answers provided to the following question: Please indicate for each problem whether it should receive more or less attention from policy makers, compared to how much attention it currently receives: Greenhouse gas emissions from transport.

This pattern was reversed for the attention policy should pay to curbing greenhouse gas emissions from transport. Support for policies addressing greenhouse gas emissions was 74% in the general sample, but only 67% in participants of the tracking study, at baseline. It grew only marginally during the experiment (67-69%) (Fig. 21). The pattern for support of policies to address health impacts from transport was very similar to that for greenhouse gas emission policies (Fig. A.2 in the Appendix).

Build-out of road capacity is a common measure to counter congestion. Only 41% of the general sample, and 53% of the tracking sample consider road infrastructure capacity too low. A large fraction of participants was undecided, while 14% in the general sample consider it too high. Likewise, support for the notion that the government should build road capacity to meet demand at all times aligns well with the perception of insufficient road infrastructure capacity (Fig. A.3 in the Appendix). Public transport enjoys even stronger support. Around 80% of all participants support the notion that the government should provide public transport capacity that meets demand at all times (Fig. A.4).

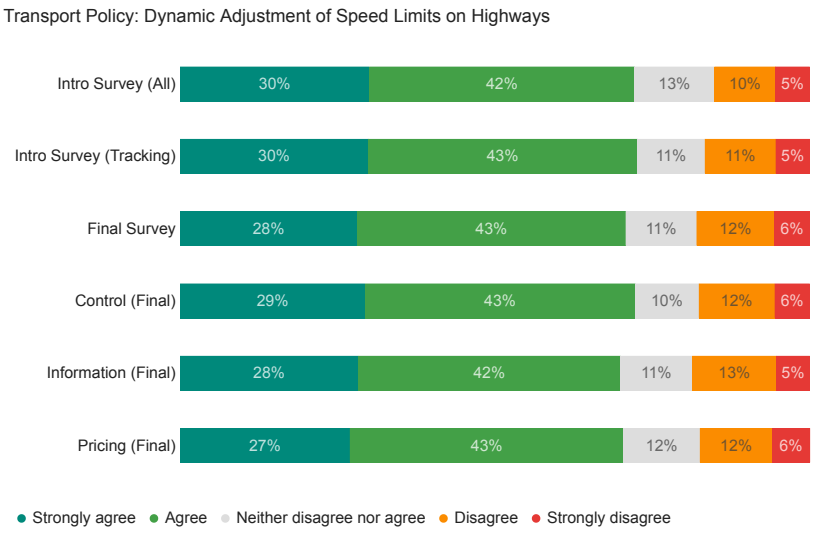
Figure 22 – Is current road infrastructure capacity sufficient?



Answers provided to the following question: Please indicate for each factor whether you find its current level to be too low or too high: Road infrastructure.

A measure that enjoys strong support among the general sample (Intro Survey all) and the tracking sample, which skews towards drivers, is the dynamic regulation of speed limits on highways to optimize traffic flows (Fig. 23). Widening highways, in contrast, is considerably less popular, in particular with the general sample (Fig. A.5 in the Appendix).

Figure 23 – Support for dynamic speed regulation on highways



Answers provided to the following question: Please indicate whether you agree or disagree with each policy: Dynamic adjustment of speed limits on highways to optimize traffic flow.

4.2.2 Descriptive statistics from the tracking data

Table 18 shows the summary statistics of the tracking data for overall travel, and Table 19 shows the data separately for each mode.

Table 18 – Tracking summary statistics

		Pre-treatment			Post-treatment		
Dimension	Outcome	Control	Info	Pricing	Control	Info	Pricing
Ext. costs (CHF)	Total	4.498	4.579	4.686	4.218	4.252	4.218
		(5.690)	(5.650)	(5.811)	(5.392)	(5.549)	(5.408)
	Congestion	1.045	1.076	1.151	0.858	0.878	0.904
		(1.584)	(1.582)	(1.705)	(1.445)	(1.539)	(1.524)
	Climate	0.880	0.883	0.894	0.849	0.838	0.829
		(1.295)	(1.293)	(1.295)	(1.235)	(1.286)	(1.222)
	Health	2.573	2.619	2.640	2.510	2.536	2.485
		(3.551)	(3.546)	(3.609)	(3.476)	(3.561)	(3.460)
Private costs (CHF)		26.103	26.683	26.827	25.719	25.988	25.476
		(33.824)	(34.080)	(34.587)	(33.403)	(34.068)	(33.134)
Tracking	Trips	4.85	4.87	4.90	4.67	4.64	4.71
		(3.11)	(3.08)	(3.04)	(2.89)	(2.88)	(2.92)
	Distance (km)	47.408	48.388	49.854	45.954	47.789	47.784
		(55.789)	(54.978)	(57.720)	(54.331)	(56.246)	(55.269)
	Duration (min)	96.364	97.176	98.453	92.698	95.443	95.421
		(92.890)	(88.568)	(93.527)	(88.397)	(93.972)	(92.736)

Notes: Average values per participant and day during the experiment (standard dev. in parentheses).

The distances and external costs are similar between the groups (by construction).

Figure 24 displays the mode distribution recorded in MOBIS in terms of distance (a) and number of trips (b), and panel (c) shows the (constant) per-km external costs for public transport, walking and bicycling, as well as the distribution of external per-km costs for cars, which vary over space and time due to the inclusion of congestion.

Figure 25 displays the level and evolution of the tracking data over the course of the experiment. There is a seasonal variation in the travel distance by mode (Fig. 25a-d), which translates to a negative seasonal trend in external costs (Fig. 25e). In addition, there is an "observation" effect in the sense that the recorded distances decrease with the study day (this is true even when controlling for seasonality). This could potentially challenge our identification strategy if it differs between the treatment and control groups. Fortunately, this is not the case: As we show in section 4.6.1, the observation effect is the same across the three experimental groups during the observation period.

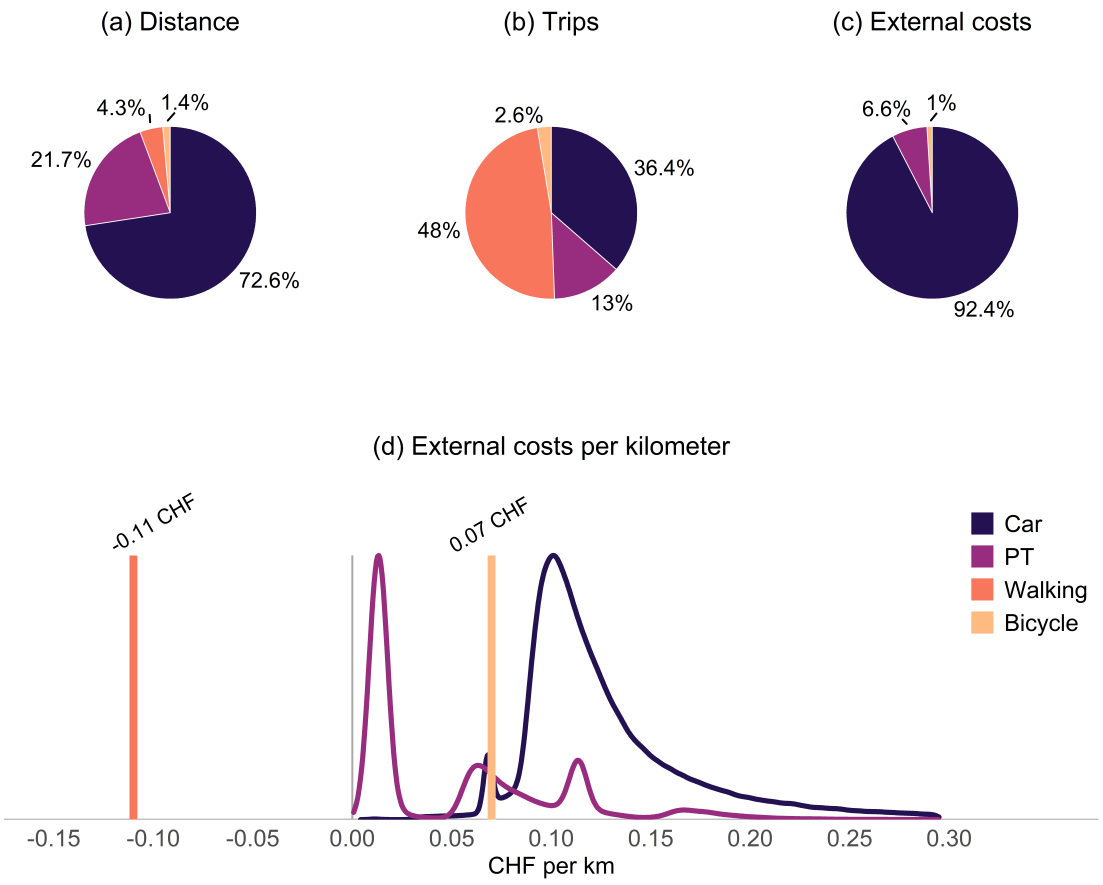
The presence of seasonality and observation effects highlight the need of a control group, which is subject to the same unobservable variables as the treatment groups. By including day of calendar and day of study fixed effects we control for the unobserved characteristics that give rise to the time trends that we observe in the data, but which are unrelated to the treatment.

Table 19 – Tracking summary statistics, by mode

		Car						Public transport					
		Pre-treatment			Post-treatment			Pre-treatment			Post-treatment		
Dimension	Outcome	Control	Info	Pricing	Control	Info	Pricing	Control	Info	Pricing	Control	Info	Pricing
Ext. costs	Total	4.39	4.45	4.51	4.12	4.11	4.05	0.28	0.30	0.35	0.27	0.32	0.35
(CHF)		(5.72)	(5.69)	(5.84)	(5.41)	(5.57)	(5.43)	(0.99)	(1.03)	(1.20)	(0.92)	(1.09)	(1.11)
	Congestion	0.94	0.95	0.99	0.75	0.74	0.75	0.11	0.13	0.16	0.10	0.13	0.16
		(1.45)	(1.43)	(1.51)	(1.31)	(1.34)	(1.33)	(0.73)	(0.78)	(0.91)	(0.68)	(0.83)	(0.84)
	Climate	0.86	0.87	0.88	0.83	0.82	0.81	0.02	0.02	0.02	0.02	0.02	0.02
		(1.30)	(1.30)	(1.30)	(1.24)	(1.29)	(1.22)	(0.07)	(0.07)	(0.09)	(0.06)	(0.06)	(0.08)
	Health	2.58	2.63	2.64	2.53	2.55	2.49	0.15	0.16	0.17	0.15	0.17	0.18
		(3.58)	(3.57)	(3.64)	(3.49)	(3.59)	(3.48)	(0.41)	(0.40)	(0.45)	(0.38)	(0.41)	(0.44)
Private cost		24.40	24.99	24.96	24.05	24.20	23.58	1.70	1.69	1.87	1.67	1.79	1.90
(CHF)		(34.01)	(34.32)	(34.81)	(33.58)	(34.29)	(33.36)	(4.53)	(4.29)	(4.85)	(4.42)	(4.50)	(4.67)
Tracking	Distance	34.91	35.76	35.76	34.42	34.70	33.91	9.86	9.98	11.40	9.17	10.65	11.34
	(km)	(48.59)	(49.02)	(49.86)	(48.00)	(49.04)	(47.82)	(32.97)	(31.18)	(35.35)	(30.89)	(33.72)	(33.89)
	Duration	50.62	51.37	51.32	49.94	49.27	48.98	16.32	16.59	17.77	16.50	18.77	18.80
	(min)	(55.87)	(56.99)	(57.94)	(56.54)	(56.89)	(59.43)	(53.26)	(50.28)	(53.61)	(52.68)	(56.90)	(53.51)
		Bicycle						Walking					
		Pre-treatment			Post-treatment			Pre-treatment			Post-treatment		
Dimension	Outcome	Control	Info	Pricing	Control	Info	Pricing	Control	Info	Pricing	Control	Info	Pricing
Ext. costs	Total	0.05	0.05	0.05	0.04	0.03	0.04	−0.21	−0.22	−0.22	−0.21	−0.22	−0.22
(CHF)		(0.28)	(0.25)	(0.30)	(0.21)	(0.21)	(0.25)	(0.28)	(0.28)	(0.28)	(0.27)	(0.28)	(0.28)
	Congestion												
	Climate												
	Health	0.05	0.05	0.05	0.04	0.03	0.04	−0.21	−0.22	−0.22	−0.21	−0.22	−0.22
		(0.28)	(0.25)	(0.30)	(0.21)	(0.21)	(0.25)	(0.28)	(0.28)	(0.28)	(0.27)	(0.28)	(0.28)
Private cost													
(CHF)													
Tracking	Distance	0.72	0.67	0.71	0.51	0.50	0.56	1.92	1.98	1.99	1.86	1.94	1.98
	(km)	(3.98)	(3.62)	(4.34)	(3.06)	(2.99)	(3.57)	(2.51)	(2.55)	(2.51)	(2.39)	(2.48)	(2.48)
	Duration	2.49	2.33	2.34	1.86	1.72	1.90	26.93	26.89	27.03	24.40	25.68	25.74
	(min)	(13.70)	(12.03)	(13.58)	(12.79)	(9.72)	(11.14)	(55.05)	(49.89)	(52.77)	(46.82)	(53.48)	(50.94)

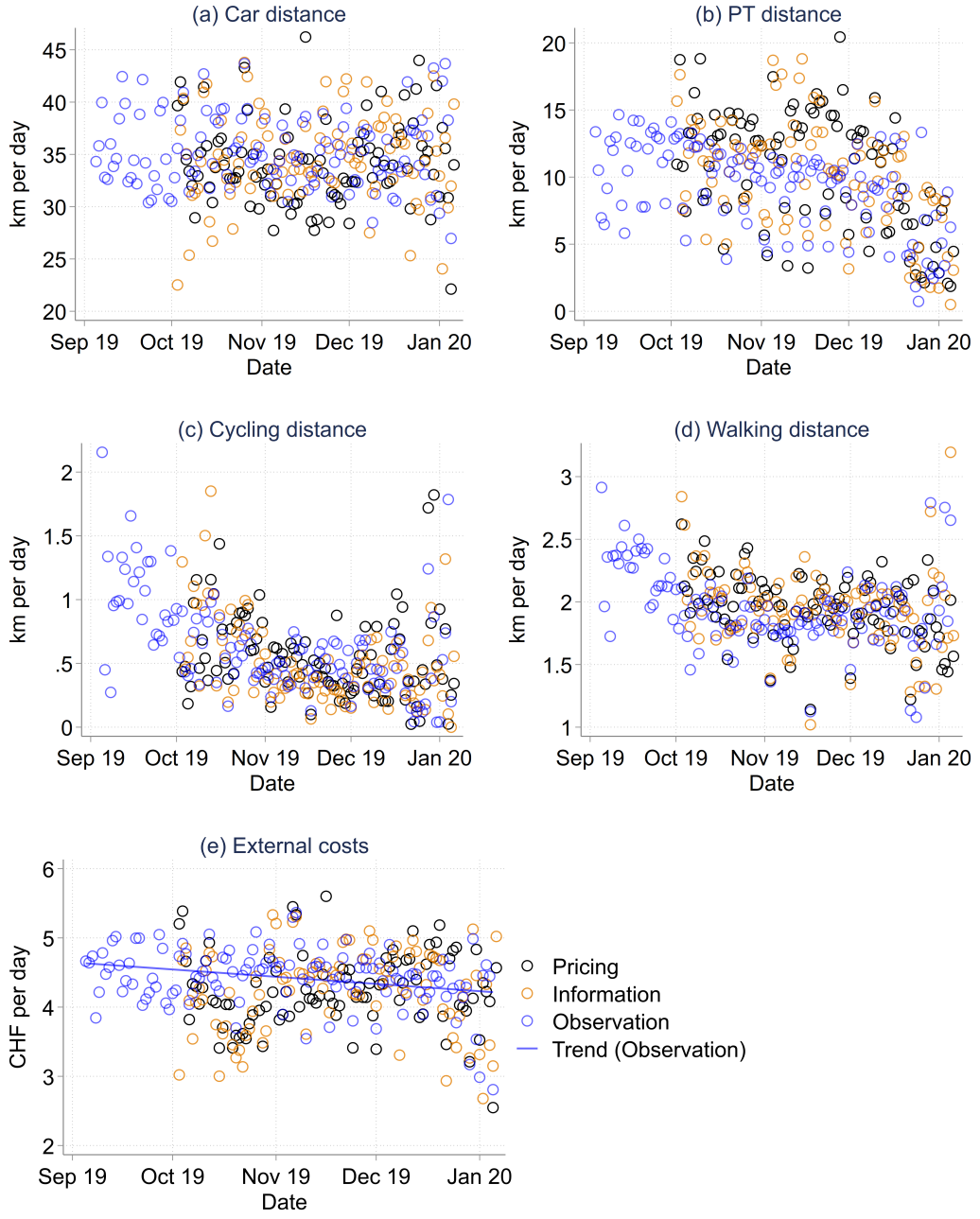
Notes: Average values per participant and day during the experiment. Standard deviations in parentheses.

Figure 24 – Mode distribution of distances, trips and external costs



Notes: For the external costs of walking and cycling, fixed values per person-km were used. The external costs from driving and for public transport (PT) are continuous as the congestion component varies over time and space. Since the external costs from walking are negative, these are not included in panel (c). For a further breakdown of the average external costs, see Section 3.4.2

Figure 25 – Distances and external costs, by treatment status



Note: The figures plot averages by treatment status and calendar date. The treatment status "Observation" refers to the absence of treatment and includes all observations from the control group plus the observations from the treatment groups before the treatment.

4.3 Treatment effects of the experiment

In this section, we report the estimates from the econometric analysis of the experiment using the data aggregated to the participant-day level. The results from the discrete choice models that rely on individual trip data are reported in section 4.4.

4.3.1 Average treatment effects

Table 20 – Average treatment effects on external costs

	Total Ext. Cost		Health Cost		Climate cost		Congestion Cost	
Pricing	-0.215**	-0.215**	-0.108**	-0.109*	-0.036*	-0.035*	-0.070**	-0.070**
	(0.069)	(0.072)	(0.043)	(0.045)	(0.016)	(0.017)	(0.023)	(0.023)
Information	-0.087	-0.091	-0.046	-0.048	-0.019	-0.020	-0.022	-0.022
	(0.069)	(0.069)	(0.043)	(0.043)	(0.016)	(0.016)	(0.022)	(0.022)
Pricing-Inf.	-0.127'	-0.125'	-0.063	-0.061	-0.017	-0.016	-0.048*	-0.048*
	(0.071)	(0.071)	(0.044)	(0.044)	(0.016)	(0.016)	(0.022)	(0.022)
Precipitation		0.002		0.000		0.000		-0.002**
		(0.004)		(0.003)		(0.001)		(0.001)
Heat		0.177**		0.148**		0.055**		-0.026**
		(0.018)		(0.012)		(0.004)		(0.004)
Cold		-0.501**		-0.357**		-0.128**		-0.016
		(0.075)		(0.050)		(0.017)		(0.019)
Adj. R^2	0.232	0.234	0.225	0.227	0.221	0.223	0.268	0.269
Clusters	3,656	3,656	3,656	3,656	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$ (based on two-sided testing). The dependent variable is the external cost of transport aggregated to the person-day level. Standard errors (in parentheses) are clustered at the participant level. Precipitation ("rain") is measured in mm per hour; heat and cold are as defined be eqs. (2)-(3). All regressions include calendar day, day of study and person fixed effects.

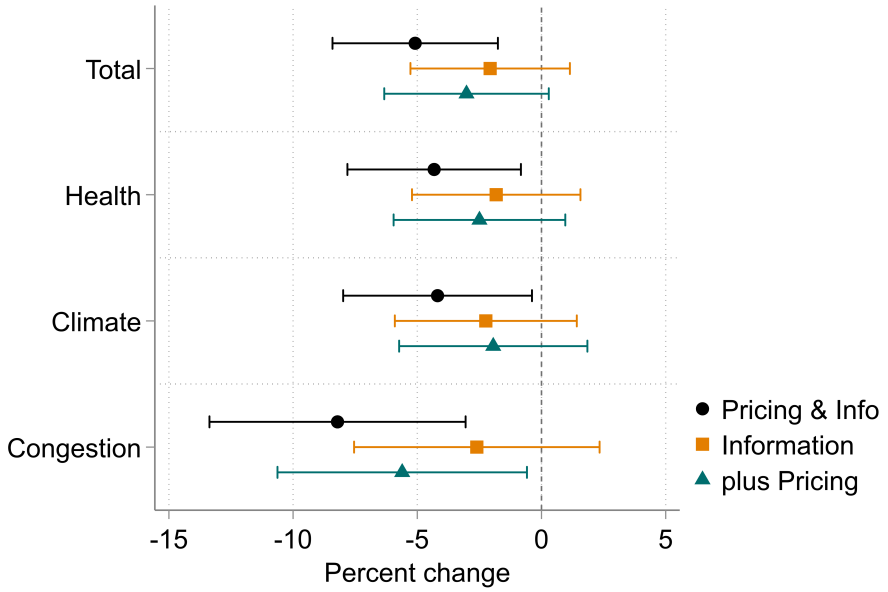
Table 20 shows the average treatment effect (ATE) on the external costs of travel. Due to the randomization and the presence of the control group, these are the causal effects of introducing price incentives and/or providing information. The first two columns report the results from regressing the total external costs of transport, with and without controlling for the weather, whereas the next three pairs of columns contain the ATE on the health, climate and congestion costs. These estimates come from levels-regressions and thus are in CHF per day. About half of the reduction in total external costs is due to a decrease in health costs, followed in magnitude by congestion and then climate costs.

Including the weather could potentially increase the precision of the estimates, but this comes at the cost of introducing a parametric assumption. We see, however, that the difference in point estimates is very small.

Figure 26 shows the proportional reduction of the external costs of transport caused by the two treatments (based on the model without the weather). The respondents in the pricing group reduced their external costs of transport by 5.1% relative to the control group. This is the core result of our experiment and statistically significant at p<0.001. The proportional effect for the external costs related to health and climate is similar to the overall effect, whereas the effect on congestion is somewhat stronger.

There may be an effect of providing only information (yellow bars with squares indicating the point estimates), but this effect is weaker and not statistically significant at conventional levels. The figure also shows the differential effect between the two treatments (green bars with triangles), which can be interpreted as the effect of adding pricing to information. This effect is statistically significant for congestion costs, indicating that the monetary component is relatively more important (or the information component less important) for congestion than for the other types of external costs. A possible explanation is that the external costs in terms of health and climate may be more intuitive (and thus more salient) than the external

Figure 26 – Treatment effect on the external costs of transport



Notes: The figure shows the Average Treatment Effect for overall travel. The bars denote 95%-confidence intervals. The treatment effects are computed by linearly regressing the external costs of transport on a Difference-in-Differences term and fixed effects for person, day of study and day of calendar. Errors are clustered on the participant level. Proportional effects were computed by scaling the regression coefficients by the average external cost of the control group during the treatment period.

costs associated with congestion, which capture the time loss of other road users.

Overall, the results imply that Pigovian transport pricing has an effect, and that this effect is a combination of pricing and the information supplied along with (and implicit in) the pricing. If only the information component were important, the bars corresponding to the information treatment would be identical to those associated with pricing & information. If, on the other hand, information were completely irrelevant, the bars associated with adding pricing to information would be identical to those of the pricing treatment (and the information-only treatment would be zero). The fact that we do not observe any of these extremes implies that people respond to both pricing and information, and that providing information alone is not enough.[53]

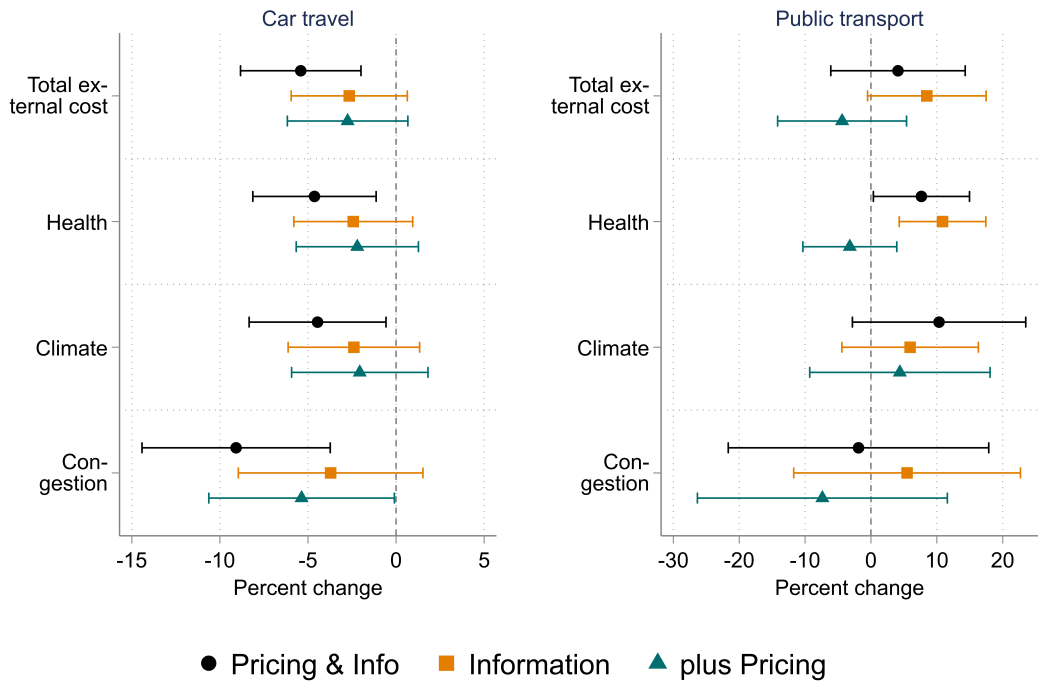
Figure 27 shows the treatment effects associated with the driving and public transport modes.[54]. Whereas the proportional reduction of the external costs is similar for car travel (left panel) as for overall travel, there is no significant effect on the total external costs associated with PT travel (right panel), and a positive effect for health and climate costs. This suggests a mode shift that we will address in more detail below.

In order to interpret the magnitude of the effect, we have to compute the price increase implied by pricing in the external costs of transport. There are different ways of computing the private costs of transport, depending on whether one focuses on marginal or average costs and on the estimates for these costs. We make the following assumptions: The private cost of active transport (cycling and walking) is zero; we thus abstract from the purchase or

[53] Equivalently, one might say that pricing alone is not enough; however, since every price contains information, there is no such thing as "pricing only without information". To avoid that people infer different types of information from the pricing, we made the information explicit in our treatment.

[54] To be clear, this is not an analysis conditional on mode, but we simply use the total recorded km for car and PT travel per person as the dependent variable, including zeroes for those that do not use these modes of transport on any given day

Figure 27 – Treatment effect for car travel and public transport



Note: The figure shows the average treatment effect for driving (left) and public transport (right). For additional notes, see Fig. 26.

rental price of bicycles. For public transport, we use the ticket price as a reference, either full cost or half-fare depending on whether a particular participant holds a half-fare card. For participants that hold a transport subscription (=public transport pass), we approximated the average cost by multiplying the half-fare ticket with a factor that is less than one. The level of this factor is determined by comparing the cost of a regional PT subscription with the corresponding cost if one were to buy a daily pass on 22 days per month. The savings implicit in the subscription varies by region and ranges from 24% in Geneva to 76% in Basel. For driving, we use an average value of CHF 0.70 per km, which is the official value used for deducting commuting expenses from taxable income, and also very close to the value that respondents provided in the final survey about what they perceived their average costs of driving to be.

Given these assumptions, the average daily private cost of transport for the control group during the treatment period was CHF 25.72. The external cost was CHF 4.22, which corresponds to a price increase of 16.4%. Dividing the ATE by the average external costs leads to a proportional reduction of 5.1% (this is the point estimate in Figure 26). The resulting elasticity, in terms of a percentage reduction in external costs in response to a one-percent increase in the costs of transport is therefore -5.1/16.4=-0.31. In other words, introducing a transport pricing scheme based on external costs that raises transport costs, on average, by 10 % would lead to a reduction in the external costs of transport by 3.1%.

Table 21 shows the impact of including the fixed effects, controlling for the weather and using a control group on the proportional effect and the resulting elasticity estimate. The preferred model is in column (1). Adding the weather variables has no effect in this setting, as already shown above. Removing either the study day fixed effects (columns 3-4) or the calendar day fixed effects (columns 5-6) only slightly changes the results; however, when removing both, the elasticity more than doubles (columns 7-8). In columns (9)-(12), we compute the ATE using only before-vs-after data for the pricing group. The resulting elasticity is around -0.38 when including calendar day FE (columns 9 and 10), and between -0.57 and -0.71 without

calendar day FE. This highlights the importance of including a control group that is exposed to the same unobserved shocks as the treatment group. The elasticity is significantly overestimated in the before-vs.-after setting, because the treatment absorbs also a part of the seasonal and study day-effects. Controlling for the weather or calendar day FE mitigates the problem, but it cannot fully remove the bias. The results for the remainder of the paper are based on the preferred model (1)-(2), as this controls for most unobserved heterogeneity by comparing treated and control individuals that started the experiment on the same day.

Table 21 – Sensitivity analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pricing	-0.215**	-0.216**	-0.228**	-0.231**	-0.218**	-0.214**	-0.470**	-0.536**				
	(0.072)	(0.072)	(0.064)	(0.064)	(0.072)	(0.072)	(0.052)	(0.054)				
Information	-0.087	-0.091	-0.101'	-0.105'	-0.088	-0.085*	-0.341**	-0.408**				
	(0.069)	(0.069)	(0.060)	(0.060)	(0.069)	(0.069)	(0.049)	(0.051)				
Precipitation		0.0002		0.002		-0.003**		-0.005*		0.003		-0.006
		(0.004)		(0.004)		(0.002)		(0.002)		(0.007)		(0.004)
Heat		0.177**		0.177**		0.042**		0.024**		0.193**		0.043**
		(0.018)		(0.018)		(0.006)		(0.005)		(0.030)		(0.010)
Cold		-0.501**		-0.499**		-0.250**		-0.189**		-0.388**		-0.256**
		(0.075)		(0.075)		(0.039)		(0.037)		(0.136)		(0.076)
Post									-0.310**	-0.312**	-0.470**	-0.584**
									(0.106)	(0.106)	(0.052)	(0.057)
Prop. effect	-0.051	-0.051	-0.054	-0.055	-0.052	-0.051	-0.111	-0.127	-0.066	-0.067	-0.100	-0.125
	(0.017)	(0.017)	(0.015)	(0.015)	(0.017)	(0.017)	(0.013)	(0.013)	(0.022)	(0.022)	(0.010)	(0.011)
Elasticity	-0.310	-0.312	-0.330	-0.333	-0.315	-0.310	-0.679	-0.774	-0.378	-0.381	-0.574	-0.714
	(0.104)	(0.104)	(0.092)	(0.092)	(0.104)	(0.104)	(0.078)	(0.080)	(0.128)	(0.127)	(0.060)	(0.065)
Person FE	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑	☑
Cal. day FE	☑	☑	☑	☑	□	□	□	□	☑	☑	□	□
Study day FE	☑	☑	□	□	☑	☑	□	□	□	□	□	□
Adj. R^2	0.232	0.234	0.232	0.234	0.229	0.230	0.229	0.229	0.228	0.229	0.224	0.225
Cluster	3,656	3,656	3,656	3,656	3,656	3,656	3,656	3,656	1,193	1,193	1,193	1,193
N	161,208	161,208	161,208	161,208	161,208	161,208	161,208	161,208	52,229	52,229	52,229	52,229

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. Standard errors in parentheses and clustered at participant level. The dummy variable "post" takes the value of one during the treatment period (study days 29-56), and zero otherwise. The daily external cost and the price increase implied by Pigovian transport pricing is based on the control group during the treatment phase and is 4.22 CHF and 16.4%, respectively (columns 1-8). For the before-vs.-after analysis in columns (9)-(12), the daily external cost (CHF 4.69) and price increase (17.5%) was computed for the pricing group during the observation phase.

4.3.2 Heterogeneity of treatment effects

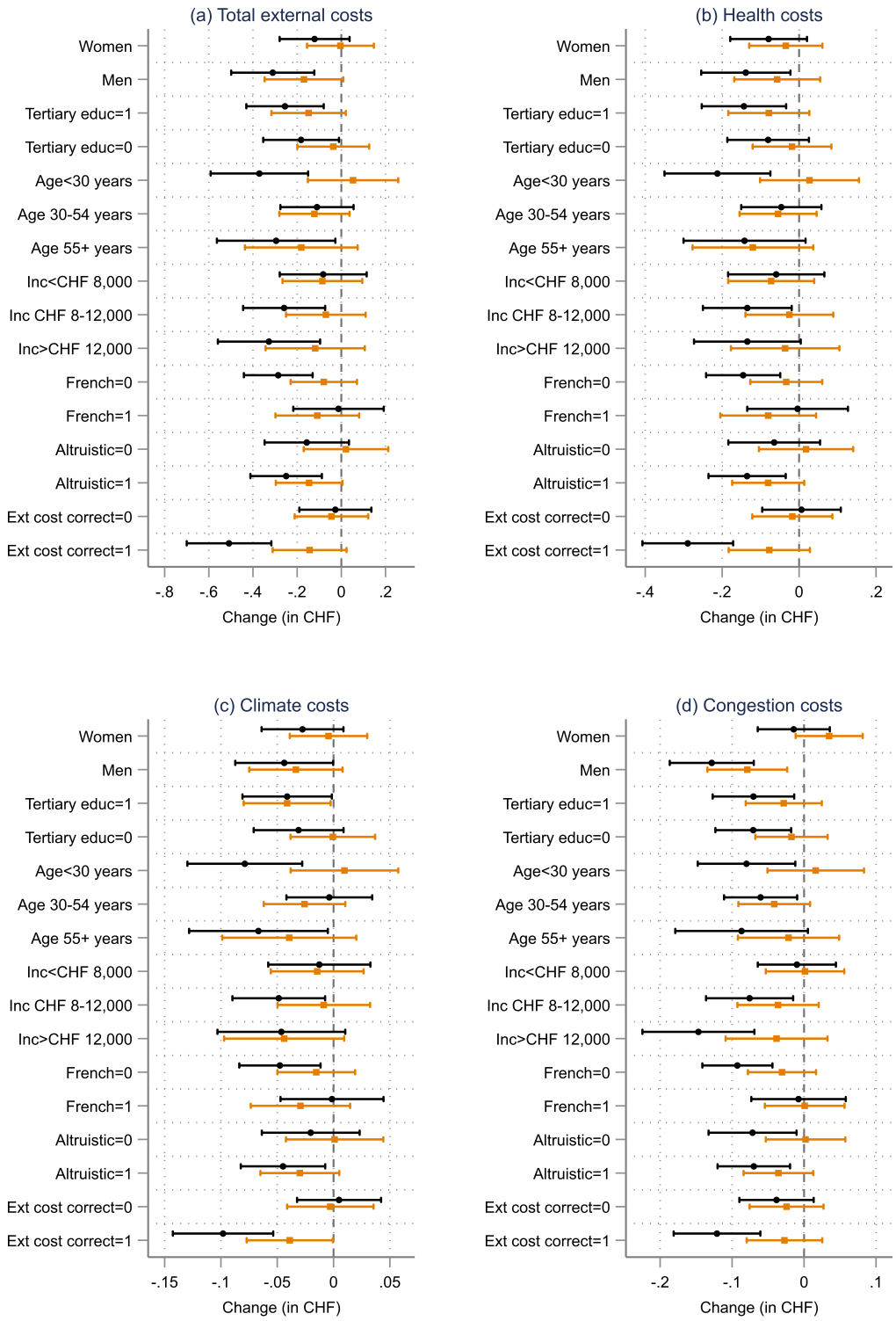
The overall effect could mask heterogeneity within different segments of the population. Figure 28 shows the treatment effects for different subgroups of the sample. Panel (a) shows the effects on total external costs, whereas panels (b)-(d) display the effects for health, climate and congestion costs. We see that men respond more strongly to both treatments than women, and the difference is particularly pronounced for congestion costs.[55] Moreover, the effect is concentrated among German speakers, whereas there is no statistically significant effect for French speakers. We cannot say whether this is due to some cultural difference or simply because the number of French speakers in our sample is too small to yield a test with adequate power.

There is no significant effect heterogeneity in terms of education, age group and household income (with the exception of congestion costs, which are reduced much more by people with high income). A number of additional interaction terms were examined, most of which did not lead to statistically significant differences. The effect of pricing is thus relatively homogeneous across the sample with respect to the most important socio-demographic characteristics, with the exception of gender and language regions.

In the final survey conducted after the experiment was concluded, a battery of questions was asked to elicit respondents' personal values (based on the work by Schwartz, 1992; De Groot and Steg, 2010). Using this methodology, respondents were assigned a numerical value along four dimensions labeled "altruistic", "egoistic", "hedonic" and "biospheric", as explained in section 3.6.3. The study participants that scored above the median in terms of

[55] The graphs show the coefficient on the base category (e.g., women) and the sum of the coefficient on the base category and the coefficient on the interaction term (e.g., Pricing x male). Whether two groups have statistically different effects can be seen from the p-value of the coefficient of the interaction term, which is reported in Tables A.1-A.15 in the Appendix.

Figure 28 – Treatment effect heterogeneity



Note: Results from including interaction dummies in the DiD regression, in CHF per day. The bars denote 95%-confidence intervals. The point estimates show the total effects (base plus interaction).

the "altruistic" dimension responded significantly not only to pricing, but also to information alone. There were no statistically significant differences along the other three values dimensions. The effect of values and lifestyles on travel choices (unrelated to the experiment) are shown in Appendix A.5.

Because both the information and the pricing treatments were based on the external costs of transport, their definition within the context of the study had been explained at the beginning of the treatment. But since participants differ with respect to the attention they pay to the experimental instructions (and possibly also with respect to pre-existing information about transport issues), we included an "exam" question in the final survey to gauge the heterogeneity with respect to the understanding of the concept underlying the experiment. More specifically, the participants in the treatment groups were asked to identify the correct definition of the external costs of transport (as defined in the experiment) among a list of four possible options.[56] The last group of coefficients in Figure 28 shows the ATE separately for those that correctly identified the definition of the external costs of transport used in the experiment (45% of the sample) vs. those that did not. The treatment effect for pricing is driven by the respondents that answered the question correctly. On the other hand, knowledge about the definition of external costs was not generally associated with an increased response to the information-only treatment, with the exception of the effect on climate costs.

Tables A.1-A.14 in the appendix contain the regression results that underlie Figure 28, as well as additional interactions. For example, we found no differential effect between weekdays and weekends, which indicates that Pigovian transport pricing affects work and leisure trips about equally Table A.15).

Table 22 presents the proportional effects, price increases and resulting elasticities for the sub-samples for which we found the largest effect heterogeneity. We see that the elasticity of the participants that correctly identified the external costs in the "exam" question is in fact -0.64, whereas the elasticity of the rest of the sample (around 55%) is precisely centered around zero. The effect is thus exclusively driven by those participants that understood the concept of external costs and thus nature of the experiment. The table also shows the elasticity for men vs. women, French- vs. German-speakers and people with a monthly household income above or below CHF 8,000.

Table 22 – Elasticities for subsamples

	Treatment effect (%)			Price increase (%)			Elasticity				
	Estimate	Lower Bound	Upper Bound	Estimate	Lower Bound	Upper Bound	Estimate	Lower Bound	Upper Bound	p	N
Male=1	-5.88	-10.48	-1.27	16.47	16.21	16.73	-0.36	-0.64	-0.08	0.012	80,338
Male=0	-4.09	-8.81	0.63	16.32	16.06	16.58	-0.25	-0.54	0.04	0.089	80,863
Correct=1	-10.57	-14.93	-6.20	16.40	16.22	16.59	-0.64	-0.91	-0.38	<0.001	103,685
Correct=0	0.03	-3.72	3.78	16.40	16.22	16.58	0.00	-0.23	0.23	0.989	115,038
French=1	2.33	-4.72	9.37	16.79	16.40	17.19	0.14	-0.28	0.56	0.518	42,014
French=0	-7.39	-11.20	-3.57	16.29	16.09	16.50	-0.45	-0.69	-0.22	<0.001	119,190
Inc. <8000	-2.51	-51.10	20.04	16.15	15.87	16.44	-0.16	-0.51	0.20	0.392	59,779
Inc >=8000	-6.28	-10.29	-2.28	16.55	16.31	16.79	-0.38	-0.62	-0.14	0.002	101,425

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. Standard errors in parentheses and clustered at participant level. The dummy variable "post" takes the value of one during the treatment period (study days 29-56), and zero otherwise.

4.3.3 Mechanisms

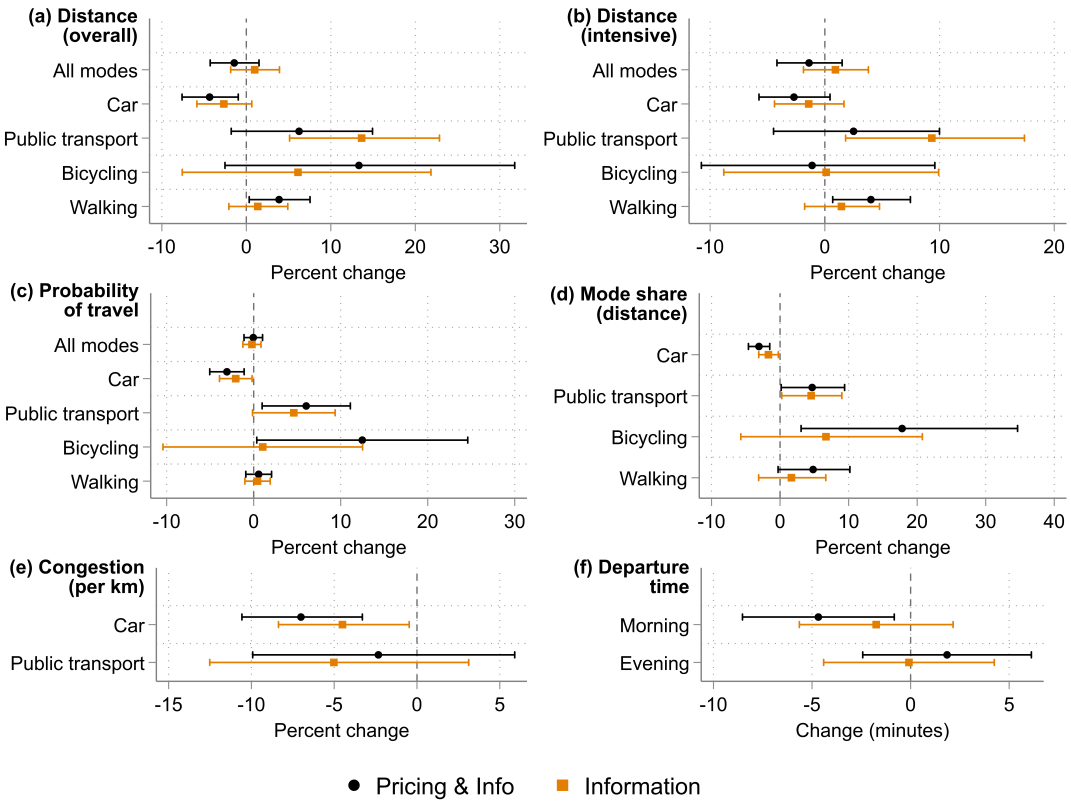
There are several ways in which people can reduce their external costs of transport: Reduce travel overall, substitute modes, and choose different routes and departure times. To shed light on potential mechanisms, Figure 29 shows the effect of the pricing treatment on various outcomes. The regression results underlying this figure are shown in Tables A.16 - A.21 in the Appendix.

The treatment did not significantly reduce overall travel distances, but there is a statistically

[56] Besides the correct answer, the available alternatives were the private costs, the total costs (sum of private + external) and "I don't know"; see Appendix B.4.

significant reduction in car distance countered by increases of the other modes (panel a). The effect can be seen separately on the intensive margin in panel b (the distance conditional on traveling on a given day) and on the extensive margin in panel c (the probability of traveling). The mode shift becomes even more pronounced if the treatment effect is shown for mode share in terms of distance (panel d). There is a statistically significant reduction in the share of car distance by about 3% and an increase in the share of public transport, bicycling and walking.

Figure 29 – Mechanisms underlying the reduction in external costs



Notes: The bars denote 95%-confidence intervals, corresponding to a two-sided test at $p<0.05$. In panels (a), (b), (d) and (e), the treatment effects are computed using a Poisson pseudo-maximum-likelihood (PPML) regression controlling for temperature and precipitation. Panel (c) shows the marginal results of a logit regression in the form of semi-elasticities. In panel (f), a linear DiD-specification is chosen, with the departure time (measured in minutes after midnight) as the dependent variable. All regressions include three levels of fixed effects (person, day of study and day of calendar).

The pricing treatment significantly reduced congestion costs per km of car travel (panel e), implying that modal shift is not the only mechanism responsible for the reduction in external costs. The reduction in congestion per km can be due to a change in route and/or a change in departure time. Whereas route choice has to be addressed using a discrete choice framework, a shift in departure time can be examined using the DiD framework of this section. Using the departure time (in minutes) as the dependent variable, we observe a significant shift in the departure times for car trips in the morning towards earlier departures, but no clear effect in the evening (panel f). There was no reduction in crowding for public transport, nor was there an effect on PT departure time. The treatment did not change the average car and PT speed on a daily level.

4.4 Treatment effects on mode choice

The effects of the pricing and information treatment on mode choice can also be analyzed through classical mode choice modeling. Using a choice model, it is possible to predict modal shifts while controlling for other variables that might have changed between the study periods and groups. Within this section, we focus on revealed preferences data, i.e. the tracking data from the participants of the study.

To be able to estimate a choice model on the tracking data, the trip information of the modes not chosen is needed. Within this section, we distinguish between the modes walking, cycling, private car (either driver or passenger), and public transport. For walking and cycling, this information was computed through MATSim (Horni *et al.*, 2016b). For the alternatives car and public transport, the Google Maps Directions API[57] was used. The ticket prices of the public transport connections were computed through software developed by Hörl and Molloy (2019). Public transport season tickets were accounted for.

Furthermore, it is crucial to determine whether the mode was available to the traveler or whether the traveler even considered it. For this reason, cycling and walking are only available if the respective travel time does not exceed 60 minutes. Longer trips are regarded as recreational and are therefore excluded. Also, public transport is only available, if Google Maps did not suggest walking instead of taking public transport.

For the pricing group, we considered only trips where the budget balance was positive. Furthermore, each participant needed to show records for at least 18 days in each study period.

Due to the size of the data (approx. 310,000 observations), we chose a multinomial logit model (MNL) to explain the travelers' mode choices. There are currently no implementations known to the authors that handle either large scale Fixed-Effects MNL models, or Random-Effects models with a sufficient number of draws within reasonable runtimes.

To explain people's mode choice behavior, we used standard trip attributes such as travel times and costs. For public transport, the model distinguishes between the different components of the travel time (access time, in-vehicle time, transfer time). The frequency of the connection and the number of transfers are also included. As the preferences differ between local public transport and train trips, separate sets of parameters were estimated. We did not include car travel costs as their computation, especially for trips where the mode was not chosen, is subject to large uncertainty. For example, it is difficult to evaluate where the person would have parked had they chosen the car. Rain and temperature of the respective days are also included in the model, as they can affect the choice of slow modes substantially. The effects of socio-demographics such as age and income classes as well as the accessibility of the home location were tested. However, none of the associated parameters was significant at the 5% level.

The modeling of the treatment effects makes it necessary to control for differences in the mode choices among groups and study periods. Therefore, the group association, which is independent of the study phase, is included in the model (variables: *Pricing Group*, *Information Group*). Also, the study phase is included. Prior descriptive analysis has shown that the treatment effects differ among distance classes. Therefore, binary variables are introduced that indicate the car distance class of the respective trip. The routed car distance was used, as the euclidean distance can differ substantially from the traveled distance due to the geography of Switzerland.

Using the difference in differences approach, all main effects of the variables treatment group, study phase, and distance class are included in the model as well as all two-way and three-way interactions. The resulting utility function for the alternative car is depicted in Equation 6. While α denotes the alternative-specific constant, X includes all mode-specific attributes. The remaining variables refer to the differences in differences approach. For the sake of brevity, we only depict the effect of distance class 3 to 5 kilometers. The remaining

[57] https://developers.google.com/maps/documentation/directions/overview

distance classes ([5,15),[15,30), [30, inf)) are included in the utility functions using the same structure. The distance class referring to trips below 3 kilometers is the reference level. The real treatment effect of pricing or informing about the external costs is modeled through the terms $\beta^c_{Gr,Studyph.}$ and $\beta^c_{Gr,Distcl.3-5,Studyph.}$ for this distance class. While the utility functions for the alternatives bicycle and walk are defined analogously, public transport is the reference alternative.

$$\begin{aligned} V^c =& \alpha^c + X\beta^c + \beta^c_{Gr.} \cdot x_{Group} + \beta^c_{Distcl.3-5} \cdot x_{Distcl.3-5} + \beta^c_{Studyph.} \cdot x_{Studyph.} + \\ & \beta^c_{Gr,Distcl.3-5} \cdot x_{Group} \cdot x_{Distcl.3-5} + \beta^c_{Gr,Studyph.} \cdot x_{Group} \cdot x_{Studyph.} + \\ & \beta^c_{Distcl.3-5,Studyph.} \cdot x_{Distcl.3-5} \cdot x_{Studyph.} + \\ & \beta^c_{Gr,Distcl.3-5,Studyph.} \cdot x_{Group} \cdot x_{Distcl.3-5} \cdot x_{Studyph.} \cdots \end{aligned} \tag{6}$$

The model results of this specification are presented in Tables 23 to 26. The naming of the parameters includes the units of the respective independent variable. *[Bin]* denotes a binary variable. The parameters of the reference levels are set to zero. For the treatment group association, the control group was chosen as the reference level. Similarly, the effect of study phase one is set to zero.

As mentioned before, the interaction between study group and study phase as well as all higher-order three-way interactions with the distance class refer to the actual treatment effects through pricing participants external costs or informing them about them. As these effects are relative to the base level, their semi-elasticities are reported further below. The reader is advised, however, that their effects are not significantly different from zero at the 5% level according to the robust t-values. In a reduced model that does not include distance classes and is not depicted here, the effects were not significant as well.

However, compared to the car, travelers did use the bicycle substantially less with increasing rainfall, see Table 23. The opposite is observed for the temperature. For the alternative walking, the temperature does not have a significant effect, see Table 26.

Table 23 – Model results: Mode choice model on RP data, bicycle parameters.

Bicycle	Est.	Rob. SE	Rob. T-Val.
Alternative-specific constant	-1.9914	0.1804	-11.04
Traveltime [min]	-0.0792	0.0039	-20.09
Distance [3,5) km [Bin]	-0.3934	0.1509	-2.61
Distance [5,15) km [Bin]	-0.7449	0.1727	-4.31
Study phase 2 [Bin]	-0.1372	0.1172	-1.17
Daily precipitation [mm]	-0.2398	0.0383	-6.26
Daily mean temperature [C]	0.0194	0.0098	1.98
Pricing Group	-0.2001	0.1645	-1.22
Information Group	-0.1355	0.1629	-0.83
Pricing Group x Distance [3,5) km [Bin]	0.2009	0.2170	0.93
Pricing Group x Distance [5,15) km [Bin]	0.1503	0.2484	0.60
Information Group x Distance [3,5) km [Bin]	0.2035	0.2102	0.97
Information Group x Distance [5,15) km [Bin]	0.1833	0.2289	0.80
Study Phase 2 x Distance [3,5) km [Bin]	-0.0456	0.1403	-0.32
Study Phase 2 x Distance [5,15) km [Bin]	-0.1234	0.1437	-0.86
Pric. Gr. x St. Ph. 2 [Bin]	0.0566	0.1420	0.40
Pric. Gr. x St. Ph. 2 x Dist. [3,5) km [Bin]	0.0606	0.1864	0.33
Pric. Gr. x St. Ph. 2 x Dist. [5,15) km [Bin]	0.1112	0.2087	0.53
Inf. Group x St. Ph. 2 Base [Bin]	-0.0026	0.1544	-0.02
Inf. Group x St. Ph. 2 x Dist. [3,5) km [Bin]	0.0413	0.1939	0.21
Inf. Group x St. Ph. 2 x Dist. [5,15) km [Bin]	-0.0260	0.2119	-0.12

Table 24 – Model results: Mode choice model on RP data, car parameters.

Car	Estimate	Rob. SE	Rob. T-Value
Traveltime [min]	-0.1207	0.0044	-27.69
Distance [3,5) km [Bin]	0.0666	0.0776	0.86
Distance [5,15) km [Bin]	-0.0288	0.0855	-0.34
Distance [15,30) km [Bin]	-0.4678	0.1360	-3.44
Distance [30,inf) km [Bin]	-0.4910	0.1894	-2.59
Study phase 2 [Bin]	-0.0588	0.0556	-1.06
Pricing Group	-0.1171	0.0792	-1.48
Information Group	-0.1789	0.0744	-2.40
Pricing Group x Distance [3,5) km [Bin]	0.1372	0.1115	1.23
Pricing Group x Distance [5,15) km [Bin]	0.0498	0.1147	0.43
Pricing Group x Distance [15,30) km [Bin]	0.0298	0.1671	0.18
Pricing Group x Distance [30,inf) km [Bin]	-0.1122	0.2290	-0.49
Information Group x Distance [3,5) km [Bin]	0.0762	0.1030	0.74
Information Group x Distance [5,15) km [Bin]	0.1023	0.1060	0.97
Information Group x Distance [15,30) km [Bin]	0.0470	0.1619	0.29
Information Group x Distance [30,inf) km [Bin]	-0.1339	0.1995	-0.67
Study Phase 2 x Distance [3,5) km [Bin]	0.0479	0.0839	0.57
Study Phase 2 x Distance [5,15) km [Bin]	0.0404	0.0768	0.53
Study Phase 2 x Distance [15,30) km [Bin]	0.0805	0.1049	0.77
Study Phase 2 x Distance [30,inf) km [Bin]	0.3453	0.1573	2.20
Pric. Gr. x St. Ph. 2 [Bin]	-0.0305	0.0839	-0.36
Pric. Gr. x St. Ph. 2 x Dist. [3,5) km [Bin]	-0.0564	0.1219	-0.46
Pric. Gr. x St. Ph. 2 x Dist. [5,15) km [Bin]	-0.0298	0.1124	-0.27
Pric. Gr. x St. Ph. 2 x Dist. [15,30) km [Bin]	0.0208	0.1535	0.14
Pric. Gr. x St. Ph. 2 x Dist. [30,inf) km [Bin]	-0.1310	0.2179	-0.60
Inf. Group x St. Ph. 2 Base [Bin]	0.0383	0.0737	0.52
Inf. Group x St. Ph. 2 x Dist. [3,5) km [Bin]	-0.0995	0.1105	-0.90
Inf. Group x St. Ph. 2 x Dist. [5,15) km [Bin]	-0.0243	0.1052	-0.23
Inf. Group x St. Ph. 2 x Dist. [15,30) km [Bin]	0.1690	0.1389	1.22
Inf. Group x St. Ph. 2 x Dist. [30,inf) km [Bin]	-0.1204	0.2111	-0.57

Table 25 – Model results: Mode choice model on RP data, PT parameters.

PT	Estimate	Rob. SE	Rob. T-Value
Alternative-specific constant	1.0712	0.0833	12.86
Incl. train connection [Bin]	-0.0235	0.0989	-0.24
Costs [CHF]	-0.1199	0.0068	-17.61
Traveltime Train [min]	-0.0387	0.0035	-11.04
Traveltime Feeder to train [min]	-0.0695	0.0046	-14.97
Transfer time train [min]	-0.0456	0.0066	-6.86
Access time train [min]	-0.2800	0.0060	-46.55
Traveltime local PT [min]	-0.0515	0.0031	-16.83
Transfer time local PT [min]	-0.0375	0.0111	-3.39
Access time local PT [min]	-0.3510	0.0065	-54.16
Frequency train [min]	-0.0062	0.0016	-3.89
Frequency local PT [min]	-0.0164	0.0017	-9.67
Number of transfers train	-1.1680	0.0557	-20.99
Number of transfers local PT	-1.4124	0.0728	-19.41
Daily precipitation local PT [mm]	0.0127	0.0149	0.85
Daily mean temperature local PT [C]	-0.0108	0.0044	-2.46

Table 26 – Model results: Mode choice model on RP data, walk parameters and goodness of fit statistics.

Walk	Estimate	Rob. SE	Rob. T-Value
Alternative-specific constant	1.1308	0.0738	15.32
Traveltime [min]	-0.0910	0.0017	-55.02
Distance [3,5) km [Bin]	-0.2431	0.0959	-2.54
Study phase 2 [Bin]	-0.0499	0.0549	-0.91
Daily precipitation [mm]	-0.0452	0.0151	-2.99
Daily mean temperature [C]	0.0047	0.0041	1.15
Pricing Group	-0.0816	0.0758	-1.08
Information Group	-0.0764	0.0716	-1.07
Pricing Group x Distance [3,5) km [Bin]	0.2279	0.1402	1.63
Information Group x Distance [3,5) km [Bin]	0.1989	0.1299	1.53
Study Phase 2 x Distance [3,5) km [Bin]	0.1085	0.1017	1.07
Pric. Gr. x St. Ph. 2 [Bin]	0.0412	0.0791	0.52
Pric. Gr. x Dist. [3,5) km [Bin]	-0.0214	0.1508	-0.14
Inf. Group x St. Ph. 2 Base [Bin]	0.0341	0.0707	0.48
Inf. Group x St. Ph. 2 x Dist. [3,5) km [Bin]	-0.1034	0.1375	-0.75
Estimated parameters	82		
Respondents	2,644		
Choice observations	313,299		
LL(null)	-332,321.07		
LL(final)	-158,607.59		
Rho2	0.52		

As indicated previously, the magnitudes of the estimated parameters cannot be interpreted directly. Besides, the signs of binary variables are always relative to the base level and can therefore provide wrong intuitions. For this reason, the effects of the treatments *pricing* and *information* on the modal splits of the different alternatives were computed. Similarly to the model, the results are distinguished between different distance classes.

In general, elasticities provide useful insights into the changes of modal splits. In this case, however, the treatment is a categorical variable. Furthermore, the treatment effects themselves relate to the interactions of the group assignation (control, pricing, or information) and phase two of the experiment. This includes higher-order interactions with distance.

To compute the relative influence on the modal splits of the treatment effects, we follow the method described by Karaca-Mandic *et al.* (2012). For pricing, for example, we first assume that all data were collected in study phase 2 and every person was associated with the pricing group. Subsequently, we predict modal shares using the model presented above. However, it is assumed that the parameters referring to the interaction of the Pricing Group with study phase 2 are zero. The results are the *base modal shares*. Afterwards, the full model with all interactions is applied to the same data, resulting in the *treatment modal shares*. The relative differences of the treatment modal shares to the base modal shares show how much the modal shares have changed (in %) due to the pricing. In order to provide confidence intervals, the model is estimated 100 times with bootstrapping on the level of the respondent. For each one of the data sets, the elasticities are calculated.

The results for the pricing treatment are presented in Table 27. Next to the elasticities, we show the 95% confidence interval based on the bootstrapping. It can be observed that the participants of the study mainly switch from the car, which has the highest external costs, to other modes. For short distances, the relative changes are most pronounced. Although the bicycle is also priced, its usage increases for all distance classes. Due to the sparsity of the data, we do not report the bicycle modal shifts for distances larger than 15 kilometers.

Table 27 – Semi-Elasticities of the pricing treatment (in %).

Car distance in km	Car	PT	Bike	Walk
Distance All	-1.49 [-2.82,0.01]	1.55 [-2.23,6.56]	14.25 [-6.27,42.52]	3.58 [-1.86,10.04]
Distance <3	-3.15 [-8.11,1.10]	0.04 [-6.75,8.19]	9.34 [-13.27,42.30]	3.17 [-3.00,9.70]
Distance [3,5)	-2.78 [-5.45,0.12]	3.59 [-4.14,12.62]	20.61 [-11.30,52.68]	8.11 [-9.23,26.37]
Distance [5,15)	-0.96 [-2.27,0.53]	2.25 [-4.03,9.35]	22.96 [-14.05,60.68]	
Distance [15,30)	-0.13 [-1.57,1.27]	0.52 [-5.43,8.31]		
Distance [30, inf)	-0.59 [-1.85,1.17]	3.16 [-5.21,9.93]		

Note: The values in parentheses show the bootstrapped 95% confidence interval with 100 samples.

Similarly, the participants tend to walk more, which is the only mode not priced. However, none of the elasticities are statistically different from zero.

Table 28 reports on the relative modal shifts for the information treatment. Compared to the previous analysis, these effects are less pronounced. For example, car usage only decreases for two distance classes and bike usage decreases for distances between 5 and 15 kilometers. Again, the reported elasticities are not significantly different from zero.

Table 28 – Semi-Elasticities of the information treatment (in %).

Car distance in km	Car	PT	Bike	Walk
Distance All	0.14 [-1.45,1.58]	-0.58 [-4.09,2.70]	1.57 [-15.08,26.47]	-0.13 [-5.92,6.51]
Distance <3	0.64 [-4.84,5.14]	-1.42 [-7.07,5.10]	1.09 [-22.44,32.24]	0.03 [-6.18,6.64]
Distance [3,5)	-1.46 [-4.42,2.12]	3.41 [-4.90,12.23]	12.65 [-16.13,49.01]	-1.32 [-16.88,15.11]
Distance [5,15)	0.20 [-1.07,1.55]	-0.05 [-5.72,4.76]	-4.06 [-29.21,29.53]	
Distance [15,30)	1.23 [-0.17,2.64]	-5.42 [-10.21,0.58]		
Distance [30, inf)	-0.40 [-1.92,1.27]	2.20 [-5.71,9.78]		

Note: The values in parentheses show the bootstrapped 95% confidence interval with 100 samples.

4.5 Stated choice experiment

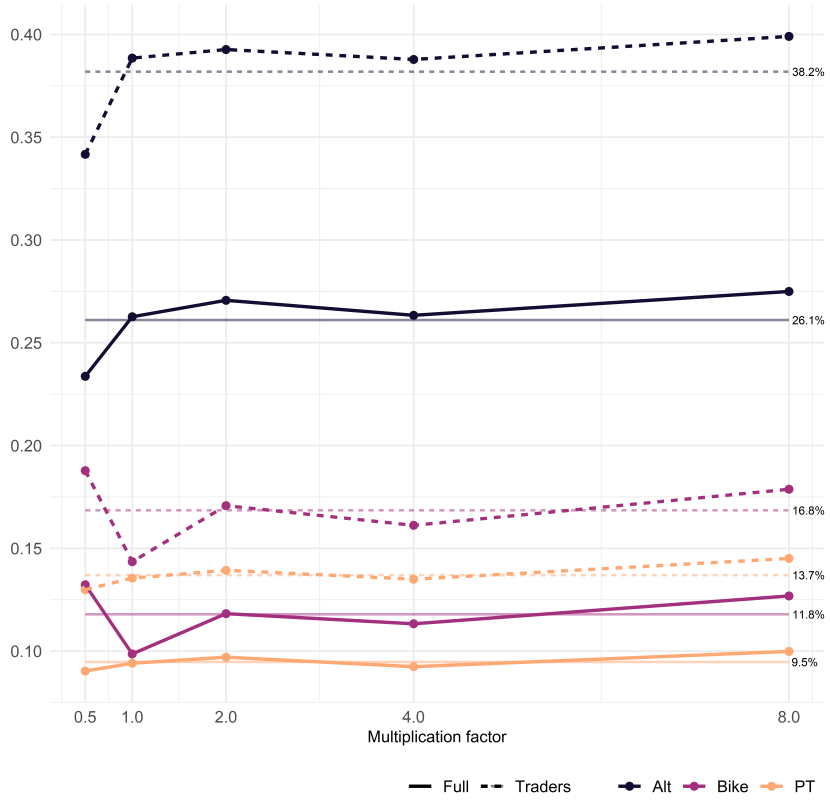
In this section, we present the results of the SCE as described in Section 3.6.2. We show results for both the full sample and the sample of respondents who selected an alternative other than the baseline car trip on at least one occasion (so-called “traders”), since this may be an indication of closer engagement with the choice task[58]. The response time data suggests a difference between the two groups for the time taken to answer a choice task, with the average difference ranging from 0.7 seconds (4%) for the Car-Alt SCE to 1.8 seconds (12%) for the Car-Bike SCE. Tables A.22 and A.23 show the descriptive statistics of the SCE for both samples. We do not see any significant changes between the samples along the presented dimensions, which suggests that whether a respondent traded or not is independent of any SCE-specific characteristics.

Effect of multiplication factors on choice probabilities

Figure 30 presents the predicted probabilities based on equation 5. The corresponding model estimates are presented in Table A.24. Overall, we see differences in the choice probabilities across the multiplication factors and across the modes, where the horizontal lines annotated with percentage values show the overall predicted probability for that alternative. By construction, the “traders” chose the alternative options with a higher probability, however, the overall trends are very similar. The Car-Alt and Car-PT choice probabilities for factor 0.5 are below the choice probabilities for the other factors, which suggests that these levels of external costs are too low to induce a shift away from the status quo. For the Car-Alt SCE, the choice probabilities increase from factor 0.5 to factor 1, and remain stable between factors 1 and 4, with a notable increase again at multiplication factor 8. For the Car-PT SCE, the pattern is similar, however, with much smaller deviations from the

[58]We also restrict the overall sample to between the 5th and 99th percentile of the introduction time distribution (21 to 201 seconds) and the response time distribution for each type of SCE (which differed in length).

Figure 30 – Predicted choice probabilities for non-reference alternatives



Note: Predicted probabilities shown for full sample (solid lines) and traders (dotted lines). Horizontal lines with annotation show the overall predicted probability independent of the multiplication factors.

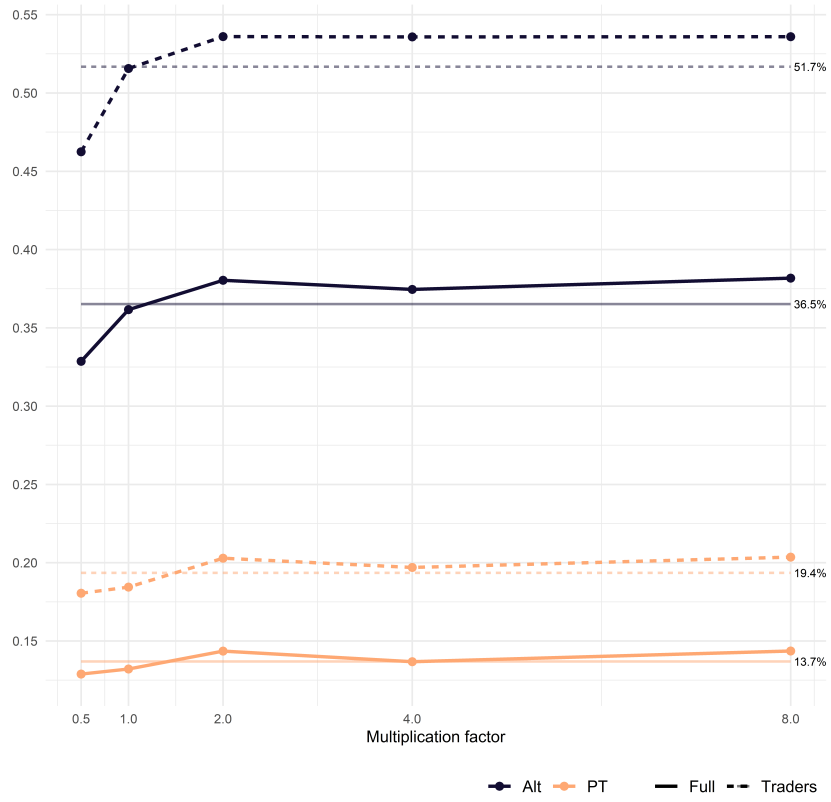
overall average. The Car-Bike SCE shows a different pattern with no clear trend. All the factors in the Car-Bike SCE have a negative effect on the choice probability, which suggests that even after controlling for a large number of respondent characteristics, there still exists some unobserved information that makes the reference car trip more attractive.

For the calculation of the demand elasticities presented in Table 29, we focus on the Car-Alt and Car-PT SCEs due to the difficulty in interpreting the Car-Bike SCE. Figure 31 presents the predicted probabilities in the same format as in Figure 30, and the full model estimates are presented in Table A.25. We see a similar pattern for the choice probabilities as above. For the Car-Alt SCE, the choice probability for factor 0.5 is significantly different from all the other factors, whereas the confidence intervals for factors 1 to 8 all overlap (see column 4 in Table 29). For the Car-PT SCE the trends are similar as before with the choice probability for none of the factors statistically different from each other.

The final column in Table 29 shows the demand elasticities by sample, choice alternative and factor, where the price change is the average change in the total cost for the chosen alternative and factor relative to the total costs at factor 1. The changes in choice probabilities in column 5 are the percentage changes in the choice probability for the respective factor relative to factor 1. The elasticities in the Car-Alt SCE are statistically different from zero for factors 0.5, 2, and 8, with the elasticity for factor 0.5 significantly different from the other factors. For the Car-PT SCE, the results are less conclusive, with significant elasticities only for factors 2 and 4 (for the “full” sample) and factors 2 and 8 (for the “traders” sample), with overlapping confidence intervals for all factors.

The results for the Car-Alt SCE provide an indication of a nonlinearity in demand in the

Figure 31 – Predicted choice probabilities for non-reference alternatives (excluding bicycle)



Note: Predicted probabilities shown for full sample (solid lines) and traders (dotted lines). Horizontal lines with annotation show the overall predicted probability independent of the multiplication factors.

presence of multiplication factors. This is not unexpected, since a doubling of the external costs is associated with a less than doubling of total costs. The elasticities at factor 2 are the closest in magnitude to that from the field experiment. Furthermore, the results from the Car-Alt SCE suggest that respondents were willing to shift departure times in the presence of transport pricing, with departures 30 minutes earlier or later preferred to departures 60 minutes earlier or later. This is in line with the evidence from the field experiment, where we observe departure time shifts in the morning (see Table A.21). In contrast to the field experiment (see Figure 29), we cannot make any definitive statement on an overall mode shift effect in the Car-PT SCE, since we do not have a control group in this instance. There is some suggestive evidence, however, that the PT share is increasing in the externalities multiplication factor.

Effects of attributes and respondent characteristics on choice probabilities

In this section we analyze the impact of the attributes of the SCEs and respondent characteristics on the choice probabilities of the alternatives presented in the choice sets. The model estimates can be found in Table A.24.

Among the generic parameters, travel time consistently influences utility negatively, ceteris paribus, whereas the the external cost parameter is only statistically less than zero for the traders sample. Total costs do not affect utility significantly in this model. Looking at the choice set attributes, reliability has the expected sign for Car, Alt, and PT, however not significantly so for PT across all levels. As mentioned above, the departure time shift parameter is significant for Alt, with departure times closer to the original departure time preferred. For PT, utility is decreasing in the number of transfers and the length of time

Table 29 – Demand elasticities by factor (MNL Model)

Sample	Choice	Factor	Probability	Diff. wrt factor 1	Avg. price change	Elasticity
Full	Alt	0.5	0.329	-0.091	-0.108	0.846
			[0.319, 0.339]	[-0.129, -0.053]	[-0.109, -0.106]	[0.491, 1.195]
		1	0.362			
			[0.352, 0.373]			
		2	0.380	0.052	0.213	0.244
			[0.368, 0.392]	[0.003, 0.099]	[0.210, 0.217]	[0.014, 0.464]
		4	0.375	0.036	0.641	0.056
			[0.363, 0.385]	[-0.007, 0.078]	[0.630, 0.652]	[-0.011, 0.122]
		8	0.382	0.056	1.521	0.037
			[0.370, 0.394]	[0.012, 0.098]	[1.493, 1.546]	[0.008, 0.064]
	PT	0.5	0.129	-0.024	-0.109	0.224
			[0.121, 0.136]	[-0.098, 0.053]	[-0.112, -0.107]	[-0.495, 0.885]
		1	0.132			
			[0.124, 0.139]			
		2	0.144	0.087	0.221	0.394
			[0.136, 0.152]	[0.005, 0.180]	[0.216, 0.226]	[0.021, 0.821]
		4	0.137	0.036	0.674	0.053
			[0.130, 0.144]	[-0.039, 0.123]	[0.659, 0.689]	[-0.058, 0.183]
		8	0.144	0.087	1.532	0.057
			[0.136, 0.152]	[0.015, 0.175]	[1.493, 1.570]	[0.010, 0.115]
Traders	Alt	0.5	0.462	-0.103	-0.106	0.972
			[0.449, 0.474]	[-0.136, -0.069]	[-0.108, -0.104]	[0.651, 1.294]
		1	0.516			
			[0.502, 0.528]			
		2	0.536	0.040	0.207	0.191
			[0.522, 0.550]	[0.000, 0.079]	[0.204, 0.211]	[0.002, 0.380]
		4	0.536	0.039	0.625	0.063
			[0.521, 0.551]	[0.004, 0.077]	[0.614, 0.636]	[0.007, 0.124]
		8	0.536	0.039	1.498	0.026
			[0.521, 0.551]	[-0.001, 0.080]	[1.473, 1.529]	[-0.001, 0.053]
	PT	0.5	0.181	-0.021	-0.104	0.201
			[0.169, 0.193]	[-0.106, 0.082]	[-0.108, -0.100]	[-0.792, 1.019]
		1	0.184			
			[0.174, 0.196]			
		2	0.203	0.100	0.207	0.483
			[0.188, 0.217]	[0.004, 0.209]	[0.199, 0.214]	[0.018, 1.015]
		4	0.197	0.068	0.632	0.108
			[0.184, 0.211]	[-0.031, 0.160]	[0.608, 0.654]	[-0.048, 0.258]
		8	0.204	0.104	1.446	0.072
			[0.190, 0.218]	[0.006, 0.208]	[1.390, 1.499]	[0.004, 0.145]

Note: Average price changes calculated as percentage change in total cost for the respective factor and alternative relative to the total costs at factor 1. 95% confidence intervals calculated with 500 bootstrap replications in square brackets.

between connections, whereas the occupancy level and PT mode have plausible signs, but are not statistically significant. The weather attributes have the expected sign for both PT and Bicycle, with dry weather generally preferable to wet weather. The suggested internal health benefits for Bicycle do not influence utility, however, the availability of an E-bike significantly increases the choice probability for the bicycle alternative. As expected, the presence of a bicycle path is associated with a significantly higher marginal utility than cycling on a main road with or without a bicycle lane.

Turning to the mobility tools, we see that owning a car and higher values for the car access measure are associated with higher probabilities of choosing the reference car trip. The PT access measure is not statistically significant. The signs on the various PT subscriptions parameters are as expected, with only the full fare subscription not significant in either sample.

Respondents who stated that health and congestion issues related to transport require more policy attention were more likely to choose the earlier/later departure option. For PT, those who supported more efforts to address emissions and health impacts preferred the PT option, whereas those concerned about congestion issues were more likely to choose the reference car trip. We do not see any significant effects for respondents in favor of transport pricing or incorporating social costs into the cost of mobility. We also do not see any differential effect for those individuals who correctly defined the external costs of transport.

Considering the values as described in Section 3.6.3, we see that a high value for “biospheric” is associated with a higher probability of choosing the bicycle alternative, whereas higher values for “egoistic” result in higher choice probabilities for the reference car trip in the Car-Alt SCE for the traders sample. “Altruistic” values have the same sign for all alternatives, however, are only significant for the PT alternative in the full sample.

Of the demographic variables included in the model, having German as the language of correspondence is generally associated with a higher probability of remaining with the reference car trip. Females are significantly less likely to choose the bicycle or PT alternatives, whereas younger and more highly educated respondents are likelier to choose the reference car trip in the Car-Alt SCE. The dummies for the MOBIS treatment groups and whether the experiment was presented in blocks or randomly are not significant for any of the SCEs, which suggests that these variables did not have any systematic impact on the choice probabilities.

Finally, the elasticities have the expected signs, however, the magnitude of the income elasticity of cost is very high. Comparing this value with the estimated parameter in Table A.25, we see that this may be driven by the Car-Bike SCE, since the absolute value is between 0 and 1, although not statistically significant. Overall, estimating the Car-Alt and Car-PT SCEs jointly only slightly improves model fit compared to the improvement in estimating either model with the traders sample.

4.6 Challenges

In this subsection, we list problems that could potentially threaten the validity of our results. Additional issues that are not essential for the validity of our results are described in Appendix D.

4.6.1 Observation effect

As mentioned in Section 4.2.2, there is a reduction in the external costs of travel during the course of the experiment. This is partly due to a seasonal effect, but we observe an “observation” effect also when controlling for seasonality. Table 30 shows the results from regressing the daily external costs of travel during the observation period on dummies denoting membership in the Pricing and the Information groups, calendar FE and a linear day-of-study trend. This trend is significant and indicates that the external costs from all travel decrease by 1.5 cents per study day (column 1). However, there is no difference in this trend across the groups (column 2). Columns 3-6 show that the trend is caused by a

reduction in the external costs of driving. When using distance as the dependent variable (Table 31), the results indicate that there may be a shift away from driving and towards public transport over the course of the experiment, for all groups.

Table 30 – Trends in external costs

	All Travel	All Travel	Car	PT	Bicycle	Walking
Info	8.574	-4.206	-6.704	4.167	-0.452	-1.217
	(12.071)	(15.902)	(16.114)	(2.887)	(0.801)	(0.743)
Pricing	18.853	5.115	-0.062	6.375*	0.236	-1.434*
	(12.245)	(16.079)	(16.268)	(3.039)	(0.936)	(0.721)
Day of study trend	-1.115**	-1.703**	-1.715**	0.099	-0.006	-0.081**
	(0.397)	(0.539)	(0.542)	(0.102)	(0.026)	(0.027)
Pricing x Day-of-study trend		0.921	0.864	0.033	-0.022	0.046
		(0.640)	(0.647)	(0.102)	(0.032)	(0.046)
Info x Day-of-study trend		0.957	0.900	-0.090	0.006	0.040
		(0.638)	(0.642)	(0.104)	(0.030)	(0.040)
Adj. R^2	0.005	0.005	0.005	0.009	0.007	0.012
N	83,081	83,081	83,081	83,081	83,081	83,081

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. The dependent variable is the external cost of transport (in cents per day), aggregated to the person-day level, and restricted to study days 1-28 (pre-treatment). Standard errors (in parentheses) are clustered at the participant level. The regressions additionally include calendar day FE.

Table 31 – Trends in distance travelled

	All Travel	All Travel	Car	PT	Bicycle	Walking
Info	0.099	0.242	-0.093	0.291	-0.067	0.111'
	(1.107)	(1.461)	(1.329)	(0.835)	(0.115)	(0.067)
Pricing	2.456*	2.546'	0.694	1.689'	0.034	0.129*
	(1.133)	(1.510)	(1.348)	(0.908)	(0.134)	(0.065)
Study Day	0.042	0.027	-0.046	0.066*	-0.001	0.007*
	(0.038)	(0.053)	(0.046)	(0.032)	(0.004)	(0.002)
Pricing x Study Day		-0.006	0.012	-0.011	-0.003	-0.004
		(0.063)	(0.055)	(0.037)	(0.005)	(0.003)
Info x Study Day		0.051	0.066	-0.013	0.001	-0.004
		(0.063)	(0.055)	(0.037)	(0.004)	(0.003)
Calendar day FE	☑	☑	☑	☑	☑	☑
Adj. R^2	0.005	0.005	0.005	0.007	0.007	0.012
N	83,081	83,081	83,081	83,081	83,081	83,081

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. The dependent variable the travel distance (in km), aggregated to the person-day level. Standard errors (in parentheses) are clustered at the participant level.

Since these regressions include calendar day FE, the trend is not driven by seasonality but some other reason. What is important from an identification point of view is that the trend is the same across groups. Due to the presence of the control group, it is differenced out in the analysis and thus will not lead to a bias in the ATE.

4.6.2 Strategic mode corrections

One possible explanation for the trend discussed in the previous section is a strategic correction of modes. Participants were invited to use the validation interface to confirm the detected mode and purpose of their trips and activities. This was optional, but they were encouraged in the weekly email reports to do so, during both phases. As the mode is crucial

in determining the external costs deducted from the mobility budget for the pricing group, this consequently gave them the opportunity to 'game' the experiment, e.g. by 'correcting' actual car trips to another transport mode.

On the other hand, mode changes could also be a true correction. The key question is therefore whether we observe a systematically different mode correction behavior for the pricing group relative to the control and information groups. To test for this, we regress the number of daily mode corrections during phase 2 on dummies indicating membership in the pricing and information groups while controlling for day of sample and day of calendar effects. We focus on phase 2 because there was no incentive to act strategically during the observation period. The results are shown in column 1 of Table 32. We see no difference in the number of corrections per day, and the results remain stable if we add a series of control variables (column 2) or replace the study day FE with a trend.[59]

Columns 4-6 show the marginal effects of a logit regression, using the same explanatory variable but with a dummy that is equal to one if a person has corrected a mode on a given day, and zero otherwise. We find no differential correction on the extensive margin either.[60]. This suggests that our trust in the participants was justified.

To test the robustness of our results to the mode corrections, we re-run our base regression after removing all observations (on the person-day-level) that contain at least one mode correction (this removes 9.4% of the data in phase 2). The resulting treatment effect, proportional effect and elasticity are shown in column 2 of Table 33, along with the baseline results. Although the point estimates change somewhat, the effects remain largely stable. This implies that our results are not driven by strategic mode correction on behalf of participants.

4.6.3 Self-selection due to nonrandom attrition

The assignment into groups was randomized, but people chose whether or not they wanted to continue with the study. If people in the pricing group were more or less likely to drop out of the study than the control group, then this could lead to a bias due to self-selection. We address this issue in detail in section 4.1.2, where we investigate participant retention and find no differential attrition across groups.

If attrition were influenced by the group assignment, any bias due to self-selection should increase over the course of phase 2. As an additional robustness test, we therefore re-estimate our base model using only the first two weeks (column 3 of Table 33) or the last two weeks of the treatment period (column 4). The results remain largely unchanged, indicating that nonrandom attrition is unlikely to play an important role.

4.6.4 Treatment of missing tracking data

Many participants did not deliver tracks on all days. To differentiate between zeroes (i.e., participants staying at home for one or several days) and missings (participants switching off the app), we rely on imputed activities. Suppose that a participant travels home on Friday evening and does not deliver another track until Monday. If the app (and our algorithm) impute an uninterrupted activity "at home" that spans the trips on Friday and Monday, then we assume that this person stayed at home and assign a travel distance of zero. However, the imputation of activities is not always correct, and this method may thus assign zeros to data that should in fact be coded as missing. To gauge the sensitivity or our results to the issue of missings vs. zeroes, we re-estimate the model using only data from days with nonzero travel distances. The resulting ATE is shown in column 5 of Table 33. The point estimate is almost identical to the base regressions. Due to the exclusion of zero-travel days, the average external cost increases, and the proportional effect and the elasticity therefore decrease somewhat, but the results are overall quite stable.

[59] Note that we cannot use person FE in this regression as these would absorb the group dummies.

[60] Additional regressions were run with a focus on understanding the correction behavior along socio-demographic characteristics, independent of the treatment group. These analyses are contained in the Molloy *et al.* (2021)

Table 32 – Mode Correction

	Corrections	Corr.	Corr.	Prob. (Corr.)	Prob. (Corr.)	Prob. (Corr.)
Pricing	1.024	1.009	1.024	0.002	0.000	0.002
	(0.066)	(0.065)	(0.066)	(0.006)	(0.007)	(0.006)
Information	0.981	0.975	0.981	0.000	-0.001	0.000
	(0.063)	(0.063)	(0.063)	(0.007)	(0.007)	(0.007)
Male		1.043			0.003	
		(0.056)			(0.006)	
Young		1.228**			0.021**	
		(0.084)			(0.007)	
Old		1.166*			0.009	
		(0.084)			(0.007)	
High inc.		1.040			0.006	
		(0.068)			(0.007)	
Low inc.		0.994			0.000	
		(0.065)			(0.007)	
Large household		0.949			-0.006	
		(0.093)			(0.010)	
Small household		0.962			-0.005	
		(0.056)			(0.006)	
Tertiary educ.		1.097’			0.010’	
		(0.059)			(0.006)	
French		1.377**			0.032**	
		(0.086)			(0.006)	
Correct		1.259**				
		(0.067)				
Hedonic		1.021			0.003	
		(0.058)			(0.006)	
Altruistic		0.996			-0.002	
		(0.059)			(0.006)	
Biospheric		0.929			-0.006	
		(0.056)			(0.006)	
Egoistic		0.844**			-0.019**	
		(0.046)			(0.006)	
Study Day			0.999			
			(0.002)			
Constant	0.383**	0.323**	0.397**			
	(0.018)	(0.030)	(0.037)			
Adj. R^2	0.010	0.020	0.010			
N	74,899	72,759	74,899	74,858	72,718	74,858

Notes: **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$. Standard errors in parentheses and clustered at participant level. The dependent variable in the first three columns is the number of mode corrections per day. The coefficients are proportional effects, estimated using a ppml model. Columns 4-6 display the marginal effects from logit regressions. The explanatory variables are the same as used in Figure 4 in the main text. All regressions control for calendar day FE. Columns 1-2 and 4-5 also control for study day FE, whereas columns 3 and 6 use a linear study day trend instead.

Table 33 – Subsample analyses

	Baseline	w/o corrections	w/o weeks 7-8	w/o weeks 5-6	w/o zeroes
Pricing	-0.215**	-0.237**	-0.234**	-0.228**	-0.216**
	(0.072)	(0.080)	(0.082)	(0.086)	(0.074)
Information	-0.087	-0.075	-0.080	-0.092	-0.091
	(0.069)	(0.078)	(0.081)	(0.084)	(0.071)
Constant	4.462**	4.711**	4.527**	4.486**	4.664**
	(0.020)	(0.020)	(0.015)	(0.016)	(0.020)
Prop. effect	-0.051	-0.054	-0.055	-0.049	-0.053
	(0.017)	(0.018)	(0.019)	(0.021)	(0.017)
Elasticity	-0.310	-0.329	-0.339	-0.300	-0.324
	(0.103)	(0.109)	(0.116)	(0.126)	(0.103)
Clusters	3,656	3,656	3,656	3,656	3,656
Adj.R^2	0.232	0.238	0.235	0.232	0.238
N	161,208	139,703	121,311	122,977	154,520

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. Standard errors in parentheses and clustered at participant level. All regressions include fixed effects for person, day of study and day of calendar. The proportional effect and the elasticity are computed using the averages of the control group subject to the appropriate restrictions.

4.6.5 Identified mode detection issues in the tracking app

The quality of the mode detection was key to the transport pricing field experiment. A few issues were identified which are worth considering in future studies that apply algorithmic mode detection.

The first consideration concerns those leisure activities that are movement based over a larger area, such as a bike tour, hiking and skiing. Skiing is especially important in alpine areas: In Switzerland, the percentage of the population that ski regularly is 37% (Statistica, 2018). Gondolas and chairlifts move at between 15 and 50km/h, meaning that these trips are often confused for car travel unless the algorithm has been specifically calibrated. On the downhill, skiers reach similar speeds. Taking a strict definition of a transport trip, such movement-based activities should be excluded from the calculation of external costs. If they were to be included, a person could end up being charged for a long hike in the wilderness on the weekend - which would arguably not be in the spirit of a Pigovian transport pricing scheme.

The second consideration is trip chaining. Shen and Stopher (2014) note that all methods to date (albeit in 2014) did not consider trip chains when detecting the transport mode, and only considered each individual stage. While the mode detection provided by the app was sufficient for the purpose of the transport pricing field experiment, anecdotal evidence indicates that considering trip chains could further improve the performance of the algorithm.

5 Discussion

5.1 Interpretation and implications of the results

The MOBIS experiment implemented transport pricing based on the social marginal costs and using a sample size that would give it sufficient power to detect even small behavioral changes. The external health costs were the most important, followed by congestion and climate costs. Our study implies that pricing-in the full external costs of transport leads to a behavioral change.

Our "Pigovian" transport pricing treatment reduced the external costs of transport by around 5%. Taking the private costs as a reference point, our pricing treatment increased the costs of travel by around 16%. Our results therefore imply an elasticity of the external costs with respect to the overall price of travel of -0.31. In other words, a 10% increase in travel costs due to transport pricing would result in a 3.1% reduction in external costs. This is on the same order of magnitude as previous results that were based on before-vs.-after behavior, e.g. in the context of congestion pricing in London (Leape, 2006), Stockholm (Börjesson and Kristoffersson, 2018) and Singapore (Agarwal and Koo, 2016). Our elasticity estimate is similar to the long-term elasticity of private motorized traffic based on stated preference studies Axhausen and Fröhlich (2012), i.e. -0.35, but considerably higher than their short term estimate of -0.15. The elasticity estimate is also similar to results from toll roads (Bain, 2019), but lower than earlier estimates from before-vs.-after studies (Leape, 2006; Nielsen, 2004). However, since no previous study has examined the response of total external cost in response to multimodal transport pricing, these estimates are not directly comparable.

For the majority of socio-demographic subgroups that we examined, there is no statistically significant difference in the effect of pricing or information. However, there are a few important exceptions. First, we observe a more pronounced effect for men than for women, both in terms of the pricing and the information treatment. The difference is primarily driven by men's response to congestion-related costs, whereas the gender difference is much less pronounced for health and climate related costs. At the same time, we observe a stronger reduction in health- and climate-related damages for the young.

Interestingly, the income level did not result in significant heterogeneity. It appears that lower-income households may be less sensitive to pricing (although the difference is not significant at conventional levels). This is counter-intuitive when thinking about income effects, but consistent with an assumption that people with lower incomes tend to have jobs that are less flexible in terms of working hours.

Heterogeneity was also pronounced between the language regions, as we find no effect of the treatment for French speakers. This may be driven by other determinants that co-vary with the regions and/or the culture. We also cannot exclude the possibility that some of the intervention effect was lost in translation (even though all our messages in French were produced by a native speaker). Our results suggest, however, that it is not due to reduced access to public transportation in the French-speaking areas, as the effect does not depend on the PT or road accessibility indicator (Tables A.7-A.8), as specified by Loder and Axhausen (2018).

Quite strikingly, the pricing effect is driven by subjects who correctly identified the definition for the concept of externalities, a test question that was inserted into the final survey, i.e. after the experiment, and answered correctly by 45% of participants. We interpret this as a proxy for understanding the experiment. Loosely speaking, the elasticity of -0.3 that we measure is the average of an elasticity of -0.6 for those that answered the question correctly and zero for those that did not.

Taken together, the heterogeneities observed in the subgroup analyses suggest that the pricing may have worked better for participants of a profile that includes German-speaking and male participants that paid close attention to the study. While this finding leaves many

open questions regarding the exact mechanisms driving the effectiveness of the pricing, it equally hints at the challenge of imposing such a fairly complex and unfamiliar scheme upon participants within a short-termed experiment. It is reasonable to conclude that a future implementation of transport pricing would have to be accompanied by substantial educational efforts for consumers to understand, and likely also to accept, such a scheme. At the same time, one could speculate that improved understanding could further increase the effectiveness, compared to what we observed in MOBIS.

The reduction in external costs is the result of a mode shift away from driving and towards public transport and cycling, and also of a change in departure times that leads to a decrease in congestion. In contrast, we find no effect on the overall distance traveled and on crowding in public transport.

The participants in our pricing group received both a financial incentive and information about the monetized external costs that they themselves impose on society. The resulting behavioral change could thus be due to pricing and/or information. We examined this question by including an "information only" treatment. The provision of information alone is associated with a negative point estimate, but we cannot reject the null hypothesis of zero effect using conventional levels of statistical significance. The provision of information about the external costs of transport significantly reduced the external costs for some subgroups of the participants (e.g., for men and people scoring high on the "altruistic" scale) and it is quite possible that the effect would be significant in a larger sample. However, we cannot know this based on our experiment. Based on the point estimates, it seems highly likely that even in a large sample, the information-only effect will be much smaller than the information-with-pricing effect. Furthermore, the fact that the information-only effect is larger for altruists implies that other-regarding preferences drive at least some of the informational effect. The insignificance of the information effect in our study implies basically that the information effect, if any, is lower than 5%. This is largely in line with the findings of McKerracher and Torriti (2013), Marangoni and Tavoni (2021) and Allcott (2011) from the filed of energy, who find respectively 3-5%, 0.5-1.9% and 2% average reduction of energy consumption associated with feedback. While the findings of Delmas *et al.* (2013) and Karlin *et al.* (2015) do not deviate substantially from the above mentioned range (7.4 and 7.1% energy savings respectively), the series of trials made with the Amphiro display under the shower Tiefenbeck *et al.* (2018, 2016, 2019) with documented energy savings from 11.4 to 22% imply that there might be some unexploited potentials of information-based measures, especially if they are provided in real-time and apply appealing visualization. Whether these insights are transferable to the field of travel behavior has however to be assessed in more detail.

The difference between the pricing and the information treatment can be interpreted as the effect of pricing conditional on information (which is the same in both treatments). This effect is statistically significant for congestion costs, implying that to reduce congestion, pricing is key. However, the effect is not statistically significant for health and climate costs. This implies that information plays a role nevertheless, even if by itself it is not sufficient to change behavior. If information were completely irrelevant, then the effect of adding pricing to information would have to be the same as the effect of pricing & information. The fact that this is not the case, at least not for health and climate costs, means that information matters.

The stronger role for monetary incentives in the context of congestion, compared to the other dimensions of external costs, could be due to the lower salience of the external congestion costs. Whereas we believe that most people intuitively understand the nature of health and climate costs and in principle place some value on reducing them, the external part of road congestion costs are less obvious. They depend on the time loss of all other drivers, and it is not clear whether the study participants value a time gain for others positively (after all, they are “competitors” for road space). In this sense, it is not surprising that the informational component of pricing is less relevant for congestion, and that pricing is needed to change behavior in this context.

The results based on the average treatment effects are confirmed by the discrete-choice modeling approach. We find that travelers are more inclined to switch their mode if they are actually priced for their external costs. Especially for distances below five kilometers, the travelers from the pricing group switched from the car to slow modes. Although public transport was also priced for peak demand periods, its usage increased for all trips longer than three kilometers. The largest increases could be observed for bicycle usage for trips longer than three kilometers (up to 20%).

In sum, our results support the effectiveness of Pigovian transport pricing. Providing information alone appears only to have a significant effect in a subset of the sample, whereas information combined with pricing significantly reduces external costs of mobility in the whole sample.

5.2 Strengths and limitations

To our knowledge, MOBIS is the first multimodal randomized control trial about transport pricing, and also one of the first to include both information-based and financial incentives. Due to the use of a non-treated control group and a randomized assignment into treatments, we can cleanly identify the treatment effect, separately from other determinants of transport that change over time. The sample size of the experiment was large enough to identify even small effects. With a smaller sample, the power of the experiment would most likely not have been sufficient to detect a proportional change of 5%. Furthermore, by including a control group we are able to control for seasonality and “obervation” effects, which would not be possible in the before-vs-after setting that has been used in most of the previous studies.

Due to its focus on the whole transport system, we are able to measure multiple margins of response, including a modal shift. This is an important improvement relative to single-mode studies, and highly relevant for transport policy. The multi-model setting also leads to a better estimate of the elasticity with respect to an overall pricing scheme, which we believe to be more attractive from a policy perspective than a tax on drivers only.

By basing the price instrument on the full marginal social costs of transport, the experiment is a first-best implementation of Pigovian pricing in the transport sector. While any pricing can be used to implement an effect (and, naturally, higher prices are more likely to achieve a measurable response), using the central estimate for the Pigovian level of transport pricing provides a useful point of reference. In particular, it provides a benchmark with which we can compare pricing levels suggested in the political process. In general, pricing that is below the social marginal cost leads to some inefficient trips taking place (even though their social cost exceeds the utility), whereas pricing beyond the Pigovian level will be associated with some trips not taking place even though their benefit outweighs their social cost.

Our project also has a number of limitations. We begin with two types of selection issues. The first one is caused by our study design, as we focused on working-age drivers living in an urban agglomeration in the German- and French-speaking parts of Switzerland. This means that we cannot be sure about the population-wide effect that would also include the elderly, rural areas and the Canton of Ticino. We expect congestion costs (and thus the price signal) to be lower in rural areas, but since climate and health costs (which dominate the average transport price) also apply to rural trips, transport pricing would also lead to a strong price signal in less populated areas. Furthermore, as we found no significant heterogeneity of the effect with respect to the access to the public transport and the road network, there is no reason to believe that Pigovian transport pricing would not also work in other areas of Switzerland and abroad. The effectiveness of transport pricing will be affected by the potential for mode shift, such that it can be expected to work especially well where alternatives to driving exist. The second selection issue is due to the fact tracking was entirely voluntary. If the willingness to participate in the study is correlated with the response, then this will bias our results. At this point there is little we can do to address this issue other than to acknowledge it.

Our study is a short-term experiment and thus has limited predictive power for the long-run

response to transport pricing for several reasons. On the one hand, the long-term effects can be expected to be larger, due to the additional margins of response associated with relocating, changing jobs, bargaining over work hours/location with employers or adjusting the mobility toolbox (i.e., car and PT pass ownership) that cannot expected to be relevant in a 4-week trial. If transport pricing were instituted permanently, one would also imagine the free market to provide opportunities to reduce costs, for example by offering car pool opportunities or bicycle rentals tailored towards congestion peaks or by accelerating the transition to cleaner motor vehicles. Furthermore, our results suggest that pricing works better for those that understand it, and it stands to reason that a permanent system would be understood better over time than this rather short and fairly complex experiment. On the other hand, it may be easier to break habits for a "game" of four weeks rather than on a permanent basis, which would suggest a lower long-term response. The only way to learn about the long-term effects of transport pricing would be by performing a long-term trial.

We simulated a pricing scheme by providing participants with a budget and then subtracting the prices from that. Giving money and then taking it away may have different effects than taxing people, although it is not clear in which direction the bias would go. If people viewed there mobility budget as a token in a game, they may have been less averse to spending it compared to paying "real" francs in a tax system. Conversely, the concept of loss aversion first introduced by Tversky and Kahneman (1991) could mean that participants valued their virtual budget more highly than "general" money that was not received in the form of a gift. Having said this, the transport pricing simulated in our experiment is not very different from any actual transport tax as both involve taking money away from people. In contrast, had our experiment consisted in rewarding people for using public transport (as e.g., in Maerivoet *et al.*, 2012), this bias would likely be greater.

Participants could correct the mode assigned to each trip and turn the tracking on or off. People in the pricing group could thus have produced an entirely artificial effect by selecting low-cost modes and to turn off the app before a high-cost trip. Whereas we address the mode correction issue in our robustness tests, no similar test can be done for strategic disabling of the app. We cannot exclude the possibility that our effect is partly driven by such cheating. However, since we do not observe a systematic difference in the duration of tracking between the treatment and control groups, and since there are not many trips with "gaps" (i.e., someone traveling from Zurich to Bern and then seemingly "hopping" back to Zurich as the app was disabled during the return trip), we do not expect that cheating was a main driver of the effect that we measure.

Last, our treatment affected only a few thousand people in a country of over 8 million. This was highly advantageous to prevent contamination of the control group with the treatment (the "Stable Unit Treatment Value Assumption", or SUTVA, in the language of causal inference), but it naturally precludes general equilibrium effects. In a pricing scheme that affects the whole population, an overall shift in departure time would lead to a shift in congestion (which was held fixed here), and a large-scale mode shift from driving to public transport would lead to significant crowding and other problems for the transit system and thus counteract the mode shift. Before implementing a general pricing scheme, the general equilibrium effects would have to be approximated using a modeling approach (see below).

5.3 Policy implications

Our experiment implies that Pigovian transport pricing works both in theory and in practice. We were able to compute the marginal external costs of transport on an individual basis, implement these costs as a price, and observe a response in the desired direction.

There are a number of reasons to implement Pigovian transport pricing. First and foremost, transport pricing based on the marginal external costs would lead to a more efficient use of the transport system, and thus to less resources required to expand it. As an increasing amount of time is lost in congestion, having a flexible tool to smooth congestion peaks would be highly advantageous. Transport pricing would also help address the twin challenges of climate change and local air pollution. There is also a certain degree of regulatory pressure to move away from financing the transport system mainly due to fuel prices, given the shift

towards electric mobility in the foreseeable future. And finally, our survey results suggest that there could be a political majority to institute an external cost-based pricing scheme, provided that the revenue is used at least partly to fund infrastructure projects.

A Pigovian pricing scheme as used in the MOBIS experiment would face a number of challenges to implement in practice due to privacy concerns, limited social acceptability and the technical constraints of assessing the tax on a real-time basis (Verhoef, 2000). In order to properly price transport choices, they need to be known in some form to the regulator. This is a significant departure from the information that we are used to (and comfortable with) providing to the government. Transport pricing would therefore have be implemented such as to minimize these privacy concerns. An inspiring example is the Swiss Covid app, which can detect proximity to between people without saving the location and personal details. In the interest of data confidentiality, transport pricing would likely have to be simplified relative to our experimental approach. However, even a simplified pricing scheme should be guided by the marginal external costs of transport to increase the efficiency of the transport system. A key challenge will be to agree on the price setting (e.g., the value of time or the social cost of carbon) within the political process.

Last, it is well-known that fuel taxes are regressive (West and Williams, 2004; Bento *et al.*, 2009), and the distributional aspects of a cost-based pricing scheme like the one used here thus deserve further investigation. Efforts to advance such a scheme will need to be complemented with re-distributive measures to counteract adverse distributional implications.

5.4 Conclusions and future research

Multimodal transport pricing based on the external costs of transport is feasible and has the desired effect of shifting modes, departure times and routes. It leads to a more efficient use of the transport system and thus a reduction in the need for network expansions. If implemented in an equitable way, transport pricing could become a key pillar of a sustainable transport policy.

Our study is a first step in a new direction, but there much we currently do not know. First, transport pricing will necessarily have to be simpler than the Pigovian scheme used here. A natural follow-up question is therefore how much of the behavioral effect is achieved, relative to the first-best scheme, for different types of simplifications.

Second, future research is needed to learn more about the long-term implications of transport pricing, about which we can only speculate based on our 4-week experiment. Whereas we believe that the long-term effects will be stronger due to a higher salience and more margins of response (as discussed above), there may also be counteracting forces such as people getting used to the new prices and reverting to their old transport patterns. The extent to which the effect of long-term pricing differs from the short run will have to be assessed in the context of a long-terms study.

Third, excise taxes are known to be regressive, and Pigovian transport pricing is no exception. Specifically, we see that the amount of transport prices paid in our sample does not increase proportionally with income. In other words, households with twice the income do not pay twice the transport prices, which makes transport pricing regressive by definition. Given our limited income data we could not engage in a meaningful analysis of the distributional aspects of Pigovian transport pricing, but this will have to be studied carefully before implementation in order to design appropriate side measures to protect lower-income households.

Last but not least, our experiment included a tiny fraction of the population, such that the overall pattern of transport was held fixed. An official introduction of transport pricing would likely lead to general equilibrium effects. For example, a shift of car travel towards different modes and/or different times would likely affect the congestion or crowding level of these substitutes as well. These systemic effects will have to be understood and incorporated into any future transport pricing scheme.

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A Appendix - Additional tables and figures

A.1 Effect heterogeneity

Table A.1 – Effect heterogeneity: Gender

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.121	-0.079	-0.028	-0.014
	(0.081)	(0.051)	(0.019)	(0.026)
Information	-0.004	-0.035	-0.004	0.035
	(0.077)	(0.049)	(0.018)	(0.024)
Pricing x male	-0.189’	-0.059	-0.016	-0.114**
	(0.104)	(0.064)	(0.024)	(0.032)
Inf. x male	-0.165’	-0.022	-0.029	-0.114**
	(0.097)	(0.061)	(0.022)	(0.029)
Pricing + Pr. x male	-0.311**	-0.138*	-0.044*	-0.128**
	(0.096)	(0.059)	(0.022)	(0.030)
Inf. + Inf. x male	-0.169’	-0.057	-0.033	-0.079*
	(0.091)	(0.057)	(0.021)	(0.028)
Pricing - Inf.	-0.117	-0.045	-0.023	-0.049’
	(0.088)	(0.055)	(0.020)	(0.027)
(Pricing + Pr. x male) - (Inf. + Inf. x male)	-0.141	-0.082	-0.010	-0.049
	(0.112)	(0.069)	(0.026)	(0.035)
Adj. R^2	0.232	0.225	0.221	0.269
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at the participant level. The dummy variable “male” is equal to one for men and zero for women (reference category).

Table A.2 – Effect heterogeneity: Age

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.110'	-0.046	-0.004	-0.060*
	(0.084)	(0.053)	(0.019)	(0.026)
Information	-0.122	-0.055	-0.026	-0.041
	(0.081)	(0.051)	(0.018)	(0.025)
Pricing x old	-0.185	-0.096	-0.063'	0.026
	(0.145)	(0.086)	(0.033)	(0.049)
Inf. x old	-0.059	-0.066	-0.014	0.020
	(0.137)	(0.084)	(0.032)	(0.038)
Pricing x young	-0.261	-0.166*	-0.075**	-0.020
	(0.122)	(0.076)	(0.028)	(0.037)
Inf. x young	0.175	0.082	0.035	0.058
	(0.112)	(0.071)	(0.026)	(0.036)
Pricing + Pr. x old	-0.295*	-0.142'	-0.067*	-0.087'
	(0.137)	(0.081)	(0.031)	(0.047)
Inf. + Inf. x old	-0.181	-0.120	-0.039	-0.022
	(0.130)	(0.080)	(0.030)	(0.036)
Pricing + Pricing x young	-0.371**	-0.212**	-0.079**	-0.080*
	(0.113)	(0.070)	(0.026)	(0.035)
Inf. + Inf. x young	0.053	0.027	0.010	0.016
	(0.104)	(0.066)	(0.024)	(0.034)
Pricing - Inf.	0.112	0.008	0.022	-0.019
	(0.094)	(0.059)	(0.022)	(0.029)
(Pricing + Pr. x old) - (Inf. + Inf. x old)	-0.114	-0.022	-0.027	-0.051
	(0.175)	(0.105)	(0.041)	(0.0555)
(Pricing + Pr. x young) - (Inf. + Inf. x young)	-0.424**	-0.239**	-0.088**	-0.096*
	(0.137)	(0.085)	(0.032)	(0.043)
Adj. R^2	0.232	0.225	0.221	0.26
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level (in CHF). Standard errors (in parentheses) are clustered at the participant level. The reference category is the age group 30-54. The dummy "young" is equal to one for people less than 30 years, and the dummy "old" is equal to one for people that are 50 or older (and zero otherwise). All regressions include individual, calendar day and day of study FE.

Table A.3 – Effect heterogeneity: Education

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.182*	-0.080	-0.031	-0.071**
	(0.087)	(0.054)	(0.022)	(0.027)
Information	-0.037	-0.018	-0.001	-0.017
	(0.083)	(0.052)	(0.019)	(0.026)
Pricing x tertiary educ.	-0.073	-0.063	-0.010	0.000
	(0.104)	(0.064)	(0.024)	(0.033)
Inf. x tertiary educ.	-0.012	-0.060	-0.041'	0.011
	(0.97)	(0.061)	(0.022)	(0.030)
Pricing + Pr. x tertiary educ.	-0.255**	-0.143*	-0.041*	-0.070*
	(0.089)	(0.056)	(0.020)	(0.029)
Inf. + Inf. x tertiary educ.	-0.148'	-0.079	-0.041*	-0.028
	(0.086)	(0.054)	(0.020)	(0.027)
Pricing - Inf.	-0.146	-0.062	-0.030	-0.053'
	(0.099)	(0.061)	(0.023)	(0.030)
(Pricing + Pr. x tertiary educ.) - (Inf. + Inf. x tertiary educ.)	-0.107	-0.065	0.000	-0.042
	(0.103)	(0.064)	(0.023)	(0.033)
Adj. R^2	0.221	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at the participant level. The reference category consists of respondents with mandatory or secondary education. The dummy "tertiary educ." is equal to one for those that have a tertiary education.

Table A.4 – Effect heterogeneity: Income

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.259**	-0.135*	-0.049*	-0.076*
	(0.095)	(0.059)	(0.021)	(0.031)
Information	-0.070	-0.025	-0.009	-0.036
	(0.069)	(0.058)	(0.021)	(0.029)
Pricing x high inc.	-0.069	0.000	0.002	-0.071
	(0.135)	(0.081)	(0.032)	(0.045)
Inf. x high inc.	-0.048	-0.011	-0.035	0.002
	(0.129)	(0.081)	(0.030)	(0.040)
Pricing x low inc.	0.177	0.075	0.036	0.066’
	(0.119)	(0.075)	(0.027)	(0.035)
Inf. x low inc.	-0.016	-0.047	-0.006	0.037
	(0.110)	(0.069)	(0.025)	(0.033)
Pricing + Pr. x high inc.	-0.328**	-0.134’	-0.046	-0.147**
	(0.118)	(0.071)	(0.029)	(0.040)
Inf. + Inf. x high inc	-0.118	-0.036	-0.044	-0.038
	(0.115)	(0.072)	(0.027)	(0.036)
Pricing + Pr. x low inc.	-0.082	-0.059	-0.013	-0.010
	(0.100)	(0.064)	(0.023)	(0.028)
Inf. + Inf. x low inc	-0.086	-0.073	-0.015	0.001
	(0.092)	(0.057)	(0.021)	(0.028)
Pricing - Inf.	-0.189’	-0.109	-0.040	-0.040
	(0.112)	(0.070)	(0.025)	(0.036)
(Pricing + Pr. x high inc.) - (Inf. + Inf. x high inc.)	-0.209	-0.098	-0.002	-0.109*
	(0.149)	(0.091)	(0.036)	(0.049)
(Pricing + Pr. x low inc.) - (Inf. + Inf. x low inc.)	0.004	0.013	0.002	-0.011
	(0.117)	(0.073)	(0.027)	(0.032)
Adj. R^2	0.232	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level (in CHF). Standard errors (in parentheses) are clustered at the participant level. The reference category is given by a household income between CHF 8,000 and 12,000 per month. “high inc.” and “low inc.” are dummy variables denoting respondents that reported a monthly household income of above CHF 12,000 and below CHF 8,000, respectively. All regressions include individual, calendar day and day of study FE.

Table A.5 – Effect heterogeneity: Household size

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.135	-0.084	-0.011	-0.041
	(0.086)	(0.053)	(0.019)	(0.027)
Information	-0.082	-0.051	-0.012	-0.019
	(0.084)	(0.053)	(0.019)	(0.026)
Pricing x large size	-0.293	-0.188	-0.108*	0.002
	(0.182)	(0.114)	(0.042)	(0.046)
Inf. x large size	0.265	0.165	0.049	0.051
	(0.182)	(0.106)	(0.049)	(0.051)
Pricing x small size	-0.125	-0.015	-0.035	-0.074*
	(0.111)	(0.068)	(0.026)	(0.036)
Inf. x small size	-0.065	-0.020	-0.027	-0.018
	(0.102)	(0.064)	(0.023)	(0.032)
Pricing + Pr. x large size	-0.429*	-0.272*	-0.119**	-0.038
	(0.175)	(0.110)	(0.041)	(0.044)
Inf. + Inf. x large size	0.183	0.114	0.037	0.032
	(0.176)	(0.102)	(0.048)	(0.049)
Pricing + Pr. x small size	-0.260**	-0.099	-0.046*	-0.114**
	(0.099)	(0.064)	(0.023)	(0.032)
Inf. + Inf. x small size	-0.147	-0.071	-0.039'	-0.037
	(0.090)	(0.059)	(0.021)	(0.028)
Pricing - Inf.	-0.053	-0.033	0.001	-0.021
	(0.098)	(0.061)	(0.022)	(0.030)
(Pricing + Pr. x large size) - (Inf. + Inf. x large size)	-0.612*	-0.386**	-0.156*	-0.070
	(0.238)	(0.144)	(0.061)	(0.062)
(Pricing + Pr. x small size) - (Inf. + Inf. x small size)	-0.113	-0.028	-0.007	-0.078*
	(0.115)	(0.071)	(0.027)	(0.036)
Adj. R^2	0.232	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level (in CHF). Standard errors (in parentheses) are clustered at the participant level. The reference category is a household size with 3 or 4 persons. Participants living in households with fewer than 3 persons are denoted by the dummy “small size”, and those living in households with 5 or more persons are denoted by “large size”. All regressions include individual, calendar day and day of study FE.

Table A.6 – Effect heterogeneity: Language

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.286**	-0.145**	-0.048**	-0.093**
	(0.079)	(0.049)	(0.018)	(0.025)
Information	-0.079	-0.033	-0.015	-0.031
	(0.077)	(0.048)	(0.018)	(0.024)
Pricing x French	0.273*	0.142*	0.046'	0.085*
	(0.111)	(0.070)	(0.025)	(0.035)
Inf. x French	-0.030	-0.047	-0.014	0.032
	(0.102)	(0.066)	(0.024)	(0.030)
Pricing + Pr. x French	-0.013	-0.001	-0.003	-0.008
	(0.104)	(0.067)	(0.023)	(0.033)
Information + Inf. x French	-0.109	-0.082	-0.029	0.001
	(0.097)	(0.063)	(0.022)	(0.028)
Pricing - Inf.	-0.206*	-0.112*	-0.032	-0.062*
	(0.086)	(0.052)	(0.020)	(0.027)
(Pricing - Pr. x French) - (Inf. - Inf. x French)	0.096	0.076	0.028	-0.009
	(0.124)	(0.081)	(0.028)	(0.038)
Adj. R^2	0.232	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at participant level. The reference category are German speakers or those that chose English as their preferred language. The dummy variable "French" is equal to one for French speaker and zero otherwise.

Table A.7 – Heterogeneity: Access to public transport

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.197*	-0.107*	-0.034’	-0.055*
	(0.082)	(0.051)	(0.019)	(0.026)
Information	-0.046	-0.027	-0.009	-0.011
	(0.081)	(0.050)	(0.019)	(0.025)
Pricing x OEV Access	-0.047	-0.003	0.004	-0.041
	(0.107)	(0.067)	(0.025)	(0.033)
Inf. x OEV Access	-0.101	-0.047	-0.026	-0.029
	(0.098)	(0.062)	(0.022)	(0.030)
Pricing + Pr. x OEV	-0.244*	-0.111’	-0.037’	-0.096**
	(0.102)	(0.061)	(0.022)	(0.030)
Inf. + Inf. x OEV	-0.147’	-0.0074	-0.034’	-0.039
	(0.089)	(0.057)	(0.020)	(0.028)
Pricing - Inf.	-0.150	-0.080	-0.026	-0.044
	(0.092)	(0.057)	(0.021)	(0.028)
(Pricing + Pr. x OEV) - (Inf. + Inf. x OEV)	-0.096	-0.037	-0.003	-0.056
	(0.113)	(0.071)	(0.025)	(0.035)
Adj. R^2	0.232	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at the participant level. Access to public transport is an index constructed based on the connectivity of a particular postcode. The reference category denotes participants living in postcodes that are in the bottom three quintiles of this index, whereas the dummy “OEV Access” denotes participants living in postcodes in the top two quintiles.

Table A.8 – Heterogeneity: Access to road network

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.253**	-0.148**	-0.043*	-0.062*
	(0.084)	(0.053)	(0.019)	(0.025)
Information	-0.129	-0.061	-0.023	-0.045'
	(0.080)	(0.050)	(0.018)	(0.025)
Pricing x MIV	0.089	0.091	0.018	-0.020
	(0.106)	(0.065)	(0.024)	(0.033)
Inf. x MIV	0.113	0.041	0.012	0.061*
	(0.099)	(0.062)	(0.023)	(0.030)
Pricing + Pr. x MIV	-0.165'	-0.057	-0.026	-0.082**
	(0.095)	(0.058)	(0.022)	(0.031)
Inf. + Inf. x MIV	-0.016	-0.020	-0.012	0.016
	(0.091)	(0.058)	(0.022)	(0.027)
Pricing - Inf.	-0.124	-0.088	-0.020	-0.017
	(0.093)	(0.057)	(0.021)	(0.028)
(Pricing + Pr. x MIV) - (Inf. + Inf. x MIV)	-0.149	-0.037	-0.014	-0.098**
	(0.111)	(0.069)	(0.026)	(0.035)
Adj. R^2	0.232	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at the participant level. Access to the road network is an index constructed based on the connectivity of a particular postcode. The reference category denotes participants living in postcodes that are in the bottom three quintiles of this index, whereas the dummy "MIV" denotes participants living in postcodes in the top two quintiles.

Table A.9 – Heterogeneity: Awareness of experimental rules

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.204'	-0.083	-0.031	-0.089*
	(0.111)	(0.067)	(0.025)	(0.037)
Information	0.003	0.015	0.007	-0.019
	(0.097)	(0.060)	(0.022)	(0.030)
Pricing x aware	-0.016	-0.037	-0.006	0.027
	(0.117)	(0.070)	(0.027)	(0.038)
Inf. x aware	-0.149	-0.101	-0.043'	-0.006
	(0.102)	(0.064)	(0.023)	(0.031)
Pricing + Pr. x aware	-0.220**	-0.120**	-0.037*	-0.062**
	(0.078)	(0.049)	(0.018)	(0.024)
Information + Inf. x aware	-0.146'	-0.085'	-0.036*	-0.025
	(0.077)	(0.048)	(0.018)	(0.024)
Adj. R^2	0.232	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at the participant level. The interaction dummy "aware" is equal to one for those participants that reported in the final survey that they were aware of the experimental rules, i.e., that they could make money or reduce their external costs of travel by changing their travel patterns.

Table A.10 – Heterogeneity: Correct answer to externalities question

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.027	0.006	0.005	-0.038
	(0.083)	(0.052)	(0.019)	(0.026)
Information	-0.045	-0.018	-0.003	-0.024
	(0.085)	(0.053)	(0.020)	(0.026)
Pricing x correct	-0.481**	-0.296**	-0.103**	-0.083*
	(0.107)	(0.066)	(0.025)	(0.034)
Inf. x correct	-0.099	-0.060	-0.036	0.003
	(0.098)	(0.061)	(0.022)	(0.030)
Pricing + Pr. x correct	-0.509**	-0.289**	-0.098**	-0.121**
	(0.098)	(0.060)	(0.023)	(0.031)
Inf. + Inf. x correct	-0.144'	-0.077	-0.039*	-0.027
	(0.085)	(0.054)	(0.020)	(0.027)
Adj. R^2	0.232	0.224	0.221	0.268
Clusters	3,486	3,486	3,486	3,486
N	155,517	155,517	155,517	155,517

Notes: The interaction dummy "correct" is equal to one for those participants that correctly selected the definition of the external costs of transport among four presented options, and zero otherwise. For additional notes, see Table A.9.

Table A.11 – Heterogeneity: “Egoistic” score

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.237*	-0.136*	-0.050*	-0.050
	(0.098)	(0.060)	(0.023)	(0.031)
Information	-0.048	-0.027	-0.001	-0.022
	(0.096)	(0.061)	(0.022)	(0.029)
Pricing x egoistic	0.035	0.044	0.023	-0.032
	(0.107)	(0.066)	(0.025)	(0.034)
Inf. x egoistic	-0.060	-0.029	-0.030	-0.001
	(0.102)	(0.064)	(0.023)	(0.031)
Pricing + Pr. x egoistic	-0.202*	-0.092’	-0.027’	-0.082**
	(0.083)	(0.052)	(0.019)	(0.026)
Information + Inf. x egoistic	-0.108	-0.056	-0.029’	-0.023
	(0.078)	(0.049)	(0.018)	(0.024)
Pricing - Inf.	-0.189	-0.110	-0.051’	-0.028
	(0.118)	(0.073)	(0.027)	(0.036)
(Pricing + Pr. x egoistic) - (Inf. + Inf. x egoistic)	-0.094	-0.037	0.002	-0.060*
	(0.090)	(0.056)	(0.021)	(0.028)
Adj. R^2	0.221	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at the participant level. Based on a battery of 16 values-related questions, participants were given an index among the dimensions “altruistic”, “hedonic”, “egoistic” and “biospheric”. The dummy ”egoistic” denotes participants with an above-median value for this dimension.

Table A.12 – Heterogeneity: “Hedonic” score

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.292**	-0.150*	-0.050*	-0.093**
	(0.1041)	(0.061)	(0.023)	(0.033)
Information	-0.044	-0.041	-0.017	0.013
	(0.094)	(0.060)	(0.021)	(0.028)
Pricing x hedonic	0.128	0.068	0.023	0.037
	(0.109)	(0.068)	(0.025)	(0.035)
Inf. x hedonic	-0.069	-0.008	-0.004	-0.057’
	(0.101)	(0.064)	(0.023)	(0.030)
Pricing + Pr. x hedonic	-0.164*	-0.081	-0.026	-0.056*
	(0.081)	(0.019)	(0.064)	(0.024)
Inf. + Inf. x hedonic	-0.113	-0.049	-0.020	-0.044’
	(0.078)	(0.049)	(0.018)	(0.025)
Pricing - Inf.	-0.248*	-0.109	-0.033	-0.106**
	(0.119)	(0.073)	(0.027)	(0.038)
(Pricing + Pr. x hedonic) - (Inf. + Inf. x hedonic)	-0.051	-0.032	-0.006	-0.012
	(0.088)	(0.055)	(0.021)	(0.027)
Adj. R^2	0.232	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at the participant level. Based on a battery of 16 values-related questions, participants were given an index among the dimensions “altruistic”, “hedonic”, “egoistic” and “biospheric”. The dummy ”hedonic” denotes participants with an above-median value for this dimension.

Table A.13 – Heterogeneity: “Altruistic” score

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.157	-0.065	-0.020	-0.072*
	(0.097)	(0.061)	(0.022)	(0.031)
Information	0.021	0.018	-0.001	0.002
	(0.098)	(0.063)	(0.022)	(0.028)
Pricing x altruistic	-0.093	-0.070	-0.025	0.002
	(0.107)	(0.066)	(0.025)	(0.034)
Inf. x altruistic	-0.167	-0.098	-0.031	-0.038
	(0.103)	(0.065)	(0.024)	(0.030)
Pricing + Pr. x altruistic	-0.250**	-0.135**	-0.045*	-0.070**
	(0.083)	(0.051)	(0.019)	(0.026)
Information + Inf. x altruistic	-0.146’	-0.080’	-0.030’	-0.036
	(0.077)	(0.048)	(0.018)	(0.025)
Pricing - Inf.	-0.178	-0.083	-0.021	-0.074*
	(0.119)	(0.075)	(0.027)	(0.036)
(Pricing + Pr. x altruistic) - (Inf. + Inf. x altruistic)	-0.104	-0.055	-0.015	-0.034
	(0.089)	(0.055)	(0.021)	(0.028)
Adj. R^2	0.232	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at the participant level. Based on a battery of 16 values-related questions, participants were given an index among the dimensions “altruistic”, “hedonic”, “egoistic” and “biospheric”. The dummy ”altruistic” denotes participants with an above-median value for this dimension.

Table A.14 – Heterogeneity: “Biospheric” score

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.179’	-0.077’	-0.023	-0.078**
	(0.099)	(0.063)	(0.023)	(0.030)
Information	-0.0084	-0.042	-0.022	-0.020
	(0.105)	(0.067)	(0.024)	(0.030)
Pricing x biospheric	-0.057	-0.050	-0.020	0.012
	(0.108)	(0.067)	(0.025)	(0.033)
Info x biospheric	-0.005	-0.005	-0.043*	-0.004
	(0.109)	(0.068)	(0.019)	(0.032)
Pricing + Pr. x biosph.	-0.236**	-0.127*	-0.018	-0.0566*
	(0.082)	(0.050)	(0.019)	(0.026)
Info + Info x biosph.	-0.089	-0.047	-0.021	-0.024
	(0.075)	(0.047)	(0.017)	(0.024)
Pricing - Info	-0.095	-0.035	-0.002	-0.059
	(0.126)	(0.080)	(0.029)	(0.036)
(Pricing + Pr. x biosph.) - (Info + Info x biosph.)	-0.147’	-0.080	-0.025	-0.042
	(0.087)	(0.053)	(0.020)	(0.028)
Adj. R^2	0.232	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at the participant level. Based on a battery of 16 values-related questions, participants were given an index among the dimensions “altruistic”, “hedonic”, “egoistic” and “biospheric”. The dummy ”biospheric” denotes participants with an above-median value for this dimension.

Table A.15 – Heterogeneity: Weekend

	Total ext. costs	Health costs	Climate costs	Congestion costs
Pricing	-0.251**	-0.126**	-0.047**	-0.078**
	(0.077)	(0.048)	(0.018)	(0.024)
Information	-0.137'	-0.070	-0.024	-0.043'
	(0.075)	(0.047)	(0.017)	(0.024)
Pricing x weekend	0.125	0.059	0.040	0.026
	(0.120)	(0.076)	(0.026)	(0.034)
Info x weekend	0.172	0.083	0.017	0.071*
	(0.116)	(0.073)	(0.025)	(0.036)
Pricing + Pr. x weekend	-0.126	-0.067	-0.007	-0.052
	(0.115)	(0.073)	(0.026)	(0.034)
Info + Inf x weekend	0.034	-0.013	-0.007	0.028
	(0.111)	(0.070)	(0.024)	(0.034)
Pricing - Inf.	-0.113	-0.055	-0.023	-0.035
	(0.078)	(0.049)	(0.018)	(0.024)
(Pricing + Pr. x weekend) - (Info + Info x weekend)	-0.160	-0.080	0.000	-0.080*
	(0.133)	(0.084)	(0.029)	(0.039)
Adj R^2	0.222	0.225	0.221	0.268
Clusters	3,656	3,656	3,656	3,656
N	161,208	161,208	161,208	161,208

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. The dependent variable contains the external costs of transport aggregated to the person-day level. The coefficients show absolute effects (in CHF). Standard errors (in parentheses) are clustered at the participant level. The week-end dummy is equal to one for week-ends and holidays, and zero otherwise.

A.2 Mechanisms

Table A.16 – ATE on travel distance (overall margin)

	Total distance	Car	Public transport	Bicycle	Walk
Pricing	0.986	0.957*	1.062	1.133	1.039*
	(0.015)	(0.017)	(3)	(0.087)	(0.018)
Information	1.010	0.973	1.136**	1.061	1.014
	(0.015)	(0.017)	(0.045)	(0.075)	(0.018)
Difference	0.976’	0.983	0.935’	1.068	1.025
	(0.014)	(0.017)	(0.034)	(0.084)	(0.018)
Precipitation	0.998*	1.000	0.992**	0.978**	0.994
	(0.001)	(0.001)	(0.002)	(0.006)	(0.001)
Heat	1.046**	1.059**	1.004	1.051**	1.026**
	(0.004)	(0.005)	(0.010)	(0.017)	(0.004)
Cold	0.860**	0.826**	0.930	0.903’	0.943**
	(0.018)	(0.022)	(0.046)	(0.053)	(0.017)
Adj. R^2	0.273	0.299	0.416	0.471	0.263
Clusters	3,656	3,653	3,525	2,186	3,655
N	161,208	161,139	155,765	97,342	161,201

Notes: **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$. The dependent variable contains the distance travelled aggregated to the person-day level. Standard errors (in parentheses) are clustered at the participant level. The coefficients were estimated using a Poisson pseudo-maximum-likelihood (PPML) model and then exponentiated to derive proportional effects (with 1.00 representing no effect). The regressions include three levels of fixed effects: Person, calendar day and day of study.

Table A.17 – ATE on travel distance (intensive margin)

	Total travel	Car	Public transport	Bicycle	Walking
Pricing	0.986	0.973'	1.025	0.989	1.040*
	(0.014)	(0.016)	(0.037)	(0.052)	(0.017)
Information	1.009	0.986	1.093*	1.001	1.014
	(0.014)	(0.015)	(0.040)	(0.048)	(0.017)
Difference	0.977	0.987	0.938'	0.988	1.025
	(0.014)	(0.016)	(0.032)	(0.056)	(0.017)
Precipitation	0.999	1.000	0.997	0.999	0.995**
	(0.001)	(0.001)	(0.002)	(0.004)	(0.001)
Heat	1.047**	1.064**	1.023*	1.026**	1.029**
	(0.004)	(0.004)	(0.009)	(0.009)	(0.004)
Cold	0.857**	0.845**	0.943	0.945	0.941**
	(0.017)	(0.020)	(0.041)	(0.042)	(0.016)
Adj. R^2	0.280	0.298	0.486	0.647	0.261
Clusters	3,656	3,651	3,373	1,541	3,654
N	154,520	125,452	55,889	12,645	135,651

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. The dependent variable contains the distance travelled aggregated to the person-day level, conditional on travel taking place. Standard errors (in parentheses) are clustered at the participant level. The coefficients were estimated using a Poisson pseudo-maximum-likelihood (PPML) model and then exponentiated to derive proportional effects (with 1.00 representing no effect). The regressions include three levels of fixed effects: Person, calendar day and day of study.

Table A.18 – ATE on probability to travel (extensive margin)

	Total travel	Car	Public Transport	Bicycling	Walking
Pricing	1.000	0.970**	1.062*	1.133*	1.006
	(0.005)	(0.010)	(0.027)	(0.070)	(0.008)
Infomation	0.998	0.980*	1.047'	1.011	1.004
	(0.005)	(0.009)	(0.025)	(0.059)	(0.007)
Difference	1.002	0.990	1.014	1.121'	1.001
	(0.005)	(0.010)	(0.026)	(0.072)	(0.008)
N	101,787	151,263	155,620	97,342	151,458

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. Standard errors in parentheses and clustered at participant level. The coefficients in the table are marginal effects in the form of semi-elasticities (dlny/dx) after estimating a logit regression that includes the weather variables and a series of dummies to capture person, day of study and calendar day FE effects.

Table A.19 – ATE on the mode distance share

	Car	Public transport	Bicycle	Walking
Pricing	0.969**	1.047*	1.178*	1.048'
	(0.008)	(0.024)	(0.080)	(0.027)
Information	0.983*	1.045*	1.067	1.017
	(0.007)	(0.022)	(0.067)	(0.025)
Difference	0.986'	1.001	1.104	1.031
	(0.008)	(0.021)	(0.076)	(0.026)
Precipitation	1.002**	0.995**	0.980**	0.996*
	(0.000)	(0.001)	(0.004)	(0.001)
Heat	1.005*	0.969**	0.993	1.015*
	(0.002)	(0.005)	(0.013)	(0.006)
Cold	0.969**	1.033	0.979	1.019
	(0.010)	(0.023)	(0.042)	(0.021)
Adj. R^2	0.056	0.201	0.303	0.121
Clusters	3,653	3,525	2,186	3,655
N	154,483	149,507	93,927	154,518

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. Standard errors in parentheses and clustered at participant level. The dependent variable is the share of total daily distance covered by mode. The coefficients were estimated using a Poisson pseudo-maximum-likelihood (PPML) model and then exponentiated to derive proportional effects (with 1.00 being no effect). All regressions include person, day of study and calendar day FE.

Table A.20 – ATE on congestion per km and speed

	Congestion (car)	Congestion (PT)	Speed (car)	Speed (PT)
Pricing	0.930**	0.977	1.001	1.010
	(0.019)	(0.040)	(0.006)	(0.013)
Information	0.955*	0.950	1.001	1.023'
	(0.020)	(0.040)	(0.006)	(0.013)
Difference	0.974	1.028	1.000	0.986
	(0.020)	(0.041)	(0.006)	(0.012)
Precipitation	0.999	0.997	0.999'	0.999
	(0.001)	(0.002)	(0.000)	(0.001)
Heat	0.950**	0.948**	1.017**	1.007*
	(0.004)	(0.008)	(0.001)	(0.003)
Cold	1.073**	1.077	0.960**	0.996
	(0.028)	(0.059)	(0.008)	(0.015)
Adj. R^2	0.028	0.038	0.189	0.294
Clusters	3,651	2,517	3,651	3,373
N	125,452	48,295	125,453	55,889

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. Standard errors in parentheses and clustered at participant level. The dependent variable is the congestion externality per car-km (first column); the crowding externality per PT-km (second column); the average daily car speed (column 3), and the average daily pt speed (column 4). The coefficients were estimated using a Poisson pseudo-maximum-likelihood (PPML) model and then exponentiated to derive proportional effects (with 1.00 representing no effect). All regressions include individual, calendar day and day of study FE.

Table A.21 – ATE on departure time for car trips

	Overall	Morning	Evening
Pricing	0.381	-4.680*	1.850
	(2.525)	(1.964)	(2.181)
Info_post	-3.179	-1.745	-0.083
	(2.499)	(1.989)	(2.207)
Difference	3.560	-2.934	1.933
	(2.528)	(2.096)	(2.242)
Adj. R^2	0.054	0.204	0.116
Clusters	2,886	2,885	2,886
N	285,077	102,410	182,665

Notes: **: $p < 0.01$, *: $p < 0.05$, ': $p < 0.1$. Standard errors (in parentheses) clustered at participant level. The regressions include observations from participants that travelled at least once by car in the morning peak (departure between 6:30 and 8:30) and the evening peak (departure between 16:30 and 18:30) during the observation period. In column 1, all trips were combined, whereas columns 2 and 3 focus on departure before or after noon, respectively. All regressions include day of calendar, day of study and person fixed effects.

A.3 Stated choice experiment tables

Table A.22 – Summary statistics for the SCE experiments (full sample)

SCE	Category	Variable	Mean	Median	SD	N
Car-Alt	Generic	Distance (km)	14.17	10.57	11.22	12248
	Car	Travel time (min)	24.29	21.00	14.36	12248
		Total cost	19.40	14.10	17.87	12248
		Private cost	9.92	7.40	7.85	12248
		External cost	9.48	4.75	13.04	12248
		Congestion cost	4.71	2.15	6.95	12248
		Climate cost	1.43	0.60	3.17	12248
		Health cost	3.34	1.65	4.58	12248
	Alt	Travel time (min)	17.45	15.00	11.35	12248
		Total cost	17.07	12.45	15.33	12248
		Private cost	9.92	7.40	7.85	12248
		External cost	7.15	3.60	10.06	12248
		Congestion cost	2.39	0.95	3.96	12248
		Climate cost	1.43	0.60	3.17	12248
		Health cost	3.34	1.65	4.58	12248
	Demographics	Age	41.99	43.00	13.06	12248
		Female	0.49	0.00	0.50	12248
		German	0.69	1.00	0.46	12248
		Income p.c. (CHF)	3957.82	3333.33	2529.37	12248
		Household size	2.89	3.00	1.19	12248
		Higher edu.	0.46	0.00	0.50	12248
Car-PT	Generic	Distance (km)	14.22	11.14	10.84	7886
	Car	Travel time (min)	24.79	22.00	13.64	7886
		Total cost	19.54	14.35	17.31	7886
		Private cost	9.96	7.80	7.59	7886
		External cost	9.59	4.90	12.80	7886
		Congestion cost	4.87	2.25	6.99	7886
		Climate cost	1.39	0.60	2.79	7886
		Health cost	3.33	1.75	4.70	7886
	PT	Travel time (min)	47.61	43.00	23.10	7886
		Total cost	4.96	3.50	4.40	7886
		Private cost	2.91	2.10	2.95	7886
		External cost	2.05	1.05	2.68	7886
		Congestion cost	0.25	0.00	1.19	7886
		Climate cost	0.31	0.15	0.45	7886
		Health cost	1.50	0.80	1.78	7886
	Demographics	Age	42.51	43.00	13.06	7886
		Female	0.48	0.00	0.50	7886
		German	0.70	1.00	0.46	7886
		Income p.c. (CHF)	4029.21	3333.33	2562.63	7886
		Household size	2.87	3.00	1.18	7886
		Higher edu.	0.47	0.00	0.50	7886
Car-Bike	Generic	Distance (km)	9.28	8.43	4.49	8726
	Car	Travel time (min)	19.19	17.00	10.54	8726
		Total cost	13.42	10.75	10.24	8726
		Private cost	6.50	5.90	3.15	8726
		External cost	6.92	3.70	8.79	8726
		Congestion cost	3.75	1.65	5.68	8726
		Climate cost	0.95	0.45	1.86	8726
		Health cost	2.22	1.30	2.39	8726
	Bicycle	Travel time (min)	33.30	30.00	16.68	8726
		Total cost	2.74	1.95	2.62	8726
		Private cost	0.73	0.00	1.08	8726
		External cost	2.01	1.20	2.17	8726
		Health cost	2.01	1.20	2.17	8726
	Demographics	Age	42.19	43.00	13.49	8726
		Female	0.52	1.00	0.50	8726
		German	0.69	1.00	0.46	8726
		Income p.c. (CHF)	3877.37	3333.33	2452.26	8726
		Household size	2.90	3.00	1.19	8726
		Higher edu.	0.43	0.00	0.50	8726

Notes: Statistics shown for full estimation sample.

Table A.23 – Summary statistics for the SCE experiments (Traders)

SCE	Category	Variable	Mean	Median	SD	N
Car-Alt	Generic	Distance (km)	14.29	10.57	11.40	10107
	Car	Travel time (min)	24.68	21.00	14.67	10107
		Total cost	19.58	14.25	18.25	10107
		Private cost	10.00	7.40	7.98	10107
		External cost	9.58	4.80	13.33	10107
		Congestion cost	4.78	2.20	7.03	10107
		Climate cost	1.45	0.60	3.36	10107
		Health cost	3.35	1.65	4.63	10107
	Alt	Travel time (min)	17.75	15.00	11.59	10107
		Total cost	17.22	12.50	15.62	10107
		Private cost	10.00	7.40	7.98	10107
		External cost	7.22	3.60	10.27	10107
		Congestion cost	2.42	0.95	3.99	10107
		Climate cost	1.45	0.60	3.36	10107
		Health cost	3.35	1.65	4.63	10107
	Demographics	Age	41.58	42.00	13.29	10107
		Female	0.49	0.00	0.50	10107
		German	0.67	1.00	0.47	10107
		Income p.c. (CHF)	3954.22	3333.33	2555.24	10107
		Household size	2.88	3.00	1.19	10107
		Higher edu.	0.45	0.00	0.50	10107
Car-PT	Generic	Distance (km)	13.37	10.57	9.86	3985
	Car	Travel time (min)	26.14	23.00	14.10	3985
		Total cost	19.21	14.15	17.22	3985
		Private cost	9.36	7.40	6.90	3985
		External cost	9.85	5.05	13.30	3985
		Congestion cost	5.26	2.50	7.35	3985
		Climate cost	1.33	0.60	2.88	3985
		Health cost	3.25	1.75	4.93	3985
	PT	Travel time (min)	42.64	40.00	16.54	3985
		Total cost	4.42	3.20	3.75	3985
		Private cost	2.57	1.95	2.30	3985
		External cost	1.85	0.95	2.57	3985
		Congestion cost	0.23	0.00	1.27	3985
		Climate cost	0.28	0.10	0.42	3985
		Health cost	1.35	0.75	1.61	3985
	Demographics	Age	42.59	44.00	13.37	3985
		Female	0.51	1.00	0.50	3985
		German	0.63	1.00	0.48	3985
		Income p.c. (CHF)	3985.97	3333.33	2601.27	3985
		Household size	2.88	3.00	1.19	3985
		Higher edu.	0.50	0.00	0.50	3985
Car-Bike	Generic	Distance (km)	8.67	7.93	4.17	5444
	Car	Travel time (min)	18.71	17.00	10.32	5444
		Total cost	12.65	10.05	9.59	5444
		Private cost	6.07	5.55	2.92	5444
		External cost	6.58	3.60	8.25	5444
		Congestion cost	3.60	1.60	5.31	5444
		Climate cost	0.90	0.45	1.77	5444
		Health cost	2.09	1.25	2.23	5444
	Bicycle	Travel time (min)	31.12	28.00	15.40	5444
		Total cost	2.54	1.80	2.43	5444
		Private cost	0.67	0.00	1.01	5444
		External cost	1.87	1.10	2.00	5444
		Health cost	1.87	1.10	2.00	5444
	Demographics	Age	42.13	43.00	13.57	5444
		Female	0.52	1.00	0.50	5444
		German	0.67	1.00	0.47	5444
		Income p.c. (CHF)	3749.16	3000.00	2436.97	5444
		Household size	2.99	3.00	1.18	5444
		Higher edu.	0.45	0.00	0.50	5444

Notes: Statistics shown for sample of traders.

Table A.24 – MNL model with attributes and covariates (jointly estimated)

			Parameter estimates	
Category	Subgroup	Variable	Full sample	Traders
Generic	Attributes	External costs	0.000	−0.173*
		Total cost	0.000’	0.137
		Travel time	−3.252***	−4.115***
Car	Attributes	Low reliability	−0.155*	−0.326***
		Medium reliability	−0.176**	−0.245**
		High reliability	−0.155*	−0.287***
		Very high reliability (ref.)		
Alt	Factors	Factor = 0.5	2.037**	1.335’
		Factor = 1	1.982**	1.300’
		Factor = 2	1.958**	1.153
		Factor = 4	2.135**	1.339’
		Factor = 8	2.156**	1.358’
	Attributes	High reliability	−0.308***	−0.417***
		Very high reliability (ref.)		
		-60min departure shift (ref.)		
		-30min departure shift	0.558***	0.826***
		+30min departure shift	0.474***	0.709***
		+60min departure shift	−0.294**	−0.275**
	Mobility tools	Owns car	−0.377	−0.309
		Car access	−0.197	−0.046
		General access	−0.009	−0.012
	Survey responses	Emissions	−0.032	−0.119
		Health	0.226*	0.036
		Congestion	0.258**	0.144
		Mobility pricing	0.120	0.095
		Social cost	−0.023	−0.086
		Externalities exam	−0.016	0.082
	Values	Biospheric	0.284	−0.020
		Hedonic	0.233	0.110
		Egoistic	−0.283	−0.422*
		Altruistic	0.253	0.456
	Demographics	Age	−0.102***	−0.040’
		Age (squared)	0.001***	0.000
		Female	−0.023	0.063
		German	−0.362***	−0.267*
		Income p.c.	0.000	0.000
		HH size	−0.017	0.016
		Higher education	−0.175*	−0.175’
	MOBIS groups	Control (ref.)		
		Information	0.026	0.079
		Pricing and Info	−0.025	−0.087
		All SCE random	0.002	−0.025
PT	Factors	Factor = 0.5	0.259	0.891
		Factor = 1	0.324	1.202
		Factor = 2	0.443	1.804
		Factor = 4	0.293	1.225
		Factor = 8	0.560	1.100
	Attributes	Low reliability	0.003	−0.006
		Medium reliability	−0.243*	−0.552
		High reliability	−0.118	−0.213
		Very high reliability (ref.)		
		Transfers	−0.159**	−0.350*

Table A.24 – MNL model with attributes and covariates (jointly estimated) *(continued)*

Category	Subgroup	Variable	Full sample	Traders
		Frequency	−0.716*	−1.204
		Low occupancy (ref.)		
		Medium occupancy	0.034	0.097
		High occupancy	−0.059	−0.273
		Bus	−0.036	−0.019
		Subway	0.071	−0.201
		Tram	0.116	0.091
		Train (ref.)		
		Cold, wet weather (ref.)		
		Cold, dry weather	0.188’	0.664’
		Warm, wet weather	0.238*	0.576’
		Warm, dry weather	0.165’	0.607’
	Mobility tools	Half fare subscription	0.301*	0.277
		Regional subscription	0.618**	0.693’
		Full fare subscription	0.362	0.430
		Owns car	−0.869	−0.298
		Car access	−0.461*	−1.037’
		PT access	−0.036	−0.223
		General access	0.009	−0.082
	Survey responses	Emissions	0.260’	0.966**
		Health	0.442**	0.182
		Congestion	−0.325*	−0.911**
		Mobility pricing	0.220’	−0.039
		Social cost	0.049	0.067
		Externalities exam	0.207’	−0.230
	Values	Biospheric	0.491	1.466
		Hedonic	−0.228	−0.071
		Egoistic	0.206	0.873
		Altruistic	0.872*	0.878
	Demographics	Age	−0.007	0.005
		Age (squared)	0.000	0.000
		Female	−0.127	−0.582*
		German	−0.676***	−0.597’
		Income p.c.	0.000’	0.000
		HH size	−0.066	0.359
		Higher education	0.008	−0.156
	MOBIS groups	Control (ref.)		
		Information	−0.086	−0.174
		Pricing and Info	−0.018	−0.225
		All SCE random	−0.101	0.075
Bicycle	Factors	Factor = 0.5	−5.491**	−9.217*
		Factor = 1	−5.717**	−9.913*
		Factor = 2	−5.485**	−9.041*
		Factor = 4	−5.541**	−9.822*
		Factor = 8	−5.171**	−8.904*
	Attributes	Low health benefit (ref.)		
		Medium health benefit	0.928	2.140
		High health benefit	0.547	1.692
		Bicycle (ref.)		
		E-bike	0.466**	2.524**
		Main road, no bikelane (ref.)		
		Main road, bikelane	0.210	0.461
		Bike path	0.412*	1.043*
		Cold, wet weather (ref.)		

Table A.24 – MNL model with attributes and covariates (jointly estimated) *(continued)*

Category	Subgroup	Variable	Full sample	Traders
		Cold, dry weather	1.562***	3.925***
		Warm, wet weather	1.126***	3.630***
		Warm, dry weather	2.506***	8.028***
	Mobility tools	Owns bicycle	1.183***	0.748
		Owns car	0.535	0.907
		Car access	−0.319	−0.887
		General access	−0.014	0.056
	Survey responses	Emissions	0.363	0.599
		Health	0.138	0.099
		Congestion	−0.133	−0.522
		Mobility pricing	0.330’	0.029
		Social cost	0.235	−0.013
		Externalities exam	0.142	0.433
	Values	Biospheric	2.107**	4.377*
		Hedonic	−0.400	−1.945
		Egoistic	0.255	0.916
		Altruistic	0.878	1.442
	Demographics	Age	0.006	0.185’
		Age (squared)	0.000	−0.002’
		Female	−0.611**	−1.252**
		German	−1.387***	−3.139***
		Income p.c.	0.000’	0.000
		HH size	0.174	−0.272
		Higher education	−0.228	−0.367
	MOBIS groups	Control (ref.)		
		Information	−0.281	−0.826
		Pricing and Info	−0.263	−0.691
		All SCE random	−0.347’	0.398
Scale and λ		$\lambda_{distance,time}$	−0.349***	−0.545***
		$\lambda_{distance,cost}$	0.039	−0.737***
		$\lambda_{income,cost}$	−4.967***	0.223
		Scale SCE (PT)	0.928***	0.404***
		Scale SCE (Bicycle)	0.471***	0.222***
Model statistics		Number of individuals	2058	1862
		Number of observations	22412	15241
		Estimated parameters	125	125
		LL(final)	-13462.69	-8618.631
		Adj.Rho-square (0)	0.1253	0.1723
		AIC	27175.39	17487.26
		BIC	28177.56	18441.23

Notes: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$.

Table A.25 – MNL model with attributes and covariates (jointly estimated, no bicycle)

			Parameter estimates	
Category	Subgroup	Variable	Full sample	Traders
Generic	Attributes	External costs	−0.015’	−0.050*
		Total cost	−0.005	0.011*
		Travel time	−3.300***	−4.102***
Car	Attributes	Low reliability	−0.184*	−0.343***
		Medium reliability	−0.194**	−0.230**
		High reliability	−0.181**	−0.293***
		Very high reliability (ref.)		
Alt	Factors	Factor = 0.5	1.777*	1.360’
		Factor = 1	1.699*	1.329’
		Factor = 2	1.681*	1.234
		Factor = 4	1.768*	1.433’
		Factor = 8	1.653*	1.558*
	Attributes	High reliability	−0.286***	−0.400***
		Very high reliability (ref.)		
		−60min departure shift (ref.)		
		−30min departure shift	0.569***	0.846***
		+30min departure shift	0.462***	0.707***
		+60min departure shift	−0.331***	−0.293**
	Mobility tools	Owns car	−0.326	−0.244
		Car access	−0.192	−0.034
		General access	−0.018	−0.010
	Survey responses	Emissions	−0.034	−0.119
		Health	0.232*	0.050
		Congestion	0.245*	0.131
		Mobility pricing	0.091	0.053
		Social cost	−0.021	−0.065
		Externalities exam	−0.043	0.047
	Values	Biospheric	0.331	−0.022
		Hedonic	0.204	0.014
		Egoistic	−0.278	−0.379’
		Altruistic	0.175	0.425
	Demographics	Age	−0.095***	−0.032
		Age (squared)	0.001***	0.000
		Female	−0.009	0.052
		German	−0.342**	−0.263*
		Income p.c.	0.000	0.000
		HH size	−0.024	0.002
		Higher education	−0.164’	−0.167’
	MOBIS groups	Control (ref.)		
		Information	0.027	0.073
		Pricing and Info	−0.036	−0.080
		All SCE random	0.016	−0.033
PT	Factors	Factor = 0.5	0.290	0.302
		Factor = 1	0.330	0.648
		Factor = 2	0.406	1.275
		Factor = 4	0.123	0.725
		Factor = 8	0.195	0.577
	Attributes	Low reliability	0.002	0.036
		Medium reliability	−0.274*	−0.553
		High reliability	−0.133	−0.165
		Very high reliability (ref.)		
		Transfers	−0.174**	−0.440*

Table A.25 – MNL model with attributes and covariates (jointly estimated, no bicycle) *(continued)*

Category	Subgroup	Variable	Full sample	Traders
		Frequency	−0.817*	−1.296
		Low occupancy (ref.)		
		Medium occupancy	0.033	0.073
		High occupancy	−0.058	−0.288
		Bus	−0.028	0.077
		Subway	0.021	−0.163
		Tram	0.067	0.238
		Train (ref.)		
		Cold, wet weather (ref.)		
		Cold, dry weather	0.194’	0.728’
		Warm, wet weather	0.265*	0.622’
		Warm, dry weather	0.174’	0.657’
	Mobility tools	Half fare subscription	0.338*	0.292
		Regional subscription	0.701***	0.785’
		Full fare subscription	0.403	0.419
		Owns car	−1.045	−0.441
		Car access	−0.460’	−1.136’
		PT access	−0.052	−0.200
		General access	0.002	−0.065
	Survey responses	Emissions	0.289’	1.010*
		Health	0.498**	0.221
		Congestion	−0.359*	−0.989**
		Mobility pricing	0.237’	−0.020
		Social cost	0.049	0.064
		Externalities exam	0.236’	−0.269
	Values	Biospheric	0.585	1.540
		Hedonic	−0.280	−0.119
		Egoistic	0.240	1.008
		Altruistic	0.927*	1.040
	Demographics	Age	−0.011	−0.004
		Age (squared)	0.000	0.000
		Female	−0.134	−0.574’
		German	−0.738***	−0.576
		Income p.c.	0.000’	0.000
		HH size	−0.045	0.346
		Higher education	0.022	−0.176
	MOBIS groups	Control (ref.)		
		Information	−0.085	−0.189
		Pricing and Info	−0.007	−0.284
		All SCE random	−0.111	0.051
Scale and λ		$\lambda_{distance,time}$	−0.373***	−0.420*
		$\lambda_{distance,cost}$	−1.043***	−0.219
		$\lambda_{income,cost}$	−0.343’	0.049
		Scale SCE (PT)	0.845***	0.369***
Model statistics		Number of individuals	2014	1741
		Number of observations	15499	10785
		Estimated parameters	87	87
		LL(final)	-9251.374	-6061.034
		Adj.Rho-square (0)	0.1308	0.1776
		AIC	18676.75	12296.07
		BIC	19342.17	12929.94

Notes: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, ’: $p < 0.1$.

A.4 Survey results

Figure A.1 – Agreement with the statement “The transport network should be used more efficiently by introducing dynamic pricing (e.g., higher prices during rush hour)”

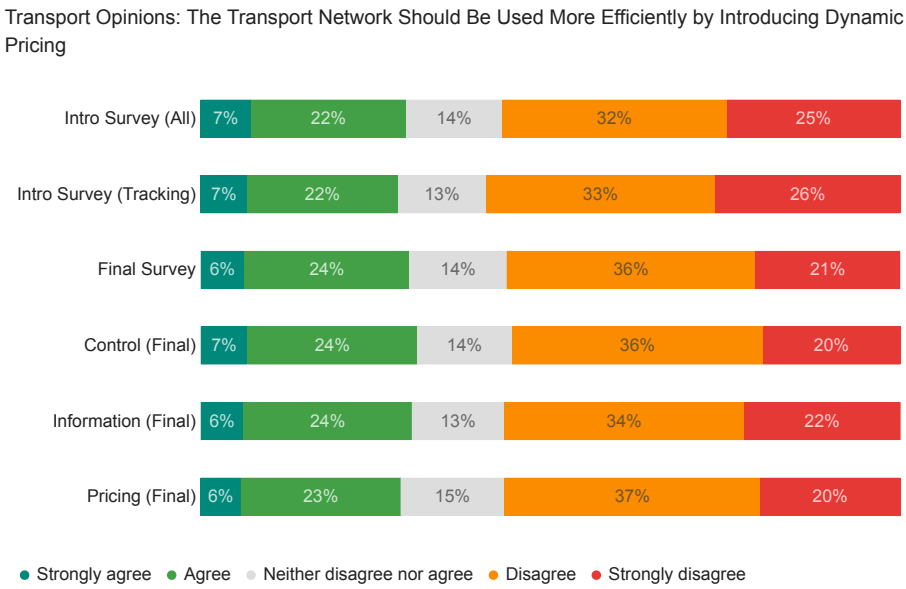


Figure A.2 – Support for increased policy efforts to address health impacts of transport.

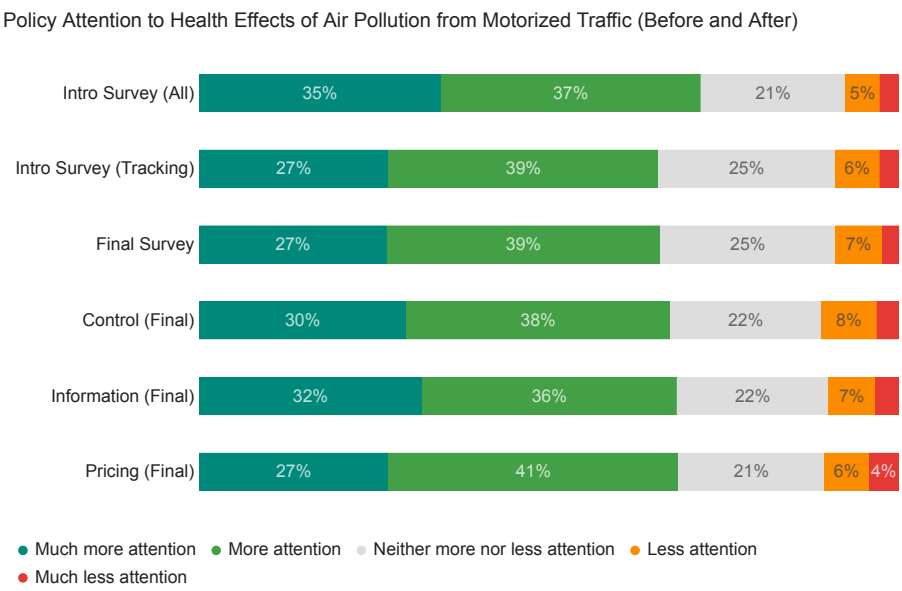


Figure A.3 – Should road capacity meet demand at all times?

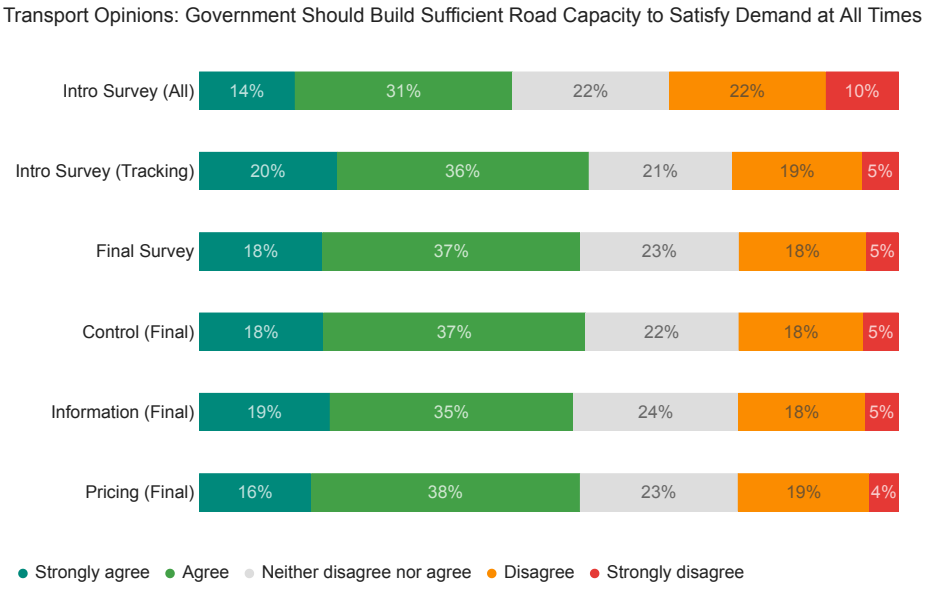


Figure A.4 – Support for sufficient public transport capacity

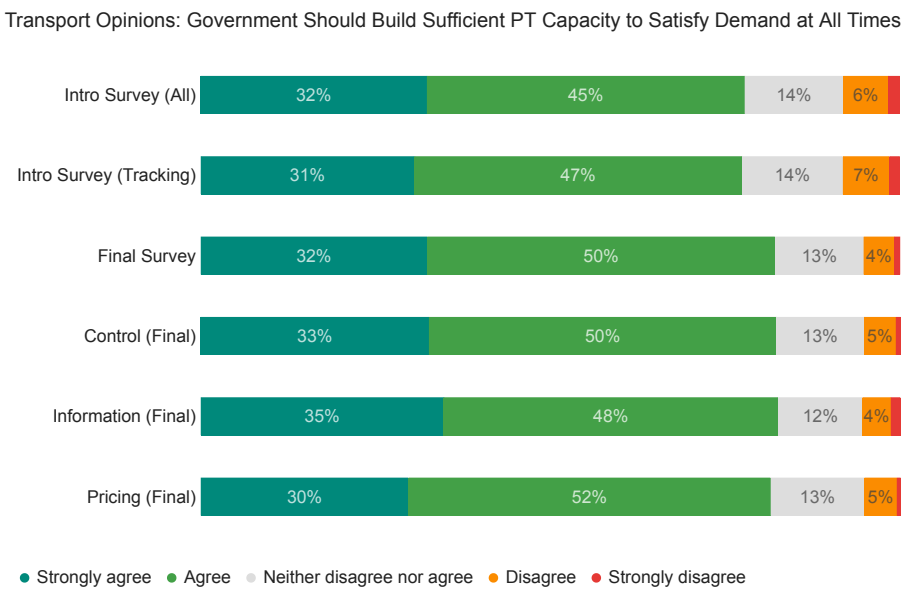
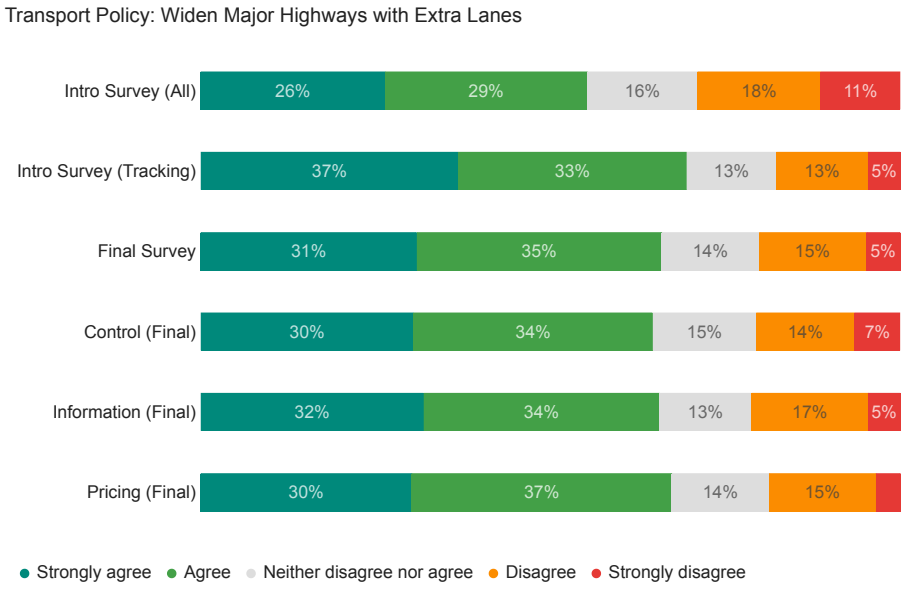


Figure A.5 – Support for widening highways



A.5 Effect of values and lifestyles on transport choices

In this section we present the results from a model where we use the information about values and lifestyles to explain respondents' travel choices. The dependent variable is the share (%) of the total average daily distance in the observation phase covered by bicycle, walking, car and public transport. Our main explanatory are the egoistic, altruistic, hedonic and biospheric values, as described in 3.6.3. The results of this linear regression analysis are shown in Table A.26 and indicate that after controlling for age, gender, income and education, biospheric values have positive effect on bike share; hedonic values have positive and biospheric values a negative effect on car share; egoistic values have a negative effect on PT share; and egoistic and biospheric values have a positive effect on the share of walking. However, it has to be highlighted that the share of explained variance is very low for car (R^2=0.021) and public transport (R^2=0.020) and in the case of bike (R^2=0.002) and walking (R^2=0.003) even extremely low. The results suggest that the campaigns targeting the reduction of car use should highlight negative convenience and environmental consequences of car (activate hedonic and biospheric values). On the other hand, campaigns targeting the promotion of public transport should highlight positive financial consequences of public transport (highlight egoistic values).

Table A.26 – Values Regression

	Car	Public transport	Bicycle	Walking
Hedonic	1.593	-0.673	-0.455	-0.195
	(0.623)	(0.631)	(0.343)	(0.105)
Egoistic	0.741	-1.349	-0.295	0.256
	(0.663)	(0.669)	(0.364)	(0.112)
Altruistic	-0.542	0.567	-0.314	0.111
	(0.736)	(0.742)	(0.406)	(0.124)
Biospheric	-1.711	0.274	0.756	0.240
	(0.695)	(0.699)	(0.386)	(0.118)
Income	-0.044	0.046	-0.006	0.001
	(0.015)	(0.014)	(0.008)	(0.002)
Educationt	-4.439	4.184	-0.494	-0.168
	(0.667)	(0.673)	(0.375)	(0.113)
Age	0.052	-0.044	0.015	-0.001
	(0.029)	(0.029)	(0.016)	(0.005)
Sex	0.767	-1.014	0.398	-0.159
	(0.808)	(0.812)	(0.443)	(0.137)
Constant	71.316	26.918	9.396	3.401
	(4.376)	(4.394)	(2.388)	(0.741)
Adj. R^2	0.021	0.017	0.002	0.003
N	3,303	3,055	1,709	3,307

Notes: Standard errors in parentheses. The dependent variable is the share (%) of the total average daily distance in the observation phase.

In another series of analyses we took the same dependent variable - the share (%) of the total average daily distance in the observation phase covered by bike, walking, car and public transport - and focused on Otte lifestyle instead of values. Otte lifestyles were included in the regression analysis as 8 dummy variables constructed as described in 3.6.3, taking advancement-oriented as a reference group, since this group is exactly in the middle of the modernity-endowment space. As in the case of the previous analysis we controlled for age, gender, education and income. The results of the regression analysis are shown in Table A.27. Belonging to the home-centered group has a positive effect on the car share and a negative effect on the share of public transport. Other lifestyles do not have a significant effect on the share of car and public transport. The mode specifications are however associated with low (car: R^2=0.021, public transport: R^2=0.022) to extremely low explanatory power (bike: R^2=0.006, walking: R^2=0.004). The results suggest that home-centered group

is an appropriate target group for campaigns to reduce their car use and promote the use of other, more sustainable means of transport.

Table A.27 – Lifestyle Regression

	Car	Public transport	Bicycle	Walking
Traditional workers	2.742	-3.872	-1.318	1.622
	(3.473)	(3.545)	(1.917)	(0.587)
Home-centred	3.018	-3.538	0.272	0.046
	(1.527)	(1.535)	(0.902)	(0.258)
Entertainment-oriented	2.379	-3.311	-0.396	0.320
	(1.748)	(1.757)	(0.984)	(0.296)
Conventionalists	4.000	-2.949	1.021	0.112
	(2.804)	(2.973)	(1.505)	(0.474)
Hedonists	0.235	-0.975	-0.888	0.144
	(1.18)	(1.183)	(0.64)	(0.199)
Conservatives	-3.706	4.944	-2.098	0.046
	(3.311)	(3.327)	(1.878)	(0.560)
Liberals	-1.479	0.434	-0.553	0.260
	(1.253)	(1.257)	(0.686)	(0.212)
Reflexives	-0.34	-1.852	0.293	0.397
	(1.348)	(1.349)	(0.715)	(0.228)
Income	-0.046	0.048	-0.007	0.001
	(0.015)	(0.014)	(0.008)	(0.002)
Education	-3.996	3.838	-0.438	-0.178
	(0.689)	(0.694)	(0.385)	(0.116)
Age	0.043	-0.040	0.017	0.000
	(0.029)	(0.029)	(0.016)	(0.005)
Sex	0.734	-0.931	0.368	-0.175
	(0.809)	(0.812)	(0.444)	(0.137)
Constant	69.591	25.491	8.752	4.590
	(2.444)	(2.457)	(1.323)	(0.413)
Adj. R^2	0.018	0.018	-0.001	0.001
N	3,306	3,058	1,711	3,310

Notes: Standard errors in parentheses. The dependent variable is the share (%) of the total average daily distance in the observation phase. Advancement-oriented lifestyle was taken as a reference group.

B Appendix - Recruitment and surveys

B.1 Invitation letters

Around 90,000 people were invited to participate in the MOBIS study by receiving a letter by post. People who did not react to the first letter, received a reminder (a second letter). And finally, people who did not reacted to the first and the second invitation letter received a final reminder (third invitation letter). All letters were printed on both sides. In the front size the invitation was written in the local language (German or French), while in the back side the an English version was available. In this section, the first and last letter in the three languages are shown. The second letter was a reminder and thus similar to the third letter, but without the indication that it was the last letter.

First invitation letter (English)

ETH Eidgenössische Technische Hochschule Zürich Swiss Federal Institute of Technology Zurich

Universität Basel

zhaw School of Engineering

MOBIS

(English version)

Invitation: Study about Mobility Behaviour in Switzerland

Dear Mr./Ms. XXX,

The ETH Zurich, the University of Basel and the Zurich University of Applied Sciences are conducting a joint research project on “Mobility Behaviour in Switzerland” (MOBIS). The goal of this study is to investigate the demand for private and public transport services. The project is funded by the Swiss Innovation Agency (Innosuisse) and the Federal Department of the Environment, Transport, Energy and Communications (DETEC).

You are part of a representative random sample of the Swiss population drawn by the Federal Office of Statistics. With this letter, we cordially invite you to participate in our study. You may choose to participate in either English, German or French.

Online survey

In the first part of the study, we ask you to fill out a 10-minute online survey about mobility-related topics in the next few days. To participate, please:

1. Access **www.mobis.info** in your browser, or by using the QR-code.
2. Enter your personal participant ID: XXXXX

Smartphone study

A selection of participants will be invited to take part in a smartphone study following the online survey. In this second part of our study, we will record your daily trips and chosen transport modes using a smartphone app and provide you with regular feedback. The study takes two months and ends with an additional online survey of about 30 minutes. You will be rewarded with **CHF 100** for your **full participation** in the study.

All data collected during the study will be kept strictly confidential and used exclusively for research purposes. The data will not be passed on to third parties. During the analysis and in the published results, it will not be possible to identify individual persons. Further information on the study can be found on the project website. If you have any questions, please do not hesitate to contact us. If you do not complete the online survey, we will send you a written reminder. If you prefer not to be contacted again, please let us know.

We highly appreciate your participation as it will help us gain important insights for improving mobility in Switzerland. We thank you in advance!

With kind regards,

Prof. Dr. K. W. Axhausen (project leader)

Prof. Dr. B. Hintermann (co-leader)

Your participant ID: XXXXXXXX
Project website: ivtmobis.ethz.ch
Email: mobis@ethz.ch
Telephone: 058 934 45 09 (Mo-Fr. 17:00-19:00, Sa: 10:00-12:00)

Third invitation letter (English)

ETH Eidgenössische Technische Hochschule Zürich Swiss Federal Institute of Technology Zurich

Universität Basel

zh aw School of Engineering

MOBIS

(English version)

Last reminder: Study about Mobility Behaviour in Switzerland

Dear form_of_address last_name,

You have recently received a letter from us with an invitation to participate in the project "Mobility behaviour in Switzerland" (MOBIS). The goal of this joint study by the ETH Zurich, the University of Basel and the Zurich University of Applied Sciences is to investigate the demand for private and public transport services. The project is funded by the Swiss Innovation Agency (Innosuisse) and the Federal Department of the Environment, Transport, Energy and Communications (DETEC).

You are part of a representative random sample of the Swiss population drawn by the Federal Office of Statistics. With this letter, we cordially invite you once again to participate in our study. You may choose to participate in either English, German or French. In the first part of the study, we ask you to fill out a 10-minute online survey about mobility-related topics in the next few days. To participate, please proceed as follows:

Online survey

1. Access **www.mobis.info** in your browser, or by using the QR-code.
2. Enter your personal participant ID: **participant_id**

Smartphone study

A selection of participants will be invited to take part in a smartphone study following the online survey. In this second part of our study, we will record your daily trips and chosen transport modes using a smartphone app and provide you with regular feedback. The study takes two months and ends with a second online survey of about 30 minutes. You will be rewarded with **CHF 100** for your **full participation** in the study. To participate in the smartphone study you must start tracking no later than **October 26**.

All data collected during the study will be kept strictly confidential and used exclusively for research purposes. The data will not be passed on to third parties. During the analysis and in the published results, it will not be possible to identify individual persons. Further information on the study can be found at ivtmobis.ethz.ch. If you have any questions, please do not hesitate to contact us.

We highly appreciate your participation as it will help us gain important insights for improving mobility in Switzerland. We thank you in advance!

With kind regards,

Prof. Dr. K. W. Axhausen (project leader)

Prof. Dr. B. Hintermann (co-leader)

Your participant ID: participant_id
Project website: ivtmobis.ethz.ch
Email: mobis@ethz.ch
Telephone: 058 934 45 09 (Mo-Fr. 17:00-19:00, Sa: 10:00-12:00)

First invitation letter (German)

ETH Eidgenössische Technische Hochschule Zürich Swiss Federal Institute of Technology Zurich

Universität Basel

zh aw School of Engineering

MOBIS

Name Proband X
Strasse X
PLZ, Ort X

Institut für Verkehrsplanung und
Transportsysteme
Stefano-Franscini-Platz 5
8093 Zürich

(English version on reverse side)

Einladung: Studie über das Mobilitätsverhalten in der Schweiz

Sehr geehrte/r Frau/Herr XXX

Die ETH Zürich, die Universität Basel und die Zürcher Hochschule für Angewandte Wissenschaften untersuchen das Verhalten der Verkehrsteilnehmer in der Schweiz im gemeinsamen Forschungsprojekt «Mobilitätsverhalten in der Schweiz» (MOBIS). Diese Studie hat zum Ziel, Erkenntnisse über die Nachfrage nach öffentlichen und privaten Verkehrsleistungen zu gewinnen. Das Projekt wird finanziert von der Schweizerischen Agentur für Innovationsförderung (Innosuisse) und dem Eidgenössischen Departement für Umwelt, Verkehr und Kommunikation (UVEK).

Sie sind Teil einer vom Bundesamt für Statistik zufällig gezogenen, repräsentativen Stichprobe der Schweizer Bevölkerung. Mit diesem Schreiben laden wir Sie herzlich ein, an der Studie teilzunehmen. Sie können diese auf entweder Deutsch, Englisch oder Französisch ausführen

Online-Umfrage

In einem ersten Teil bitten wir Sie, in den nächsten Tagen eine 10-minütigen Online-Umfrage zu verschiedenen Verkehrsthemen auszufüllen. Dazu gehen Sie wie folgt vor:

1. Rufen Sie in Ihrem Browser **www.mobis.info** auf oder benutzen Sie den QR-Code.
2. Geben Sie Ihre persönliche Teilnehmer-ID ein: **XXXXX**

Smartphone-Studie

Eine Auswahl von Teilnehmenden wird im Anschluss an die Umfrage zu einer Smartphone-Studie eingeladen. In diesem zweiten Teil der Studie erfassen wir Ihre täglich zurückgelegten Strecken und die dafür gewählten Verkehrsmittel mit Hilfe einer Smartphone-App und geben Ihnen dazu regelmässig Rückmeldung. Wir begleiten Sie für insgesamt zwei Monate. Die Studie endet mit einer zweiten Online-Umfrage von ca. 30 Minuten. Zum Dank für die **vollständige Teilnahme** erhalten Sie **CHF 100**.

Sämtliche während der Studie erfassten Daten werden streng vertraulich behandelt und ausschliesslich für Forschungszwecke verwendet. Die Daten werden nicht an Dritte weitergegeben. Bei der Auswertung der Daten sowie der Publikation der Resultate sind keine Rückschlüsse auf Einzelpersonen möglich. Weitere Informationen zur Studie finden Sie auf der Projektwebseite. Bei Fragen können Sie uns gerne kontaktieren. Wir werden uns allenfalls erlauben, Ihnen einen Erinnerungsbrief zu schicken. Falls Sie nicht nochmals kontaktiert werden möchten, können Sie uns das gerne mitteilen.

Mit Ihrer Teilnahme an dieser Studie leisten Sie einen wichtigen Beitrag für die Verbesserung der Mobilität in der Schweiz. Dafür danken wir Ihnen im Voraus herzlich!

Mit besten Grüssen

Prof. Dr. K. W. Axhausen (Projektleiter)

Prof. Dr. B. Hintermann (stv. Projektleiter)

Ihre Teilnehmer-ID: XXXXXXXX
Projektwebseite: ivtmobis.ethz.ch
E-Mail: mobis@ethz.ch
Telefon: 058 934 45 09 (Mo-Fr. 17:00-19:00, Sa: 10:00-12:00)

Third invitation letter (German)

ETH Eidgenössische Technische Hochschule Zürich Swiss Federal Institute of Technology Zurich

Universität Basel

zh aw School of Engineering

MOBIS

first_name last_name
street house_number dwelling_number
zip_code municipality

Institut für Verkehrsplanung und
Transportsysteme
Stefano-Franscini-Platz 5
8093 Zürich

(English version on reverse side)

Letztes Erinnerungsschreiben: Studie über das Mobilitätsverhalten in der Schweiz

Sehr geehrte/r form_of_address last_name

Vor kurzem haben Sie von uns einen Brief erhalten mit der Anfrage, am Projekt «Mobilitätsverhalten in der Schweiz» (MOBIS) teilzunehmen. Diese gemeinsame Studie der ETH Zürich, der Universität Basel und der Zürcher Hochschule für Angewandte Wissenschaften hat zum Ziel, Erkenntnisse über die Nachfrage nach öffentlichen und privaten Verkehrsleistungen zu gewinnen. Das Projekt wird finanziert von der Schweizerischen Agentur für Innovationsförderung (Innosuisse) und dem Eidgenössischen Departement für Umwelt, Verkehr und Kommunikation (UVEK).

Sie sind Teil einer vom Bundesamt für Statistik zufällig gezogenen, repräsentativen Stichprobe der Schweizer Bevölkerung. Mit diesem Schreiben laden wir Sie nochmals herzlich ein, an der Studie teilzunehmen. Als Studiensprache können Sie Deutsch, Französisch oder Englisch wählen. In einem ersten Teil bitten wir Sie, in den nächsten Tagen eine 10-minütigen Online-Umfrage zu verschiedenen Verkehrsthemen auszufüllen. Dazu gehen Sie wie folgt vor:

Online-Umfrage

1. Rufen Sie in Ihrem Browser **www.mobis.info** auf oder nutzen Sie den QR-Code.
2. Geben Sie Ihre persönliche Teilnehmer-ID ein: **participant_id**

Smartphone-Studie

Eine Auswahl von Teilnehmenden wird im Anschluss an die Umfrage zu einer Smartphone-Studie eingeladen. In diesem 2. Teil der Studie erfassen wir Ihre täglich zurückgelegten Strecken und die dafür gewählten Verkehrsmittel mit Hilfe einer Smartphone-App und geben Ihnen dazu regelmässig Rückmeldung. Wir begleiten Sie für insgesamt zwei Monate. Die Studie endet mit einer zweiten Befragung (ca. 30 Minuten). Zum Dank für die **vollständige Teilnahme** erhalten Sie **CHF 100**. Um an der Smartphonestudie teilzunehmen müssen Sie spätestens bis am **26. Oktober** mit den Aufzeichnungen starten.

Sämtliche während der Studie erfassten Daten werden streng vertraulich behandelt und ausschliesslich für Forschungszwecke verwendet. Die Daten werden nicht an Dritte weitergegeben. Bei der Auswertung der Daten sowie der Publikation der Resultate sind keine Rückschlüsse auf Einzelpersonen möglich. Weitere Informationen zur Studie finden Sie auf ivtmobis.ethz.ch. Bei Fragen können Sie uns gerne kontaktieren.

Mit Ihrer Teilnahme an dieser Studie leisten Sie einen wichtigen Beitrag für die Verbesserung der Mobilität in der Schweiz. Dafür danken wir Ihnen im Voraus herzlich!

Mit besten Grüssen

Prof. Dr. K. W. Axhausen (Projektleiter)

Prof. Dr. B. Hintermann (stv. Projektleiter)

Ihre Teilnehmer-ID: participant_id
Projektwebseite: ivtmobis.ethz.ch
E-Mail: mobis@ethz.ch
Telefon: 058 934 45 09 (Mo-Fr. 17:00-19:00, Sa: 10:00-12:00)

First invitation letter (French)

ETH Eidgenössische Technische Hochschule Zürich Swiss Federal Institute of Technology Zurich

Universität Basel

zhaw School of Engineering

MOBIS

Name Proband X
Strasse X
PLZ, Ort X

Institut pour la planification du trafic
et les systèmes de transport
Stefano-Franscini-Platz 5
8093 Zürich

(*English version on reverse side*)

Étude sur le comportement en matière de mobilité en Suisse

Cher Monsieur / Chère Madame XXX

L'ETH Zurich, l'Université de Bâle et la Haute école des sciences appliquées de Zurich sont en train de mener un projet de recherche conjoint sur le "Comportement en matière de mobilité en Suisse" (MOBIS), dont l'objectif est de mieux comprendre la demande en transports publics et privés. Les résultats de l'étude contribueront à optimiser notre système de transport. Ce projet est cofinancé par l'Agence suisse pour l'encouragement de l'innovation (Innosuisse) et le Département fédéral de l'environnement, des transports, de l'énergie et des communications (DETEC).

Vous faites partie d'un échantillon représentatif de la population suisse tiré aléatoirement par l'Office fédéral de la statistique. Par ce courrier, nous vous invitons à participer à notre étude.

Enquête en ligne

Dans cette première partie, nous vous demandons de remplir dans les jours qui suivent une enquête en ligne de 10 minutes relative à la mobilité. Pour participer, veuillez:

1. Visiter la page **www.mobis.info** dans votre navigateur, ou scanner le code QR.
2. Renseigner votre identifiant: **XXXXX**

Étude sur smartphone

Certains participants seront invités à participer à une étude sur smartphone à la suite de l'enquête en ligne. Dans cette deuxième partie de l'étude, nous enregistrerons vos trajets quotidiens et leur mode de transport à l'aide d'une application smartphone, et nous vous en informerons régulièrement. L'étude dure deux mois et se termine par une deuxième enquête en ligne d'environ 30 minutes. Vous recevrez **CHF 100** en remerciement pour votre **participation complète** à l'étude.

Toutes les données recueillies sont soumises à des stricts critères de confidentialité, et ne seront utilisées qu'à des fins de recherche. Les données ne seront pas transmises à des tiers. À aucun moment, ni dans l'analyse des données, ni dans les publications des résultats, ne sera-t-il possible d'identifier une personne en particulier. Plus d'informations sur l'étude sont disponibles sur notre site internet. N'hésitez pas à nous contacter en cas de questions. Si vous ne répondez pas à l'enquête en ligne, vous recevrez un courrier de rappel. Si vous souhaitez ne plus être contacté, veuillez nous l'indiquer.

En participant à cette étude, vous nous aiderez à acquérir des connaissances importantes pour améliorer la mobilité en Suisse. Nous vous remercions d'avance!

Meilleures salutations,

Prof. Dr. K. W. Axhausen (Chef de projet)

Prof. Dr. B. Hintermann (Chef de projet adjoint)

Votre identifiant: XXXXX
Site internet du projet: www.ivtmobis.ethz.ch
Courriel: mobis@ethz.ch
Téléphone: 058 934 45 09 (lun-ven: 17:00-19:00, sam: 10:00-12:00)

Third invitation letter (French)

ETH Eidgenössische Technische Hochschule Zürich Swiss Federal Institute of Technology Zurich

Universität Basel

zhaw School of Engineering

MOBIS

first_name last_name
street house_number dwelling_number
zip_code municipality

Institut pour la planification
et les systèmes de transport
Stefano-Franscini-Platz 5
8093 Zürich

(*English version on reverse side*)

Dernier rappel : Étude sur le comportement en matière de mobilité en Suisse

Cher / Chère form_of_address last_name,

Nous vous avons contacté récemment pour vous demander de participer à l'étude MOBIS. L'objectif de cette étude jointe de l'ETH Zurich, de l'Université de Bâle et de la Haute école des sciences appliquées de Zurich est de mieux comprendre la demande en transports publics et privés. Ce projet est cofinancé par l'Agence suisse pour l'encouragement de l'innovation (Innosuisse) et le Département fédéral de l'environnement, des transports, de l'énergie et des communications (DETEC).

Vous faites partie d'un échantillon représentatif de la population suisse tiré aléatoirement par l'Office fédéral de la statistique. Par ce courrier, nous vous invitons à nouveau à participer à notre étude. Vous pouvez choisir de participer en français, allemand ou anglais. Dans une première partie, nous vous demandons de remplir dans les jours qui suivent une enquête en ligne de 10 minutes relative à la mobilité. Pour participer, veuillez procéder comme suit :

Enquête en ligne

1. Visiter la page **www.mobis.info** dans votre navigateur, ou scanner le code QR.
2. Renseigner votre identifiant: **participant_id**

Étude sur smartphone

Certains participants seront invités à participer à une étude sur smartphone à la suite de l'enquête en ligne. Dans cette deuxième partie de l'étude, nous enregistrerons vos trajets quotidiens et leur mode de transport à l'aide d'une application smartphone, et nous vous en informerons régulièrement. L'étude dure deux mois et se termine par une deuxième enquête en ligne d'environ 30 minutes. Vous recevrez **CHF 100** en remerciement pour votre **participation complète** à l'étude. Afin de participer à l'étude sur smartphone, vous devez commencer la collecte des données au plus tard le **26 octobre.**

Toutes les données recueillies sont soumises à des stricts critères de confidentialité, et ne seront utilisées qu'à des fins de recherche. Les données ne seront pas transmises à des tiers. À aucun moment, ni dans l'analyse des données, ni dans les publications des résultats, ne sera-t-il possible d'identifier une personne en particulier. Vous trouverez plus d'informations sur l'étude sur ivtmobis.ethz.ch. N'hésitez pas à nous contacter en cas de questions.

En participant à cette étude, vous nous aiderez à acquérir des connaissances importantes pour améliorer la mobilité en Suisse. Nous vous remercions d'avance!

Meilleures salutations,

Prof. Dr. K. W. Axhausen (Chef de projet)

Prof. Dr. B. Hintermann (Chef de projet adjoint)

Votre identifiant: participant_id
Site internet du projet: www.ivtmobis.ethz.ch
Courriel: mobis@ethz.ch
Téléphone: 058 934 45 09 (lun-ven: 17:00-19:00, sam: 10:00-12:00)

B.2 Introduction survey

1. What is your highest completed level of education?
   - Mandatory education
   - Secondary education (e.g., apprenticeship or diploma)
   - Higher education (e.g., university)
2. What is your age?
   _____
3. What was your citizenship at birth?
   - Swiss
   - Other
   - More than one citizenship (including Swiss)
   - More than one citizenship (not including Swiss)
4. Which country are you a citizen of?
   _____
5. Which is the first country of your dual (or multiple) citizenship?
   _____
6. Which is the second country of your dual (or multiple) citizenship?
   _____
7. What is your current employment status?
   - Employed
   - Self-employed
   - Unemployed
   - Apprentice
   - Student
   - Retired
   - Other
8. Which type of employment do you have?
   - One full-time job (100%)
   - One part-time job
   - More than one part-time job
9. What is your workload? (Percent of a full-time employment)
   - 5%
   - 10%
   - 15%
   - 20%
   - 25%
   - 30%
   - 35%
   - 40%
   - 45%
   - 50%
   - 55%
   - 60%
   - 65%
   - 70%
   - 75%
   - 80%
   - 85%
   - 90%
   - 95%

10. What is the workload of your jobs? (Percent of a full-time employment)

    - Main Job :
    - Secondary job(s) :
    - Total :

11. What is the postcode of your place of employment?

    _____

12. What are the postcodes of your places of employment?

    - Main job : _____
    - Secondary job : _____

13. Do you own any of the following vehicles?

	Yes	No, but I can arrange to borrow one from someone (e.g., partner, friend, neighbor)	No
Car			
Motorbike			
Bicycle (electric or not)			

14. What kind of fuel does your main car use (the car that use the most) ?

    - Gasoline
    - Diesel
    - Hybrid (gasoline/diesel + electric)
    - Electric
    - Other

15. What is the year of production of your main car?

    - 2015 or later
    - 2011 - 2014
    - 2006 - 2010
    - 2001 - 2005
    - 1997 – 2000
    - 1993 - 1996
    - 1992 or earlier
    - I don't know

16. Which size category applies best to your main car?

    - Small car (e.g. Fiat 500 or Volkswagen Polo)
    - Medium to large car (e.g. Skoda Octavia or Audi A4)
    - Off-road vehicle (e.g. Landrover Discovery)
    - Minivan or van (e.g. Opel Zafira)
    - Luxury car or sports coupé (e.g. Mercedes-Benz E-Class, BMW 7 Series or Porsche 911)

17. What is the engine size of your main car?
    - Less than 1.4L
    - 1.4L - 2L
    - More than 2L
    - I don't know
18. What type of bicycle do you have?
    - Regular bicycle (non-electric)
    - E-bike/Pedelec up to 25 km/h (no license plate)
    - E-bike/S-Pedelec up to 45 km/h (yellow license plate)
19. Do you have a public transport pass? Select all that apply.
    - GA Travelcard
    - Half Fare Travelcard
    - Regional or point-to-point travel card
    - Track 7
    - Other pass
    - No pass
20. How often do you typically use the car as driver, counting weekdays only?

	3 or more days per week	2 days per week	1 days per week	1-3 days per month	Less than 1 day per month	Never
Own Car						
Car sharing service (e.g. Mobility)						

21. How often do you typically use the car as passenger, counting weekdays only?

	3 or more days per week	2 days per week	1 days per week	1-3 days per month	Less than 1 day per month	Never
Car in your household (e.g. with your partner)						
Car-pooling (e.g. with a work colleague)						
Taxi						
App-based service (e.g. Uber, Lyft)						

22. How often do you typically use public transport, counting weekdays only?

	3 or more days per week	2 days per week	1 days per week	1-3 days per month	Less than 1 day per month	Never
Train						
Local public transport (tram, bus, etc.)						

23. How often do you typically use the bicycle, counting weekdays only?

	3 or more days per week	2 days per week	1 days per week	1-3 days per month	Less than 1 day per month	Never
Own non-electric bicycle						
Own electric bicycle						
Bike-sharing						

24. Please indicate for each problem whether it should receive more or less attention from policy makers, compared to how much attention it currently receives.

	Much less attention	Less attention	Neither more nor less attention	More attention	Much more attention	I don't know
Road congestion						
Greenhouse gas emissions from motorized traffic						
Health effects of air pollution from motorized traffic						
Extent of mobility overall (people travel too much)						
Noise from motorized traffic						
Noise from public transport						
Crowding in public transport						
Speeding						
Driving under the influence of alcohol or drugs						
Distracted driving (phone use while driving)						
Accident risk for pedestrians						
Accident risk for cyclists						
Accident risk for drivers						

On the left is a list of factors influenced by transport policy.

25. Please indicate for each factor whether you find its current level to be too low or too high.

	Much too low	Too low	Neither too low nor too high	Too high	Much too high	I don't know
Price of mobility in general						
Capacity of road infrastructure						
Capacity of public transport						
Price of public transport tickets						

26. Please indicate whether you agree or disagree with each policy.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree	I don't know
Time- and route-specific mobility pricing, made revenue-neutral by lowering other taxes						
Reduction of speed limit from 50 to 30km/h on selected streets						
Dynamic adjustment of speed limits on highways to optimize traffic flow						
Widen major highways with extra lanes						
Creation of more bus-only lanes in cities						
Expansion of cycling infrastructure						
Expansion of car-free zones in cities						
Increasing of the cost of public parking in city centers						
Subsidization of the purchase of electric vehicles						
Permission to pass on the right on highways						
Stricter noise regulations for motorcycles						
Reduction of minimum driving age to 16						
Reduction of the number of public parking spaces in cities						

27. Please indicate your level of agreement or disagreement with the following statements.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree	I don't know
The government should build sufficient road capacity to satisfy demand at all times						
The government should build sufficient public transport capacity to satisfy demand at all times						
The price for mobility should reflect the social cost (e.g., health, environment, congestion)						
The transport network should be used more efficiently by introducing dynamic pricing (e.g., higher prices during rush hour)						
A journey from A to B should						
always cost the same, regardless of when and which route one travels						
A journey from A to B should cost the same for everyone, regardless of how much they earn						
Public transportation should no longer receive public funds, such that users (rather than taxpayers) cover the full cost						
The government should not intervene in mobility other than providing infrastructure and setting and enforcing traffic laws						
The tax deduction of commuting costs should be stopped (and other taxes lowered to keep overall tax revenue the same)						
The current level of road capacity should not be increased, because more roads lead to more traffic						

28. What is your home postcode in Switzerland?

    - Field/postcode home: _____
    - Other (I recently moved):_____
    - I do not live in Switzerland anymore:_____

29. How many people (including yourself) usually live in your household?

    - 1
    - 2
    - 3
    - 4
    - 5 or more

30. What is your approximate total household income per month? Annual income divided by 12.

    - 4000 CHF or less
    - 4001 - 8000 CHF
    - 8001 - 12000 CHF
    - 12001 - 16000 CHF
    - More than 16000 CHF
    - Prefer not to say

The MOBIS project consists of two parts. You have finished the first part (i.e. this survey) - thank you! The second part of MOBIS is a smartphone study, which tracks participants' mobility using a smartphone app. For participating in this study you, you will receive CHF 100.
Are you interested in participating in the smartphone study?

- Yes
- No

31. For which reason(s) do you not want to take part in the smart phone study?

    - I don't want to be tracked
    - I don't want to receive e-mails
    - I don't use a smart phone
    - I don't want to provide my personal data
    - Other (please specify): _____

We follow the strictest guidelines in protecting your personal data and we assure you that these data will only be used for research purposes. We anonymise your personal data such that it will not be available to third parties. In addition, we will keep e-mail correspondence to a minimum.

32. Would you reconsider taking part in the smartphone study?

    - Yes, I'm interested in taking part
    - No, I don't want to take part

Thanks for your interest in the MOBIS smartphone study!
To check your eligibility, we need to ask you just a couple more questions.

33. Do you use a smartphone? (Android or iOS/iPhone only)

    - Yes
    - No

34. Do you drive in a professional capacity on all or most days (e.g. taxi driver, train driver, bus driver, tram driver, delivery driver, etc.)?

    - Yes
    - No

35. Are you capable of walking 200m without assistance?

    - Yes
    - No

Thank you very much for completing the survey!

MOBIS Einführungsfragebogen (deutsch)

1. Was ist Ihre höchste abgeschlossene Ausbildung?
   - Obligatorische Schule
   - Weiterführende Ausbildung (Lehre, Berufsschule, Matura, etc.)
   - Universität, ETH, Fachhochschule
2. Wie alt sind Sie?

   _____
3. Was ist Ihre Staatsangehörigkeit bei Geburt?
   - Schweiz
   - Sonstige
   - Mehr als eine Staatsangehörigkeit (inklusive Schweiz)
   - Mehr als eine Staatsangehörigkeit (exklusive Schweiz)
4. Was ist Ihre Staatsangehörigkeit?

   _____
5. Was ist die Erste Ihrer doppelten (oder mehreren) Staatsangehörigkeiten?

   _____
6. Was ist die Zweite Ihrer doppelten (oder mehreren) Staatsangehörigkeiten?

   _____
7. Was ist Ihr derzeitiger Beschäftigungsstatus?
   - Angestellte/r
   - Selbständig tätig
   - Arbeitslos
   - Lehrling
   - Student/in
   - Pensioniert
   - Sonstiges
8. Art von Beschäftigung üben Sie aus?
   - Vollzeitbeschäftigung (100
   - Eine Teilzeitbeschäftigung
   - Mehr als eine Teilzeitbeschäftigung
9. Was ist Ihr Beschäftigungsgrad? (Prozent einer Vollzeitbeschäftigung)
   - 5%
   - 10%
   - 15%
   - 20%
   - 25%
   - 30%
   - 35%
   - 40%
   - 45%
   - 50%
   - 55%
   - 60%
   - 65%
   - 70%
   - 75%
   - 80%
   - 85%
   - 90%
   - 95%

10. Was ist der Beschäftigungsgrad Ihrer Teilzeitarbeit?

    - Hauptbeschäftigung :
    - Nebenjob :
    - Total :

11. Was ist die Postleitzahl Ihres Arbeitsortes?

    _____

12. Was sind die Postleitzahlen Ihrer Arbeitsorte?

    - Hauptbeschäftigung : _____
    - Nebenjob : _____

13. Besitzen Sie eines der folgenden Fahrzeuge?

	Ja	Nein, aber ich kann eines ausleihen (z. B. Partner, Freunde, Nachbarn)	Nein
Auto			
Motorrad			
Velo (elektr. oder konv.)			

14. Treibstoff verwendet Ihr Hauptauto (das Auto, das Sie am meisten verwenden)?

    - Benzin
    - Diesel
    - Hybrid (Benzin/Diesel + elektrisch)
    - Elektrisch
    - Sonstiges

15. Was ist das Produktionsjahr Ihres Hauptautos?

    - 2015 oder später
    - 2011 - 2014
    - 2006 - 2010
    - 2001 - 2005
    - 1997 – 2000
    - 1993 - 1996
    - 1992 oder früher
    - Ich weiss es nicht

16. Welche Grössenkategorie trifft am besten auf das Auto zu, das Sie hauptsächlich verwenden?

    - Kleinwagen (z. B. Fiat 500 oder Volkswagen Polo)
    - Mittelgrosses bis grosses Auto (z. B. Skoda Octavia oder Audi A4)
    - Geländewagen (z. B. Landrover Discovery)
    - Minivan oder Kastenwagen (z.B. Opel Zafira)
    - Luxusauto oder Sportcoupé (z. B. Mercedes E-Klasse, BMW 7er, Porsche 911)

17. Wie gross ist der Motor Ihres Hauptautos?

    - Kleiner als 1.4L
    - 1.4L - 2L
    - Grösser als 2L
    - Ich weiss es nicht

18. Welche Art von Velo haben Sie ?

    - Normales Velo (nicht elektrisch)
    - E-Bike/Pedelec bis 25 km/h (kein Nummernschild)
    - E-Bike/S-Pedelec bis 45 km/h (gelbes Nummernschild)

19. Haben Sie ein Abonnement für den öffentlichen Verkehr? Bitte wählen Sie alle zutreffenden Antworten aus?

    - GA
    - Halbtax
    - Verbund- oder Streckenabo
    - Gleis 7
    - Sonstiges
    - Kein Abonnement

20. Wie oft nutzen Sie normalerweise das Auto als Fahrer/in, ohne Wochenenden?

	3 oder mehr Tage pro Woche	2 Tage pro Woche	1 Tage pro Woche	1-3 Tage pro Monat	Weniger als 1 Tag pro Monat	Niemals
Eigenes Auto						
Carsharing (z.B. Mobility)						

21. Wie oft nutzen Sie normalerweise das Auto als Passagier/in, ohne Wochenenden?

	3 oder mehr Tage pro Woche	2 Tage pro Woche	1 Tage pro Woche	1-3 Tage pro Monat	Weniger als 1 Tag pro Monat	Niemals
Auto in Ihrem Haushalt (z.B. mit Ihrem/r Partner/in)						
Fahrgemeinschaft (z.B. mit einem/r Arbeitskollege/in)						
Taxi						
App-basierter Dienst (z.B. Uber, Lyft)						

22. Wie oft nutzen Sie normalerweise den öffentlichen Verkehr, ohne Wochenenden?

	3 oder mehr Tage pro Woche	2 Tage pro Woche	1 Tage pro Woche	1-3 Tage pro Monat	Weniger als 1 Tag pro Monat	Niemals
Bahn Öffentlicher Nahverkehr (Tram, Bus, usw.)						

23. Wie oft nutzen Sie normalerweise das Velo, ohne Wochenenden?

	3 oder mehr Tage pro Woche	2 Tage pro Woche	1 Tage pro Woche	1-3 Tage pro Monat	Weniger als 1 Tag pro Monat	Niemals
Eigenes Velo (kein E-bike)						
Eigenes E-bike						
Bikesharing						

24. Auf der linken Seite ist eine Liste möglicher Probleme aufgeführt, die häufig mit Verkehr in Verbindung gebracht werden. Bitte geben Sie für jedes Problem an, ob es mehr oder weniger Aufmerksamkeit von politischen Entscheidungsträgern erhalten sollte im Vergleich zum aktuellen Stand.

	Deutlich weniger Aufmerk-samkeit	Weniger Aufmerk-samkeit	Weder mehr noch weniger Aufmerk-samkeit	Mehr Aufmerk-samkeit	Deutlich mehr Aufmerk-samkeit	Ich weiss es nicht
Stau im Strassenverkehr						
Treibhausgasemissionen aus dem motorisierten Verkehr						
Gesundheitliche Auswirkungen der Luftverschmutzung durch motorisierten Verkehr						
Verkehrsaufkommen an sich (Menschen reisen zu viel)						
Lärm durch motorisierten Verkehr						
Lärm durch öffentlichen Verkehr						
Kapazitätsengpässe im öffentlichen Verkehr						
Überhöhte Geschwindigkeit						
Fahren unter dem Einfluss von Alkohol oder Drogen						
Abgelenktes Autofahren (z.B. Telefonieren während der Fahrt)						
Unfallrisiko für Fussgänger/Innen						
Unfallrisiko für Velofahrer/Innen						
Unfallrisiko für Autofahrer/Innen						

25. Auf der linken Seite sehen Sie eine Liste von Faktoren aufgeführt, welche durch die Verkehrspolitik beeinflusst werden. Bitte geben Sie für jeden Faktor an, ob Sie das aktuelle Niveau als zu niedrig oder zu hoch empfinden.

	Viel zu niedrig	Zu niedrig	Weder zu niedrig noch zu hoch	Zu hoch	Viel zu hoch	Ich weiss nicht
Mobilitätskosten im Allgemeinen						
Kapazität der Strassen						
Kapazität des öffentlichen Verkehrs						
Benzinpreis						
Preise für den öffentlichen Verkehr						

26. Links ist eine Liste konkreter Verkehrsstrategien aufgeführt. Bitte geben Sie an, inwieweit Sie mit diesen Strategien einverstanden sind oder nicht.

	Lehne vollständig ab	Lehne eher ab	Lehne weder ab noch stimme zu	Stimme eher zu	Stimme vollständig zu	Ich weiss es nicht
Zeit- und routenspezifische Mobilitätspreise, die durch eine Senkung anderer Steuern aufkommensneutral wären.						
Reduzierung der Geschwindigkeitsbegrenzung von 50 auf 30 km/h auf ausgewählten Strecken.						
Dynamische Anpassung der Geschwindigkeitsbegrenzung auf Autobahnen zur Optimierung des Verkehrsflusses.						
Zusätzliche Fahrspur auf den wichtigsten Autobahnen.						
Zusätzliche Busspuren in Städten.						
Ausbau der Veloinfrastruktur.						
Ausbau von autofreien Zonen in Städten.						
Erhöhung der Kosten für öffentliche Parkplätze in Städten.						
Subventionierung des Kaufs von Elektrofahrzeugen.						
Zulässiges Rechtsüberholen auf Autobahnen						
Strengere Lärmvorschriften für Motorräder.						
Reduzierung des Mindestalters für den Führerausweiserwerb auf 16 Jahre.						
Reduzierung der Anzahl öffentlicher Parkplätze in Städten.						

27. Bitte geben Sie an, inwiefern Sie mit den folgenden Aussagen einverstanden sind.

	Lehne vollständig ab	Lehne eher ab	Lehne weder ab noch stimme zu	Stimme eher zu	Stimme vollständig zu	Ich weiss nicht
Die Regierung sollte genügend Strassenkapazität bereitstellen, um jederzeit die Nachfrage zu decken.						
Die Regierung sollte genügend öffentliche Verkehrskapazität bereitstellen, um jederzeit die Nachfrage zu decken.						
Der Preis für die Mobilität sollte die gesellschaftliche Kosten widerspiegeln (z. B. Gesundheit, Umwelt, Stau).						
Das Verkehrsnetz sollte durch die Einführung dynamischer Preise (z. B. höhere Preise während der Hauptverkehrszeit) effizienter genutzt werden.						
Eine Fahrt von A nach B sollte immer gleich viel kosten, unabhängig davon, wann und auf welcher Route sie zurückgelegt wird.						
Eine Fahrt von A nach B sollte für alle gleich viel kosten, unabhängig davon, wieviel jemand verdient.						
Öffentlicher Verkehr sollte keine Subventionen mehr erhalten, damit nur die Nutzer (und nicht die Steuerzahler) die vollen Kosten übernehmen.						
Die Regierung sollte nicht in die Mobilität eingreifen, außer Infrastruktur bereitzustellen und Verkehrsgesetze festzulegen und durchzusetzen.						
Der Steuerabzug für berufliche Fahrtkosten sollte eingestellt werden (und andere Steuern sollen gesenkt werden, um die Gesamtsteuereinnahmen gleich zu halten).						
Die derzeitige Strassenkapazität sollte nicht erhöht werden, da mehr Strassen zu mehr Verkehr führen.						

28. Was ist die Postleitzahl Ihres Wohnorts in der Schweiz?

    - Postcode: _____
    - Andere (ich bin kürzlich umgezogen):_____
    - Ich wohne nicht mehr in der Schweiz:_____

29. Wie viele Personen (Sie selbst mitgerechnet) wohnen gewöhnlich in Ihrem Haushalt?

    - 1
    - 2
    - 3
    - 4
    - 5 oder mehr

30. Wie hoch ist Ihr ungefähres Haushaltseinkommen pro Monat? Jahreslohn dividiert durch 12.

    - 4000 CHF oder weniger
    - 4001 - 8000 CHF
    - 8001 - 12000 CHF
    - 12001 - 16000 CHF
    - Mehr als 16 000 CHF
    - Keine Angabe

    Das MOBIS-Projekt besteht aus zwei Teilen. Sie haben den ersten Teil (d.h. diese Umfrage) abgeschlossen - vielen Dank! Der zweite Teil von MOBIS besteht aus einer Smartphone-Studie, die die Mobilität der Teilnehmer mit Hilfe einer Smartphone-App analysiert. Für die Teilnahme an dieser Studie werden Sie mit CHF 100 entschädigt. **Sind Sie an einer Teilnahme an der Smartphone-Studie interessiert?**

    - Ja
    - Nein

31. Aus welchen Gründen möchten Sie nicht an der Smartphone-Studie teilnehmen?

    - Ich möchte nicht mittels GPS geortet werden
    - Ich möchte keine E-Mails bekommen
    - Ich benutze kein Smartphone
    - Ich möchte nicht meine persönliche Daten angeben
    - Sonstiges (bitte angeben): _____

    Wir befolgen beim Schutz Ihrer personenbezogenen Daten die strengsten Richtlinien und versichern Ihnen, dass diese Daten nur für Forschungszwecke verwendet werden. Wir anonymisieren Ihre personenbezogenen Daten so, dass sie Dritten nicht zugänglich werden. Darüber hinaus werden wir die E-Mail-Korrespondenz auf ein Minimum beschränken.

32. Wären Sie allenfalls doch bereit, an der Smartphone-Studie teilzunehmen?

    - Ja, ich bin an der Teilnahme an der Smartphone-Studie interessiert
    - Nein, ich möchte nicht an der Smartphone-Studie teilnehmen

    Vielen Dank für Ihr Interesse an der MOBIS-Smartphone-Studie!
    Um Ihre Teilnahmeberechtigung zu prüfen, müssen wir Ihnen einige zusätzliche Fragen stellen.

33. Do you use a smartphone? (Android or iOS/iPhone only)

    - Ja
    - Nein

34. Sind Sie Berufsfahrer (z. B. Taxifahrer/In, Zugführer/In, Busfahrer/In, Strassenbahnfahrer/In, Auslieferungsfahrer/In usw.)?

    - Ja
    - Nein

35. Können Sie ohne Hilfe 200m zu Fuss gehen?

    - Ja
    - Nein

    Vielen Dank für das Ausfüllen der Umfrage!

MOBIS Introduction questionnaire (français)

1. Quel est votre niveau d'études le plus élevé?
   - Éducation obligatoire (école secondaire, cycle d'orientation)
   - Éducation secondaire (p.ex. gymnase/collège/lycée, école supérieure)
   - Enseignement supérieur (p.ex. université, ecole polytechnique, haute école spécialisée)
2. Quel âge avez-vous?
   _____
3. Quelle était votre nationalité à la naissance?
   - Suisse
   - Autre
   - Plus d'une nationalité (incluant la nationalité suisse)
   - Plus d'une nationalité (excluant la nationalité suisse)
4. De quel pays avez-vous la nationalité?
   _____
5. Quel est le premier pays de votre nationalité multiple?
   _____
6. Quel est le deuxième pays de votre nationalité multiple?
   _____
7. Quel est le deuxième pays de votre nationalité multiple?
   - Employé(e)
   - Indépendant(e)
   - Sans emploi
   - Apprenti(e)
   - Étudiant(e)
   - Retraité(e)
   - Autre
8. Quel type d'emploi avez-vous?
   - Un emploi à temps plein (100%)
   - Un emploi à temps partiel
   - Plus d'un emploi à temps partiel
9. Quelle est votre charge de travail? (Pourcentage d'un emploi à temps plein)
   - 5%
   - 10%
   - 15%
   - 20%
   - 25%
   - 30%
   - 35%
   - 40%
   - 45%
   - 50%
   - 55%
   - 60%
   - 65%
   - 70%
   - 75%
   - 80%
   - 85%
   - 90%
   - 95%

10. Quelle est la charge de travail de vos postes? (Pourcentage d'un emploi à temps plein)

    - Travail principal :
    - Travail secondaire :
    - Total :

11. Quel est le code postal de votre lieu de travail? _____

12. Quel est le code postal de vos lieux de travail?

    - Travail principal : _____
    - Travail secondaire : _____

13. Possédez-vous l'un des véhicules suivants?

	Oui	Non, mais je peux m'arranger pour en emprunter un à quelqu'un (par exemple, mon partenaire, ami, voisin)	Non
Voiture			
Moto			
Vélo (électrique ou non))			

14. Quel type de carburant votre voiture principale utilise-t-elle (la voiture que vous utilisez le plus)?

    - Essence
    - Diesel
    - Hybride (essence/diesel + électrique)
    - Électrique
    - Autre

15. Quelle est l'année de production de votre voiture principale?

    - 2015 ou plus tard
    - 2011 - 2014
    - 2006 - 2010
    - 2001 - 2005
    - 1997 – 2000
    - 1993 - 1996
    - 1992 ou avant
    - Je ne sais pas

16. Quelle catégorie de taille s'applique le mieux à la voiture que vous utilisez principalement?

    - Petite voiture (p.ex. Fiat 500 ou Volkswagen Polo)
    - Voiture moyenne à grosse voiture (p. ex. Skoda Octavia ou Audi A4)
    - Voiture tout-terrain (p.ex. Landrover Discovery)
    - Minivan ou van (p. ex. Opel Zafira)
    - Voiture de luxe ou coupé sport (p. ex. Mercedes-Benz E-Klasse, BMW 7er ou Porsche 911)

17. Quelle est la taille du moteur de la voiture que vous utilisez principalement?

    - Moins de 1.4L
    - 1.4L - 2L
    - Plus de 2L
    - Je ne sais pas

18. Quel type de vélo avez-vous?

    - Vélo ordinaire (non électrique)
    - Vélo électrique jusqu'à 25 km/h (sans plaque d'immatriculation)
    - Vélo électrique jusqu'à 45 km/h (plaque d'immatriculation jaune)

19. Avez-vous un abonnement de transports en commun? Sélectionnez tous ceux que vous avez.

    - Abonnement général
    - Abonnement demi-tarif
    - Abonnement communautaire ou de parcours
    - Voie 7
    - Autre abonnement
    - Pas d'abonnement

20. À quelle fréquence utilisez-vous généralement la voiture comme conducteur (uniquement les jours ouvrables)?

	3 jours ou plus par semaine	2 jours par semaine	1 jour par semaine	1-3 jours par mois	Moins de 1 jour par mois	Jamais
Propre voiture						
Voitures en libre-service (p.ex. Mobility						

21. À quelle fréquence utilisez-vous généralement la voiture comme conducteur (uniquement les jours ouvrables)?

	3 jours ou plus par semaine	2 jours par semaine	1 jour par semaine	1-3 jours par mois	Moins de 1 jour par mois	Jamais
Voiture dans votre ménage (p.ex. avec votre partenaire)						
Covoiturage (p.ex avec un/e collègue de travail)						
Taxi						
Service basé sur une application (p.ex. Uber, Lyft)						

22. À quelle fréquence utilisez-vous généralement les transports en commun (uniquement les jours ouvrables)?

	3 jours ou plus par semaine	2 jours par semaine	1 jour par semaine	1-3 jours par mois	Moins de 1 jour par mois	Jamais
Train						
Transports en commun locaux (tram, bus, etc.)						

23. À quelle fréquence utilisez-vous généralement le vélo (uniquement les jours ouvrables)?

	3 jours ou plus par semaine	2 jours par semaine	1 jour par semaine	1-3 jours par mois	Moins de 1 jour par mois	Jamais
Propre vélo non électrique						
Propre vélo électrique						
Vélo en libre service						

24. À gauche, vous trouverez une liste de problèmes potentiels généralement associés au transport.
Pour chaque problème, indiquez s'il convient de retenir plus ou moins l'attention des décideurs, par rapport au niveau d'attention actuel.

	Beaucoup moins d'attention	Moins d'attention	Ni plus ni moins d'attention	Plus d'attention	Beaucoup plus d'attention	Je ne sais pas
Congestion routière						
Émissions de gaz à effet de serre du trafic motorisé						
Effets sur la santé de la pollution atmosphérique due au trafic motorisé						
La mobilité globale (les gens voyagent trop)						
Bruit du trafic motorisé						
Bruit des transports en commun						
Affluence dans les transports en commun						
Excès de vitesse						
Conduite sous l'influence de l'alcool ou de drogues						
Conduite distraite (utilisation du téléphone en conduisant)						
Risque d'accident pour les piétons						
Risque d'accident pour les cyclistes						
Risque d'accident pour les conducteurs						

25. Sur la gauche, vous voyez une liste de facteurs influencés par la politique de transport. Veuillez indiquer pour chaque facteur si vous trouvez que son niveau actuel est trop bas ou trop élevé.

	Beaucoup trop bas	Trop bas	Ni trop bas ni trop haut	Trop haut	Beaucoup trop haut	Je ne sais pas
Prix de la mobilité en général						
Capacité de l'infrastructure routière						
Capacité des transports en commun						
Prix du carburant						
Prix des billets de transports en commun						

26. Vous trouverez à gauche une liste de politiques de transport concrètes.
Veuillez indiquer si vous êtes d'accord ou non avec chaque politique.

	Pas du tout d'accord	Pas d'accord	Ni en désaccord ni d'accord	D'accord	Tout à fait d'accord	Je ne sais pas
La tarification de la mobilité en fonction du temps et de l'itinéraire, rendue neutre en termes de revenus en réduisant les autres taxes						
Réduction de la limite de vitesse de 50 à 30 km / h sur certaines rues.						
Réglage dynamique de la limite de vitesse sur les autoroutes pour optimiser le flux de circulation.						
Création d'une voie supplémentaire sur les autoroutes principales.						
Création de plus de voies réservées aux bus dans les villes.						
Expansion de l'infrastructure cyclable.						
Expansion des zones sans voitures dans les villes.						
Augmentation du coût du stationnement public dans les centres-villes.						
Subvention de l'achat de véhicules électriques.						
Permission de depasser à droite sur les autoroutes.						
Une réglementation plus stricte en matière de bruit pour les motos.						
Réduction de l'âge minimum de conduite à 16 ans.						
Réduction du nombre de places de stationnement public dans les villes.						

27. Veuillez indiquer votre degré d'accord ou de désaccord avec les affirmations suivantes.

	Pas du tout d'accord	Pas d'accord	Ni en désaccord ni d'accord	D'accord	Tout à fait d'accord	Je ne sais pas
Le gouvernement devrait assurer une capacité routière suffisante pour répondre à la demande en tout temps.						
Le gouvernement devrait mettre en place une capacité de transports en commun suffisante pour répondre à la demande en tout temps.						
Le prix de la mobilité doit refléter le coût social (par exemple, la santé, l'environnement, la congestion).						
Le réseau de transport devrait être utilisé plus efficacement en introduisant une tarification dynamique (par exemple, des prix plus élevés en heure de pointe).						
Un trajet de A à B devrait toujours coûter le même montant, peu importe le moment de la journée et l'itinéraire emprunté.						
Un trajet de A à B devrait coûter le même montant pour tout le monde, quel que soit leur salaire.						
Les transports en commun ne devraient plus recevoir de subventions, de sorte que les utilisateurs (plutôt que les contribuables) assument la totalité des coûts.						
Le gouvernement ne devrait pas intervenir dans la mobilité autrement qu'en fournissant des infrastructures et en établissant et en appliquant des règles de circulation.						
La déduction fiscale des frais de déplacements pendulaires doit être supprimée (et les autres taxes réduites pour que les recettes fiscales globales restent les mêmes).						
Le niveau actuel de la capacité routière ne doit pas être augmenté, car davantage de routes entraînent plus de trafic.						

28. Quel est le code postal de votre résidence en Suisse?

    - Postcode: _____
    - Autre (j'ai récemment déménagé): _____
    - Je ne vis plus en Suisse _____

29. Combien de personnes (y compris vous-même) vivent normalement dans votre ménage?

    - 1
    - 2
    - 3
    - 4
    - 5 or more

30. Quel est le revenu total approximatif du ménage par mois? Revenu annuel divisé par 12.

    - 4000 CHF ou moins
    - 4001 - 8000 CHF
    - 8001 - 12000 CHF
    - 12001 - 16000 CHF
    - Plus de 16000 CHF
    - Je préfère ne pas le dire

Vous avez terminé la première partie du projet MOBIS. Merci!
La deuxième partie du projet MOBIS est une étude qui suit la mobilité des participants à l'aide d'une application pour smartphone. Si vous participez à cette étude, vous recevrez CHF 100.

Souhaitez-vous participer à l'étude sur smartphone?

- Oui
- Non

31. Pour quelle(s) raison(s) ne souhaitez-vous pas participer à l'étude sur smartphone?
    - Je ne veux pas être suivi
    - Je ne veux pas recevoir de courriels
    - Je n'ai pas de smartphone
    - Je ne veux pas transmettre mes données personnelles
    - Autre (veuillez spécifier): _____

Nous suivons les normes les plus strictes en matière de protection des données personnelles et nous vous assurons que ces données ne seront utilisées qu'à des fins de recherche. Nous anonymisons vos données personnelles afin qu'elles ne soient pas transmises à des tiers. De plus, nous limiterons au minimum la correspondance par courriel.

32. Souhaitez-vous reconsidérer votre participation à l'étude sur smartphone?
    - Oui, je souhaite participer
    - Non, je ne souhaite pas participer

Merci de votre intérêt pour l'étude sur smartphone MOBIS!
Pour vérifier votre éligibilité, nous devons vous poser quelques questions supplémentaires.

33. Utilisez-vous un smartphone? (Android ou iOS / iPhone uniquement)
    - Oui
    - Non

34. Devez-vous conduire dans le cadre de votre travail tous les jours ou presque (p. ex. chauffeur de taxi, chauffeur de train, chauffeur de bus, chauffeur de tramway, chauffeur-livreur, etc.)?
    - Oui
    - Non

35. Êtes-vous capable de marcher 200m sans assistance?
    - Oui
    - Non

Merci beaucoup d'avoir rempli le sondage!

B.3 Registration

MOBIS Registration (English)

Welcome to the registration for the smartphone study of the MOBIS project!

Registration requires the following steps:

1. Learn about what this study involves - Provide your email address
2. Read and approve the consent form
3. Download the app and activate it

The MOBIS Smartphone Study

In this smartphone study we will record your mobility behavior over the course of two months. The study conforms to the strictest privacy and confidentiality requirements. Smartphones allow for much more precise research compared to traditional surveys. In addition to smartphone tracking, you will be required to complete an additional final online survey. We will update you weekly on the progress of the study by e-mail. You will be compensated with CHF 100 for your efforts. Detailed additional information about the study can be found here.

To participate in the study you need to provide your e-mail address and consent to the terms in the consent form.

- Please enter your e-mail address. _____
- Please re-enter your e-mail address. _____
- I agree to participate in the MOBIS smartphone study and consent to the terms in the consent form.
  - Yes
  - No

MOBIS Registration (deutsch)

Willkommen bei der Anmeldung zur Smartphone-Studie des MOBIS-Projekts!

Die Registrierung umfasst die folgenden Schritte:

1. Sie erfahren, worum es in dieser Studie geht
2. Sie geben Ihre E-Mail-Adresse an
3. Sie lesen und genehmigen das Einverständnisformular
4. Sie laden die App herunter und aktivieren sie

Die MOBIS Smartphone-Studie

In der Smartphone-Studie erfassen wir mit Hilfe einer Smartphone App Ihr Mobilitätsverhalten während 2 Monaten. Selbstverständlich unterliegt die Studie strengsten Datenschutzvorkehrungen. Smartphones ermöglichen eine viel genauere Untersuchung der Verkehrsnutzung als herkömmliche Befragungen. Neben dem Tracking mit dem Smartphone müssen Sie eine zusätzliche Online-Befragung ausfüllen. Über den Studienverlauf informieren wir Sie mit wöchentlichen E-Mails. Für Ihren Aufwand erhalten Sie eine Entschädigung in der Höhe von 100 Franken. Detaillierte Fragen und Antworten zur Studie finden Sie hier.

Um an der Studie teilnehmen zu können, müssen Ihre E-mail Adresse eingeben und bestätigen, dass Sie mit den Bedingungen in der Einverständniserklärungeinverstanden sind.

- Bitte geben Sie Ihre E-Mail-Adresse ein. _____
- Bitte geben Sie Ihre E-Mail-Adresse erneut ein. _____
- Ich bin damit einverstanden an der MOBIS Smartphone Studie teilzunehmen und mit der Einverständniserklärung.
  - Ja
  - Nein

MOBIS Registration (français)

Bienvenue à l'inscription à l'étude sur smartphone du projet MOBIS!

Bienvenue à l'inscription à l'étude sur smartphone du projet MOBIS!

1. Prendre connaissance de la description de cette enquête
2. Renseigner votre adresse courriel
3. Lire et approuver le formulaire de consentement
4. Télécharger l'application et l'activer

L'étude sur smartphone MOBIS

MOBIS Dans cette étude, nous enregistrerons votre comportement de mobilité sur une période de deux mois. L'étude est conforme aux exigences de confidentialité les plus strictes. Les smartphones permettent des recherches beaucoup plus précises que les enquêtes traditionnelles. En plus du suivi par smartphone, vous devrez remplir un sondage finale en ligne. Nous vous tiendrons au courant des progrès de l'étude chaque semaine par courriel. Vous recevrez une indemnisation de CHF 100 pour votre pleine participation à l'étude. Des informations complémentaires détaillées sur l'étude sont disponibles ici.

Pour participer à l'étude sur smartphone MOBIS, vous devez saisir votre adresse courriel et confirmer que vous consentez aux conditions énoncées dans le document de consentement.

- Veuillez entrer votre adresse courriel. _____
- Veuillez saisir à nouveau votre adresse courriel. _____
- J'accepte de participer à l'étude sur smartphone MOBIS et je consens aux conditions énoncées dans le document de consentement.
  - Oui
  - Non

B.4 Final survey

MOBIS finale questionnaire (English)

1. Were you away from home for at least two days during the MOBIS study period (e.g., on holidays or a business trip)?

   - Yes, once
   - Yes, more than once
   - No

2. When were you away?

	January	February	March	April	May	June	July	August	September	October	November	December
From												
Until												

3. When were you away? Please add up to four more trips.

	January	February	March	April	May	June	July	August	September	October	November	December
Trip From												
Trip Until												
Trip From												
Trip Until												
Trip From												
Trip Until												
Trip From												
Trip Until												

4. Has your employment status changed during the course of the study?

   - Yes
   - No

5. What is your new employment status?

   - Employed
   - Self-employed
   - Unemployed
   - Apprentice
   - Student
   - Retired
   - Other

6. What is the degree of your new employment?

   - One full-time job (100%)
   - One part-time job
   - More than one part-time job

7. What is your new workload? (Percent of a full-time job)

   - 10%
   - 20%
   - 30%
   - 40%
   - 50%
   - 60%
   - 70%
   - 80%
   - 90%

8. What is the workload of your jobs? (Percent of a full-time job)
   - Main Job :
   - Secondary job(s) :
   - Total :
9. What is the postcode of the location of your new employment?
   _____
10. What are the postcodes of the locations of your new employments?
    - Main job : _____
    - Secondary job : _____
11. To what extent are you able to organise your work schedule?
    - No flexibility (fixed start and end time)
    - Some flexibility (flexible start and/or end time, but completing a set number of hours per day)
    - Full flexibility (flexible start and end time, completing a set number of hours per week, month or year)
12. In your current job(s), do you work from home, at least in part?
    - Yes
    - No
13. How many days a week do you work from home?
    - 1
    - 2
    - 3
    - 4
    - 5
    - 6
    - 7
14. In your current job(s), would you be able to work from home, at least in part?
    - Yes
    - No
    - Don't know
15. How many days a week would you be able to work from home ?
    - 1
    - 2
    - 3
    - 4
    - 5
    - 6
    - 7
    - I don't know
16. How satisfied are you with the Swiss transport system?

	Very dissatisfied	Somewhat dissatisfied	Neither satisfied nor dissatisfied	Somewhat satisfied	Very satisfied
Road infrastructure					
Public transport					

17. Below is a list of potential problems commonly associated with transport. Please indicate for each problem whether it should receive more or less attention from policy makers, compared to how much attention it currently receives.

	Much less attention	Less attention	Neither more nor less attention	More attention	Much more attention	I don't know
Road congestion						
Greenhouse gas emissions from motorized traffic						
Health effects of air pollution from motorized traffic						
Extent of mobility overall (people travel too much)						

18. Below is a list of factors defined by transport policy. Please indicate for each factor whether you find its current level to be too low or too high.

	Much too low	Too low	Neither too low nor too high	Too high	Much too high	I don't know
Price of mobility in general						
Capacity of road infrastructure						
Capacity of public transport						
Price of public transport tickets						

19. Please indicate whether you agree or disagree with each policy.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree	I don't know
Time- and route-specific mobility pricing, made revenue-neutral by lowering other taxes						
Dynamic adjustment of speed limits on highways to optimize traffic flow						
Widen major highways with extra lanes						
Increase the cost of public parking in city centers						

20. Please indicate your level of agreement or disagreement with the following statements.

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree	I don't know
The government should build sufficient road capacity to satisfy demand at all times						
The government should build sufficient public transport capacity to satisfy demand at all times						
The price for mobility should reflect the social cost (e.g., health, environment, congestion)						
The transport network should be used more efficiently by introducing dynamic pricing (e.g., higher prices during rush hour)						
All people should pay the same for mobility, regardless of when and where they travel						

21. What is the average private cost of your car travel per kilometre?
_____ Centimes/Rappen

22. Do you agree with the following statements? Compared to public transport, using a car...

	Very much disagree	Disagree	Neither disagree nor agree	Agree	Very much agree
... saves time					
... saves money					
... is harmful for the environment					
... has negative impacts on public health					
... is pleasant					
... is comfortable					
... is convenient					
... makes me flexible/independent					
... allows me to make the best use of travel time					
... protects me from unfavorable weather conditions					
... enables me to transport luggage					
...is safe with regards to traffic					
...can increase congestion					

23. Please indicate your level of agreement with the following statements. The MOBIS study ...

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
... has affected my travel behavior during the study period					
... will continue to affect my travel behavior in the future					
... has raised my awareness about the external costs of transport					
... has made me consider alternative travel options					
... has made me re-evaluate my car use					

24. What was your motivation to participate in our smartphone study? Please select all that apply.

    - Financial reward
    - Interest in transport policies
    - Interest in impacts of transport (congestion, air pollution, health...)
    - Desire to learn more about personal travel behaviour
    - Other (please specify): _____

25. Do you agree with the following statements? The information provided in the MOBIS e-mails ...

	Strongly disagree	Disagree	Neither disagree nor agree	Agree	Strongly agree
... was clear					
... was interesting					
... made me reflect on the content					
... was difficult to understand					

26. How would you define the external costs of your travel behavior?
    - The costs associated with my travel behavior that I have to pay myself.
    - The costs imposed on society as a consequence of my travel behavior.
    - The total costs associated with my travel behavior (sum of private plus societal costs)
    - I don't know what the external costs of travel are
27. Were you aware that you could earn money by changing your travel behaviour during the second phase of the study?
    - Yes
    - No
28. Were you aware that you could reduce the external costs of your travel by changing your travel behaviour during the second phase of the study?
    - Yes
    - No
29. Due to technical reasons, it was not possible to mark a trip as "car-pooled" with someone, even though this is an effective way of reducing external costs. Did you share rides with others in order to reduce your external costs?
    - Always
    - Sometimes
    - Never
    - Often
    - Rarely

    The following questions are about the use of potential revenue from mobility pricing.

30. If dynamic mobility pricing (i.e., prices depending on mode, route and time) were introduced, what should be done with the revenue?
    - The money should be returned to households
    - The money should be used to fund new transport-related projects
    - About half of the money should be returned and the rest spent on transport-related projects
    - Other(please specify) _____
31. If the money were returned to households, which option would you prefer?
    - Returning the same amount to everyone (e.g., by lowering health insurance premia)
    - Lowering existing taxes and fees related to motorized transport (e.g., vehicle tax)
    - Lowering existing taxes that are unrelated to transport
    - Lowering public transport fares
    - Other (please specify) _____

32. If the money were used to fund transport projects, how should it be prioritized?
    - Projects related to motorized transport
    - Projects related to public transport
    - Projects related to bicycling
    - Projects related to walking
    - No particular mode should be prioritized

33. To what degree do the following statements apply to your lifestyle?

	Does not apply at all	Does not apply	Applies somewhat	Applies fully
I maintain an upscale standard of living				
I live according to religious principles				
I uphold my family traditions				
I enjoy my life to the fullest degree				
I go out often				
I find my life especially pleasing when there is constantly something going on				

34. How often do you engage in the following leisure activities?

	Never	Seldom	Sometimes	Often
Visiting art exhibitions or galleries				
Reading books				
Reading a national newspaper				

35. When you have a really nice dinner in a restaurant, how much do you spend at most per person?
    _____CHF

36. Next to each value is a short explanation. Please rate how important each value is for you as a guiding principle in your life.

	Not important at all	Not very important	Somewhat important	Very important	Extremely important
EQUALITY: equal opportunity for all					
RESPECTING THE EARTH: harmony with other species					
SOCIAL POWER: control over others, dominance					
PLEASURE: joy, gratification of desires					
UNITY WITH NATURE: fitting into nature					
A WORLD AT PEACE: free of war and conflict					
WEALTH: material possessions, money					
AUTHORITY: the right to lead or command					
SOCIAL JUSTICE: correcting injustice, care for the weak					
ENJOYING LIFE: enjoying food, sex, leisure, etc.					
PROTECTING THE ENVIRONMENT: preserving nature					
INFLUENTIAL: having an impact on people and events					
HELPFUL: working for the welfare of others					
PREVENTING POLLUTION: protecting natural resources					
SELF-INDULGENT: doing pleasant things					
AMBITIOUS: hard-working, aspiring					

37. In general, how would you say your health is?

- Very good
- Good
- Fair
- Poor
- Very poor
- Prefer not to say

MOBIS-Finale-Fragebogen

Willkommen zur letzten MOBIS-Umfrage!
In dieser Umfrage werden wir weitere Informationen über Sie und verschiedene Aspekte des Verkehrs sammeln. Dies ermöglicht uns vertiefende Analysen der wertvollen Daten, die Sie uns während der Studie geliefert haben.
Bitte klicken Sie auf den Pfeil unten, um zu beginnen.

1. Waren Sie während der MOBIS-Studie für mindestens zwei Tage abwesend von zuhause (z.B. Ferien, Berufsreise)?
   - Ja, einmal
   - Ja, mehrmals
   - Nein
2. Wann sind Sie verreist?
   - Von
   - Bis
3. Hat sich Ihre Anstellungssituation während der Studie geändert?
   - Ja
   - Nein
4. Welches ist Ihre derzeitige Anstellungssituation?
   - Angestellt
   - Selbständig
   - Arbeitslos
   - Lehrling
   - Studium
   - Pensioniert
   - Sonstiges
5. Was ist Ihr Anstellungsgrad?
   - Eine Vollzeit-Anstellung (100%)
   - Eine Teilzeit-Anstellung
   - Mehr als eine Teilzeit-Anstellung
6. What is your new workload? (Percent of a full-time job)
   - 10%
   - 20%
   - 30%
   - 40%
   - 50%
   - 60%
   - 70%
   - 80%
   - 90%
7. Was ist Ihr neuer Anstellungsgrad? (Prozent Pensum)
   - Hauptbeschäftigung:
   - Nebenjob:
   - Total:

8. Wie lautet die Postleitzahl Ihres neuen Arbeitsortes?
   _____

9. Wie lauten die Postleitzahlen Ihrer neuen Arbeitsorte?
   - Hauptbeschäftigung _____
   - Nebenjob _____

10. In welchem Mass können Sie Ihre Arbeitszeiten selbst festlegen?
    - Keine Fexibilität (fixe Anfangs- und Schlusszeiten)
    - Gewisses Mass an Flexibilität (flexible Anfangs- und Schlusszeiten, aber vorgegebene Anzahl Arbeitsstunden pro Tag)
    - Volle Flexibilität (flexible Anfangs- und Schlusszeiten, Wochen-, Montats- oder Jahresarbeitszeit)

11. In Ihrer derzeitigen Arbeitssituation, arbeiten Sie teilweise von zu Hause aus?
    - Ja
    - Nein

12. An wie vielen Tagen pro Woche arbeiten Sie von zu Hause?
    - 1
    - 2
    - 3
    - 4
    - 5
    - 6
    - 7

13. In Ihrer derzeitigen Arbeitssituation, wäre es Ihnen wenigstens an manchen Tagen möglich, von zu Hause aus zu arbeiten?
    - Ja
    - Nein
    - Weiss nicht

14. Wie viele Tage pro Woche könnten Sie von zu Hause aus arbeiten?
    - 1
    - 2
    - 3
    - 4
    - 5
    - 6
    - 7
    - I don't know

Die folgenden Fragen beziehen sich auf Ihre Meinungen bezüglich des Verkehrs in der Schweiz.
Manche Fragen sind ähnlich wie in der Einführungsbefragung. Dies ist mit Absicht.

15. Wie zufrieden sind Sie mit dem Verkehrssystem in der Schweiz?

	Sehr unfzufrieden	Eher unzufrieden	Weder un-zufrieden noch zufrieden	Eher zufrieden	Sehr zufrieden
Strasseninfrastruktur e					
Öffentlicher Verkehr					

16. Unten ist eine Liste möglicher Probleme, die häufig mit Verkehr in Verbindung gebracht werden, aufgeführt.
Bitte geben Sie für jedes Problem an, ob es mehr oder weniger Aufmerksamkeit von politischen Entscheidungsträgern erhalten sollte im Vergleich zum aktuellen Stand.

	Deutlich weniger Aufmerk-samkeit	Weniger Aufmerk-samkeit	Weder mehr noch weniger Aufmerk-samkeit	Mehr Aufmerk-samkeit	Deutlich mehr Aufmerk-samkeit	Ich weiss es nicht
Stau						
Treibhausgasemissionen aus dem motorisierten Verkehr						
Gesundheitliche Auswirkungen der Luftverschmutzung durch motorisierten Verkehr						
Verkehrsaufkommen an sich (Menschen reisen zu viel)						

17. Unten sehen Sie eine Liste von Faktoren aufgeführt, die durch die Verkehrspolitik definiert werden. Bitte geben Sie für jeden Faktor an, ob Sie das aktuelle Niveau als zu niedrig oder zu hoch empfinden.

	Viel zu niedrig	Zu niedrig	Weder zu niedrig noch zu hoch	Zu hoch	Viel zu hoch	Ich weiss es nicht
Mobilitätskosten im Allgemeinen						
Kapazität der Strassen						
Kapazität des öffentlichen Verkehrs						
Benzinpreis						
Preise für den öffentlichen Verkehr						

18. Unten ist eine Liste konkreter Verkehrsstrategien aufgeführt.
Bitte geben Sie an, inwieweit Sie mit diesen Strategien einverstanden sind oder nicht.

	Lehne vollständig ab	Lehne eher ab	Lehne weder ab noch stimme zu	Stimme eher zu	Stimme vollständig zu	Ich weiss es nicht
Zeit- und routenspezifische Mobilitätspreise, die durch eine Senkung anderer Steuern aufkommensneutral wären.						
Dynamische Anpassung der Geschwindigkeitsbegrenzung auf Autobahnen zur Optimierung des Verkehrsflusses.						
Zusätzliche Fahrspur auf den Hauptautobahnen.						
Reduzierung der Anzahl öffentlicher Parkplätze in Städten.						

19. Bitte geben Sie an, inwiefern Sie mit den folgenden Aussagen einverstanden sind.

	Lehne vollständig ab	Lehne eher ab	Lehne weder ab noch stimme zu	Stimme eher zu	Stimme vollständig zu	Ich weiss nicht
Die Regierung sollte genügend Strassenkapazität bereitstellen, um jederzeit die Nachfrage zu decken.						
Die Regierung sollte genügend Kapazität im öffentlichen Verkehr bereitstellen, um jederzeit die Nachfrage zu decken.						
Der Preis für die Mobilität sollte die sozialen Kosten widerspiegeln (z.B. Gesundheit, Umwelt, Stau).						
Das Verkehrsnetz sollte durch die Einführung dynamischer Preise (z.B. höhere Preise während der Hauptverkehrszeit) effizienter genutzt werden.						
Alle sollten gleich viel für Mobilität bezahlen, unabhängig davon, wann und wo sie reisen.						

20. Was sind die durchschnittlichen Privatkosten pro Kilometer für Ihre Autonutzung?
_____ Rappen

21. Inwiefern sind Sie mit den folgenden Aussagen einverstanden? Die Nutzung eines Autos, im Vergleich zum öffentlichen Verkehr, ...

	Lehne vollständig ab	Lehne eher ab	Lehne weder ab noch stimme zu	Stimme eher zu	Stimme vollständig zu
... spart Zeit					
... spart Geld					
... ist umweltschädlich					
... ist gesundheitsschädlich					
... ist angenehm					
... ist bequem					
... ist praktisch					
... macht mich flexibel/unabhängig					
... ermöglicht mir eine optimale Nutzung der Fahrtzeit					
... schützt mich vor schlechtem Wetter					
... ermöglicht es mir Gepäck zu transportieren					
...ist sicher bezüglich Unfallrisiko					
...kann zu mehr Stau führen					

Die folgenden Fragen beziehen sich auf das Forschungsprojekt MOBIS.

22. Die folgenden Fragen beziehen sich auf das Forschungsprojekt MOBIS.

	Lehne vollständig ab	Lehne eher ab	Lehne weder ab noch stimme zu	Stimme eher zu	Stimme vollständig zu
... hat mein Mobilitätsverhalten beeinflusst während der Studie					
... wird mein Mobiltätsverhalten in der Zukunft beeinflussen					
... hat mein Bewusstsein für die externen Kosten des Verkehrs erhöht					
... hat mich dazu bewegt, andere Verkehrsoptionen in Betracht zu ziehen					
... hat mich dazu bewegt, meine Autonutzung zu hinterfragen					

23. Was war Ihre Motivation, an unserer Smartphone-Studie teilzunehmen? Bitte markieren Sie alle Optionen, die zutreffen.

    - Finanzielle Belohnung
    - Interesse an Verkehrspolitik
    - Interesse an Auswirkungen des Verkehrs (Stau, Luftverschmutzung, Gesundheit,...)
    - Das Bedürfnis mehr über das eigene Mobilitätsverhalten zu lernen
    - Sonstige _____

24. Inwiefern stimmen Sie den folgenden Aussagen zu? Die Informationen, die die MOBIS E-Mails enthielten, ...

	Lehne vollständig ab	Lehne eher ab	Lehne weder ab noch stimme zu	Stimme eher zu	Stimme vollständig zu
... waren klar					
... waren interessant					
... haben mich zum Nachdenken über den Inhalt bewegt					
... waren schwer zu verstehen					

25. Wie würden Sie die externen Kosten Ihres Verkehrsverhaltens definieren?

    - Die Verkehrskosten, welche ich selber bezahlen muss.
    - Die Kosten, die von der Allgemeinheit getragen werden.
    - Die gesamten Kosten meines Verkehrsverhaltens.
    - Ich weiss nicht, was die externen Kosten des Verkehrs sind

Im Kontext unserer Studie definieren wir die externen Kosten des Verkehrs als diejenigen Kosten, welche nicht vom Verursacher getragen werden. Im Alltag müssen wir diese Kosten nicht begleichen. Die wichtigsten externen Kosten des Verkehrs sind Gesundheitsschäden infolge von Luftverschmutzung, Lärm und Unfällen; Klimaschäden infolge von Treibhausgasemissionen; und Zeitkosten infolge von Stau.
Die Kosten, die wir selber tragen, sind die privaten Kosten des Verkehrs und beinhalten Dinge wie den Kauf eines Fahrzeugs, Treibstoff oder Zugbillete, aber auch unsere eigenen Zeitkosten im Stau sowie die privaten Gesundheitsnutzen durch körperliche Aktivität (Velo fahren oder zu Fuss gehen).

26. Wussten Sie, dass Sie durch eine Veränderung Ihres Verkehrsverhaltens im zweiten Teil der Studie Geld verdienen konnten?

    - Ja
    - Nein

27. Wussten Sie, dass Sie durch eine Veränderung Ihres Verkehrsverhaltens im zweiten Teil der Studie Ihre externen Kosten des Verkehrs reduzieren konnten?

    - Ja
    - Nein

28. Aus technischen Gründen war es nicht möglich, eine Reise mit jemandem oder sich selbst als "Mitfahrer" zu kennzeichnen, obwohl dies ein wirksames Mittel zur Senkung der externen Kosten (insbesondere Staus) ist. Würden Sie Ihre Fahrten mit anderen teilen, um Ihre externen Kosten zu senken?

    - Immer
    - Oft
    - Manchmal
    - Selten
    - Nie

Die folgenden Fragen beziehen sich auf die Verwendung potenzieller Einnahmen durch dynamische Bepreisung des Verkehrs.

29. Falls dynamische Mobilitätspreise (d.h. transportmittel-, zeit- und routenspezifische Preise) eingeführt würden, was sollte mit den Einnahmen passieren?

    - Die Einnahmen sollten an die Bevölkerung zurückerstattet werden
    - Die Einnahmen sollten zur Finanzierung von Transportprojekten genutzt werden
    - Die Einnahmen sollten hälftig an die Bevölkerung zurückerstattet und für Transportprojekte genutzt werden
    - Anderer Verwendungszweck (bitte angeben) _____

30. Falls die Einnahmen an die Bevölkerung zurückfliessen sollten, welche Option würden Sie bevorzugen?

    - Rückerstattung pro Kopf (z.B. durch eine Senkung der Krankenversicherungsprämien)
    - Senkung bestehender Steuern und Abgaben für den motorisierten Verkehr (z.B. Fahrzeugsteuer)
    - Senkung von anderen Steuern (z.B. Mehrwertsteuer)
    - Senkung der Preise im öffentlichen Verkehr
    - Sonstige (bitte angeben) _____

31. Falls die Einnahmen für Transportprojekte verwendet würden, welche Art Projekte sollten dann priorisiert werden?

- Strassenprojekte
- Projekte des öffentlichen Verkehrs
- Fahrradprojekte
- Fussgängerprojekte
- Kein Verkehrsmittel soll priorisiert werden

32. Inwiefern stimmen die folgenden Aussagen mit Ihrem Lebensstil überein?

	Trifft überhaupt nicht zu	Trifft nicht zu	Trifft ein bisschen zu	Trifft vollkommen zu
Ich pflege einen gehobenen Lebensstandard				
Ich lebe gemäss religiösen Prinzipien				
Ich halte an alten Traditionen meiner Familie fest				
Ich geniesse das Leben in vollen Zügen				
Ich gehe viel aus				
Mein Leben gefällt mir dann besonders gut, wenn ständig etwas los ist				

33. Wie oft führen Sie folgende Freizeitaktivitäten durch?

	Nie	Selten	Manchmal	Oft
Kunstausstellungen oder Galerien besuchen				
Bücher lesen				
Eine überregionale Tageszeitung lesen				

34. Wenn Sie einmal in ein Restaurant richtig gut Essen gehen, wie viel geben Sie dann maxmial pro Person -inklusive Getränke- aus?
_____CHF

35. Unten sehen Sie eine Liste von 16 Werten, in Grossbuchstaben. Hinter jedem Wert ist eine Kurzbeschreibung des Werts. Bitte geben Sie an, wie wichtig jeder Wert ist für Sie als Leitmotiv in Ihrem Leben.

	Überhaupt nicht wichtig	Nicht sehr wichtig	Etwas wichtig	Sehr wichtig	Extrem wichtig
GLEICHSTELLUNG: Chancengleichheit für alle					
RESPEKT GEGENÜBER DER ERDE: Harmonie mit anderen Arten					
SOZIALE MACHT: Kontrolle über andere, Dominanz					
GENUSS: Freude, Befriedigung von Wünschen					
NATURVERBUNDENHEIT: Einklang mit der Natur					
WELTFRIEDEN: Frei von Krieg und Konflikt					
WOHLSTAND: Materieller Besitz, Reichtum					
AUTORITÄT: Das Recht zu führen oder zu befehlen					
SOZIALE GERECHTIGKEIT: Korrektur von Unrecht, Fürsorge für die Schwachen					
DAS LEBEN GENIESSEN: Geniessen von Essen, Sex, Freizeit, usw					
UMWELTSCHUTZ: Erhaltung der Natur					
EINFLUSS: Einen Einfluss haben auf Menschen und Ereignisse					
HILFREICH: Arbeiten für das Wohl von anderen					
VERMEIDUNG VON VERSCHMUTZUNG: Schutz von natürlichen Ressourcen					
SELBSTVERWÖHNUNG: Angenehme Dinge machen					
EHRGEIZ: Hart arbeiten, aufstreben					

36. Wie würden Sie Ihre Gesundheit im Allgemeinen bewerten?

- Sehr gut
- Gut
- Mittelmässig
- Schlecht
- Sehr schlecht
- Keine Angabe

MOBIS finale questionnaire (français)

Bienvenue à l'enquête finale MOBIS!
Par cette enquête, nous allons recueillir quelques informations supplémentaires à propos de vous ainsi que de divers aspects du transport. Ceci nous permettra d'effectuer des analyses approfondies des données précieuses que vous nous avez fournies tout au long de l'étude. Veuillez cliquer sur la flèche ci-dessous pour commencer.

1. Étiez-vous parti(e) de la maison pendant au moins deux jours pendant la période de l'étude MOBIS (par exemple, pour des vacances ou un voyage d'affaires)?
   - Oui, une fois
   - Oui, plus d'une fois
   - Non
2. Quand étiez-vous parti(e)?
   - De
   - À
3. Votre situation d'emploi a-t-elle changé au cours de l'étude?
   - Oui
   - Non
4. Quelle est votre nouvelle situation d'emploi?
   - Employé(e)
   - Indépendant(e)
   - Sans emploi
   - Apprenti(e)
   - Étudiant(e)
   - Retraité(e)
   - Autre
5. Quel type d'emploi avez-vous maintenant?
   - Un emploi à temps plein (100
   - Un emploi à temps partiel
   - Plus d'un emploi à temps partiel
6. Quelle est votre nouvelle charge de travail? (Pourcentage d'un emploi à temps plein)
   - 10%
   - 20%
   - 30%
   - 40%
   - 50%
   - 60%
   - 70%
   - 80%
   - 90%
7. Quelle est la charge de travail de vos emplois? (Pourcentage d'un emploi à temps plein)
   - Emploi principal :
   - Emploi secondaire :
   - Total :

8. Quel est le code postal de votre nouveau lieu de travail?
   _____

9. Quelles sont les codes postaux de vos nouveaux lieux de travail?
   - Travail principal : _____
   - Travail secondaire : _____

10. Dans quelle mesure êtes-vous capable d'organiser votre temps de travail?
    - Aucune flexibilité (heures fixes de début et de fin)
    - Flexibilité partielle (heures de début ou de fin flexibles, mais durée de travail quotidienne fixe)
    - Flexibilité totalle (heures de début et de fin flexibles, durée de travail définie par semaine, mois ou année)

11. Dans vos postes actuels, travaillez-vous depuis votre domicile (bureau à domicile, home office), du moins en partie?
    - Oui
    - Non

12. Combien de jours par semaine travaillez-vous depuis votre domicile?
    - 1
    - 2
    - 3
    - 4
    - 5
    - 6
    - 7

13. Dans votre/vos poste(s) actuel(s), avez-vous la possibilité de travailler depuis votre domicile (bureau à domicile, home office), du moins en partie?
    - Oui
    - Non
    - Ne sais pas

14. Combien de jours par semaine auriez-vous la possibilité de travailler depuis votre domicile?
    - 1
    - 2
    - 3
    - 4
    - 5
    - 6
    - 7
    - Ne sais pas

Les questions suivantes portent sur vos opinions concernant le transport en Suisse. Certaines questions peuvent s'apparenter à celles de l'enquête d'introduction MOBIS. Ceci est intentionnel.

15. À quel point êtes-vous satisfait(e) du système de transport suisse?

	Très insatisfait(e)	Plutôt insatisfait(e)	Ni satisfait(e) ni insatisfait(e)	Plutôt satisfait(e)	Très satisfait(e)
Infrastructure routière					
Transport public					

16. Vous trouverez ci-dessous une liste de problèmes potentiels généralement associés au transport.
Pour chaque problème, veuillez indiquer s'il convient de retenir plus ou moins l'attention des décideurs, par rapport au niveau d'attention actuel.

	Beaucoup moins d'attention	Moins d'attention	Ni plus ni moins d'attention	Plus d'attention	Beaucoup plus d'attention	Je ne sais pas
Congestion routière						
Émissions de gaz à effet de serre dues au trafic motorisé						
Effets sur la santé de la pollution atmosphérique due au trafic motorisé						
Degré de mobilité global (les gens voyagent trop)						

17. Vous trouverez ci-dessous une liste de facteurs définis par la politique de transport. Veuillez indiquer pour chaque facteur si vous trouvez que son niveau actuel est trop bas ou trop élevé.

	Beaucoup trop bas	Trop bas	Ni trop bas ni trop haut	Trop haut	Beaucoup trop haut	Je ne sais pas
Prix de la mobilité en général						
Capacité de l'infrastructure routière						
Capacité du transport public						
Prix du carburant						
Prix des billets de transport public						

18. Veuillez indiquer si vous êtes en accord ou en désaccord avec chaque politique.

	Pas du tout d'accord	Pas d'accord	Ni en désaccord ni d'accord	D'accord	Tout à fait d'accord	Je ne sais pas
La tarification de la mobilité en fonction du temps et de l'itinéraire, rendue neutre en termes de revenus en réduisant les autres taxes.						
Réglage dynamique de la limite de vitesse sur les autoroutes pour optimiser le flux de circulation.						
Création de voies supplémentaires sur les autoroutes principales.						
Augmentation du coût du stationnement public dans les centres-villes.						

19. Veuillez indiquer dans quelle mesure vous êtes en accord ou en désaccord avec les énoncés suivants.

	Pas du tout d'accord	Pas d'accord	Ni en désaccord ni d'accord	D'accord	Tout à fait d'accord	Je ne sais pas
Le gouvernement devrait construire une capacité routière suffisante pour satisfaire la demande en tout temps.						
Le gouvernement devrait mettre en place une capacité de transport public suffisante pour répondre à la demande en tout temps.						
Le prix de la mobilité devrait refléter le coût social (par exemple, la santé, l'environnement, la congestion).						
Le réseau de transport devrait être utilisé plus efficacement en introduisant une tarification dynamique (par exemple, des prix plus élevés en heure de pointe).						
Toutes les personnes devraient payer la même chose pour la mobilité, quels que soient le moment et le lieu où ils se déplacent.						

20. Quel est le coût privé moyen de vos déplacements en voiture par kilomètre?
_____ Centimes

21. Êtes-vous en accord avec les énoncés suivants? Comparé aux transports publics, l'utilisation d'une voiture ...

	Pas du tout d'accord	Pas d'accord	Ni en désaccord ni d'accord	D'accord	Tout à fait d'accord
... permet de gagner du temps					
... permet d'économiser de l'argent					
... est néfaste pour l'environnement					
... a des impacts négatifs sur la santé publique					
... est agréable					
... est confortable					
... est pratique					
... me permet d'être flexible/indépendant(e)					
... me permet d'utiliser efficacement mon temps de trajet					
... me protège de conditions météorologiques défavorables					
... me permet de transporter des bagages					
...est sécuritaire en ce qui concerne la circulation					
...peut augmenter les embouteillages					

22. Veuillez indiquer dans quelle mesure vous êtes en accord ou en désaccord avec les énoncés suivants. L'étude MOBIS ...

	Pas du tout d'accord	Pas d'accord	Ni en désaccord ni d'accord	D'accord	Tout à fait d'accord e
... a affecté mon comportement en matière de mobilité pendant la période d'étude.					
... continuera d'influer sur mon comportement en matière de mobilité à l'avenir.					
... m'a sensibilisé aux coûts externes du transport.					
... m'a fait envisager d'autres options de déplacement.					
... m'a fait réévaluer mon utilisation de la voiture.					
... a affecté mon comportement en matière de mobilité pendant la période d'étude.					
... continuera d'influer sur mon comportement en matière de mobilité à l'avenir.					
... m'a sensibilisé aux coûts externes du transport.					
... m'a fait envisager d'autres options de déplacement.					
... m'a fait réévaluer mon utilisation de la voiture.					

23. Quel était votre motivation pour participer à l'enquête sur smartphone? Veuillez cocher toutes les réponses qui s'appliquent.

    - La compensation financière
    - L'intérêt pour les politiques de transport
    - L'intérêt pour les impacts du transport (bouchons, pollution atmosphérique, santé ...)
    - Le désir d'en apprendre plus sur mon comportement en matière de mobilité
    - Autre (veuillez préciser) : _____

24. Êtes-vous en accord avec les affirmations suivantes? Les informations contenues dans les courriels MOBIS ...

	Pas du tout d'accord	Pas d'accord	Ni en désaccord ni d'accord	D'accord	Tout à fait d'accord
... étaient claires.					
... étaient intéressantes.					
... m'ont fait réfléchir sur le contenu.					
... étaient difficiles à comprendre.					

25. Comment définiriez-vous les coûts externes liés à votre comportement en matière de mobilité?

    - Les coûts associés à mon comportement en matière de mobilité que je dois payer moi-même
    - Les coûts imposés à la société en raison de mon comportement en matière de mobilité
    - Les coûts totaux associés à mon comportement en matière de mobilité (somme des coûts privés et sociétaux)
    - Je ne sais pas ce que sont les coûts externes liés à la mobilité.

26. Saviez-vous que vous pouviez gagner de l'argent en changeant vos habitudes de déplacement au cours de la deuxième phase de l'étude?

    - Oui
    - Non

27. Saviez-vous que vous pouviez réduire les coûts externes de vos déplacements en changeant vos habitudes de déplacement au cours de la deuxième phase de l'étude?

    - Oui
    - Non

28. Pour des raisons techniques, il n'a pas été possible de marquer un trajet comme étant du covoiturage, même si c'est un moyen efficace pour réduire les coûts externes. Avez-vous fait du covoiturage afin de réduire vos coûts externes?

    - Toujours
    - Parfois
    - Jamais
    - Souvent
    - Rarement

Les questions suivantes portent sur l'utilisation des revenus potentiels provenant de la tarification de la mobilité.

29. Si une tarification dynamique de la mobilité (c'est-à-dire des prix en fonction du mode, de l'itinéraire et du temps) était introduite, que devrait-on faire des revenus?

    - L'argent devrait être remis aux ménages.
    - L'argent devrait servir à financer de nouveaux projets liés aux transports.
    - Environ la moitié de l'argent devrait être remise aux ménages et le reste devrait être consacré à des projets liés aux transports.
    - Autre (veuillez préciser) _____

30. Si l'argent était remis aux ménages, quelle option préféreriez-vous?

    - Redistribution égale à tout le monde (par exemple, en réduisant les primes d'assurance maladie)
    - Réduction des taxes existantes et des frais reliés aux transports motorisés (par exemple, taxe sur les véhicules)
    - Réduire les taxes existantes qui ne sont pas liées au transport (par exemple, la TVA).
    - Réduction des tarifs des transports publics
    - Autre (veuillez préciser) _____

31. Si l'argent était utilisé pour des projets de transport, quel type de projet devrait en recevoir plus?

    - Projets liés au transport motorisé
    - Projets liés aux transports publics
    - Projets liés aux cyclistes
    - Projets liés aux piétons
    - Aucun mode particulier ne devrait être priorisé

32. Les questions suivantes portent sur votre style de vie et vos valeurs en général.

	Ne correspond pas du tout	Ne correspond pas	Correspond un peu	Correspond tout à fait
Je cultive un standard de vie haut de gamme				
Je vis suivant des principes religieux				
Je suis mes traditions familiales				
Je profite à plein de ma vie				
Je sors souvent				
Ma vie est particulièrement satisfaisante lorsque j'ai beaucoup à faire				

33. À quelle fréquence effectuez-vous les activités suivantes?

	Jamais	Rarement	Parfois	Souvent
Visiter des expositions ou galeries d'art				
Lire des livres				
Lire un journal national (p. ex. Le Temps)				

34. Lorsque vous allez prendre un très bon repas au restaurant, combien dépensez-vous au plus par personne?
_____CHF

35. Vous trouverez ci-dessous 16 valeurs, écrites en majuscules. Chaque valeur est accompagnée d'une brève explication. Veuillez évaluer l'importance de chaque valeur pour vous en tant que principe directeur dans votre vie.

	Pas important du tout	Peu important	Modérément important	Très important	Extrêmement important
ÉGALITÉ: opportunités égales pour tous					
RESPECT DE LA TERRE: harmonie avec les autres espèces					
POUVOIR SOCIAL: contrôle sur les autres, dominance					
PLAISIR: joie, satisfaction des désirs					
UNITÉ AVEC LA NATURE: adéquation à la nature					
UN MONDE EN PAIX: libéré des guerres et des conflits					
RICHESSE: biens matériels, argent					
AUTORITÉ: le droit de diriger ou de commander					
JUSTICE SOCIALE: corriger les injustices, prendre soin des plus faibles					
APPRÉCIER LA VIE: apprécier la nourriture, le sexe, les loisirs, etc.					
PROTÉGER L'ENVIRONNEMENT: préserver la nature					
INFLUENCE: exercer un impact sur les gens et les événements					
SECOURABLE: travaillant en vue du bien-être d'autrui					
ÉVITER LA POLLUTION: protéger les ressources naturelles					
ÊTRE BON AVEC SOI-MÊME: faire des choses agéables					
AMBITIEUX: travaillant dur, volontaire					

36. En général, comment évaluez-vous votre état de santé?

- Très bon
- Bon
- Passable
- Mauvais
- Très mauvais
- Préfère ne pas répondre

C Appendix - Communication with participants

The following section provides an overview of the communication with the participants over the course of the study, including both emails sent to the participants and the help-desk set up to respond to their questions.

C.1 Email communication

The study required constant communication with the study participants to ensure they participated as expected over the course of the study. Thus, each participant received tailored emails and reminders at each step of the study in their respective language of correspondence. Over the study period, a total of 103,071 emails were sent to 5,466 registered participants, an average of 18.9 emails per participant. A breakdown of the number of emails sent grouped by language of correspondence is shown in Table C.1.

Table C.1 – Number of emails sent by language of correspondence

Language	Emails sent	Emails sent (%)	Emails sent per person
German	66,907	64.9	18.8
French	28,184	27.3	18.8
English	7,980	7.7	19.7
Total	103,071	100.0	18.9

The date and time each email was sent was recorded and labeled with its subject and type. For example, the email could be a welcome email, a weekly report, an invitation to the final survey, information regarding the payment procedure or reminders to log into the app after registration, activate the tracking, etc. Although the actual contents of an email with a given subject and type might have changed over the course of the study, this gives a general indication of the nature of the email's content.

Table C.2 shows the number of emails sent per type. Weekly reports, reminders and emails regarding the payment of compensation account for over 70% of all emails sent to the participants. The reminder emails can be further broken down as shown in Table C.3. Reminders related to getting the participants to start using the app (reminder_installation, reminder_login, reminder_deadline) account for nearly 60% of all sent reminders. An additional 25% of reminders (reminder_tracking) were sent to participants who were not regularly tracking. These numbers show that a substantial number of the sent emails were related to the use of the tracking app.

Table C.2 – Number of emails sent by type

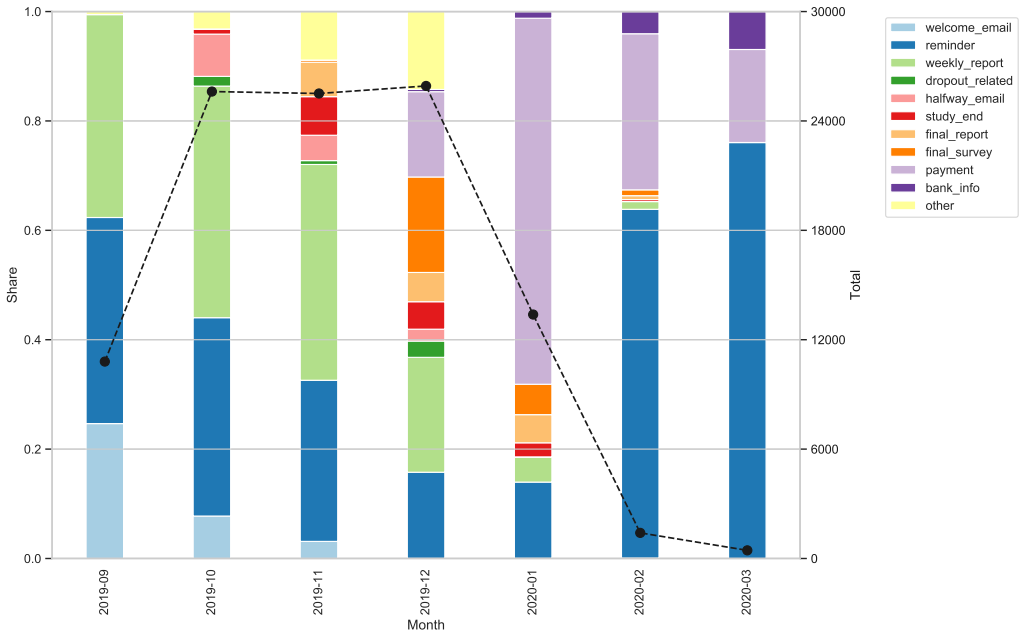
Type	Emails sent	Emails sent (%)
weekly_report	30,990	30.1
reminder	28,057	27.2
payment	13,474	13.1
other	6,826	6.6
welcome_email	5,459	5.3
final_survey	5,383	5.2
halfway_email	3,733	3.6
final_report	3,693	3.6
study_end	3,690	3.6
dropout_related	1,408	1.4
bank_info	358	0.3

Table C.3 – Share of reminder sent by type

Type	Emails sent	Emails sent (%)
reminder_installation	8,572	30.6
reminder_tracking	6,956	24.8
reminder_final_survey	4,342	15.5
reminder_login	4,337	15.5
reminder_deadline	3,586	12.8
reminder_other	264	0.9

Fig. C.1 shows the number of emails sent per study month, grouped by type, giving on good overview of the general communication procedure. During the peak months, nearly 25,000 emails per month (i.e over 800 emails a day on average) were sent to the participants.

Figure C.1 – Number of emails sent per month, per type. The dotted black line shows the total number of emails sent per month.



C.2 Help desk

Sending out emails is only one part of the communication process with the participants. Allowing participants to ask questions and raise issues is also an important part of ensuring the study progresses as planned. Thus, a help-desk service was set up for this purpose. This service consisted of both a phone line, which the participants could call during specific hours, and an email address, which the participants could write to at anytime and which was linked to the Freshdesk Customer Support Helpdesk service[61]. The help-desk consisted of three main groups:

- Student assistants (Hiwi) : 8 students hired to man the help-desk
- MOBIS: 8 members of the MOBIS project team
- Motiontag : a representative from the app developers to assist with troubleshooting

[61] www.freshdesk.com

The efficiency of the help-desk was assessed using the following performance metrics:

- number of tickets closed
- number of interactions between the participants and the agents
- time elapsed between the creation and closing of a ticket

Tickets received

Emails received via this channel were registered as tickets on the Freshdesk platform. Over the course of the study, a total of 5,218 tickets were received on the help-desk. However, some of these tickets were self-generated or consisted of automatic reply emails or spam. Excluding these, a total of 3,816 tickets sent from the participants could be accounted for.

Fig. C.2 shows the number of tickets received per study month. Most of the tickets were received in the first months of the study, with a peak occurring during the month of October 2019. This corresponds to when most participants started participating in the study and were most likely to have issues with the different parts of the study.

Figure C.2 – Number of tickets received per month via the help-desk

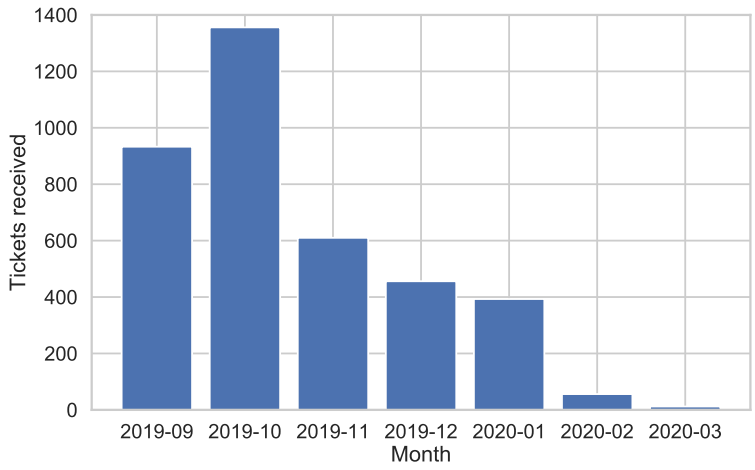


Fig. C.3 plots the distribution of the number of tickets received per day. An average of 584 tickets per month, 136 tickets per week and 19.5 tickets per day were received by the help-desk, with a maximum single day value of 131. Assuming that a ticket takes at least 5 minutes to close, 1 hour and 37 minutes would need to be allocated on average daily to resolving tickets. In the peak case, just under 11 hours would be needed for this task, clearly showing the need for an able help-desk team to tackle this workload.

Tickets closed

To aid the student assistants in resolving the tickets, a series of ready-made responses were written by the MOBIS project team and saved on the help-desk platform. The goal was to speed up the closing of similar tickets and relieve the burden on the project team.

Table C.4 shows the number of tickets closed by each agent group. The "No Agent" group refers to tickets that were closed directly, without being assigned to a specific agent or having been responded to. The data shows that the MOBIS team carried the bulk of the load, responding to over 60% of the tickets, more than twice as much as the student assistants hired specifically for the help-desk. Indeed, despite efforts to delegate as much work as possible to the students, many issues still required the expert knowledge of the members of the MOBIS project team.

Figure C.3 – Distribution of the number of tickets received per day

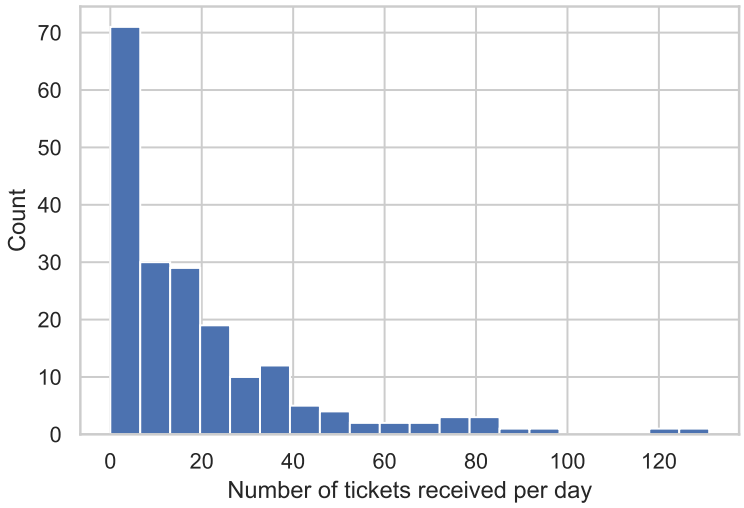


Table C.4 – Number of tickets closed by agent group

Agent group	Tickets closed	Tickets closed (%)
MOBIS	2,421	63.5
Hiwi	1,085	28.4
No Agent	264	6.9
Motiontag	45	1.2

Fig. C.4 further shows that the MOBIS project team resolved the majority of the tickets for every month except the first, and the student assistant contribution decreased as the study progressed. This was likely due to the pressure of the on-going semester, but needs to be considered when allocating resources to such a project.

Interaction with the participants

The number of interactions, that is the number of times a participant writes to the help-desk and the number of times an agent responds to a ticket, are recorded for each ticket in the dataset. Fig. C.5 shows the distribution of the number of interactions per ticket. The median value is 2 interactions, meaning the agent only needed to respond once to resolve the ticket and did not receive any further reply. This of course excludes cases where participants respond by creating a completely new ticket. The maximum number of interactions for a single ticket was 20.

Time required to close a ticket

The longer it takes to resolve a ticket, the longer the issue the participant is experiencing is likely to persist, which could potentially compromise the quality of the collected data. Depending on the nature of the issue, a delayed response can also lead to the participant losing interest and dropping out from the study. Therefore, it is important that tickets be resolved as quickly as possible.

Fig. C.6 shows the share of unresolved tickets as a function of the elapsed time since the ticket was created. Since most tickets only required 2 interactions, resolving a ticket can essentially be considered the same as simply answering it. Only about 60% of tickets were resolved within 2 days, whereas it took up to 7 days to resolve 90% of the tickets.

Figure C.4 – Share of tickets closed per agent group by month. The dotted black line shows the total number of tickets received per month.

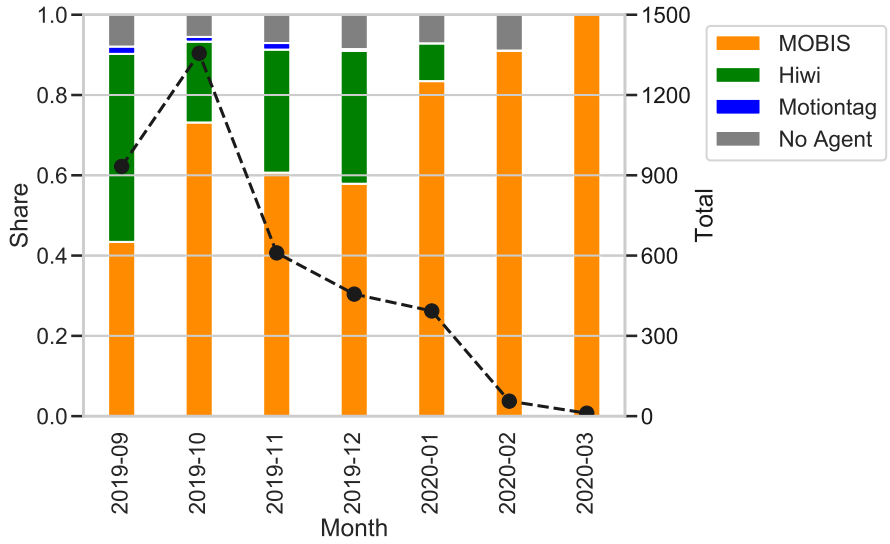


Figure C.5 – Distribution of the number of interactions per ticket

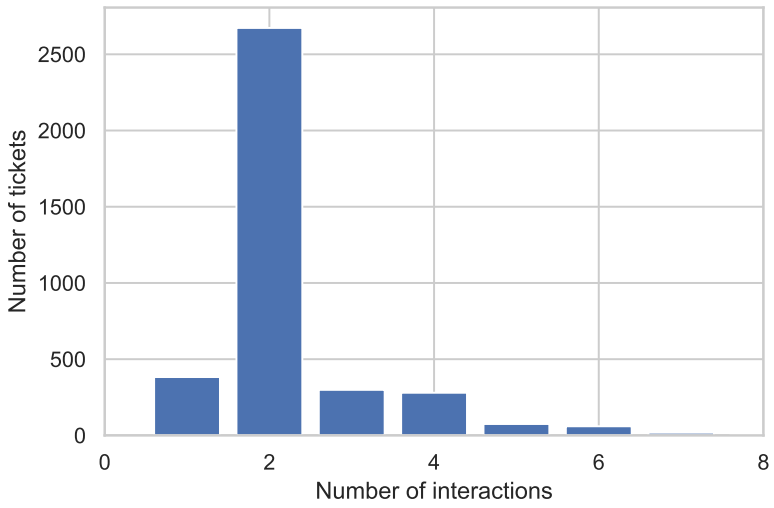
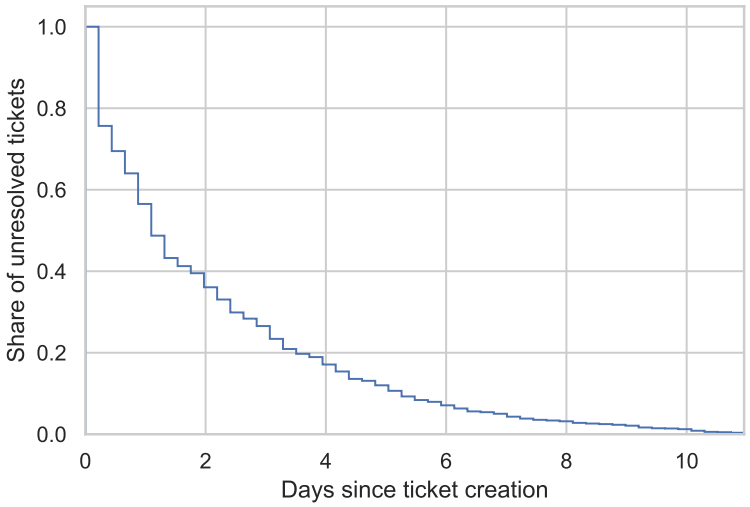


Figure C.6 – Share of unresolved tickets since ticket was created



D Appendix - Implementation issues

In this section, we describe some of the more practical problems we encountered during the experiment, and how they were solved.

D.1 Issues during recruitment

Registration

To register in the Catch-My-Day app, participants were provided with a 5-character participant ID they needed to enter as a login code, in addition to an email address and password. Many participants reported this login code to be invalid. In most cases, this was due to a misunderstanding on the participant's part, confusing login code and password. In these cases, the project team was able to manually register the participant. However, there were a few cases were participants had been provided a previously assigned participant ID, rendering the ID invalid.

App activation

To confirm their registration, participants were sent an activation link to the email address they had provided while registering. In some cases, the participants had misspelled their email addresses, meaning they had never received the activation email. A script was written to automatically detect such misspellings and activate the app for the participant.

Logging in

Once the app was activated, participants could log into the app. Some participants confused logging in with registering, others confused their password with the login code, and other simply could not remember which email address and password they had provided and were not able to request a new password through the app interface.

D.2 Issues during experiment

Participants living abroad

Although the study selection criteria clearly stated that only people living in the German- and French-speaking areas of Switzerland were allowed to participate, there were still a few participants who were tracking from abroad, without intending to return to Switzerland during the study period. After noticing this, participants who started tracking abroad were asked if they intended on returning to Switzerland during the 2-month study period. Those who did not were kindly requested to unsubscribe from the study.

Participants not tracking

A major issue during the study was participants not recording any GPS tracks for several days. If no tracks were detected for initially 2, later 3 consecutive days, an automatic email was sent to the participant, informing them to inspect both their app and phone settings. Solving this as soon as possible was crucial, as tracking issues directly result in a loss of data. However, the presence of several different mobile operating system within the study sample complicated the troubleshooting procedure. Thus, a web-based FAQ[62] was created, and made directly accessible from the app. This was regularly updated as new app-related issues were discovered and solved.

Mobile operating system updates

During the study, updates to the iOS and Android mobile operating system caused changes in how location permissions were handled, causing the app to no longer have access to the participant's location. This information, as well as the appropriate solutions for each operating system, needed to be quickly shared with the participants to ensure that the tracking could continue to function as expected.

[62] `https://ivtmobis.ethz.ch/faq/`

Participants tracking for only half the study

At the beginning of the study, participants were intentionally unaware that the study was composed of two distinct tracking phases. At first, to remain eligible for compensation, participants were required to track at least half the time over the 2-month study period to ensure that enough data would be collected in both the observation and treatment phases. Some participants took this requirement literally, tracking for the entirety of the observation phase and then stopping completely in the treatment phase. This behavior had not been expected and therefore, the requirements for compensation had to be modified during the course of the study. Participants were henceforth required to track at least 15 days per study month. Participants who failed to track sufficiently in the observation phase were automatically removed from the study, whereas participants who did not track sufficiently in the treatment phase were only offered half the promised compensation.

Payment of compensation

A form was provided at the end of the final survey in which participants could enter their bank account details. The following fields were required: IBAN, name of account holder, address of account holder, city and postal code. Since paying all participants manually would have been very time consuming, the bank account information was then compiled and sent to the ETH finance department, who could process the payment requests in bulk. However, failure of the ETH finance department to specify the exact required format of the banking details beforehand (no foreign IBAN, names and address must be less than a certain number of characters) as well as missing IBAN and postcode validation in the online form resulted in the collected data to be incompatible with the ETH finance department's data processing procedures. Therefore, a validation script was written for the provided banking data. In addition, some participants were requested to provide corrections to their banking data, further prolonging the time required for the payments.

Some participants provided the IBAN from a prepaid bank card (ex. Revolut), which could not be processed by the ETH finance department, but were initially not detected by the validation scripts.

Some participants contacted the project team, claiming to not have received their payments after the study and requesting confirmation from the ETH finance department. In all cases, the participant simply failed to see the payment on their online bank transcripts. However, this still required that the project team contact the ETH finance department to request confirmation that the payment had indeed been made.

E Appendix - Externalities pipeline

E.1 Background

Building on Pigou's two road model (Pigou, 1920), Vickery's bottleneck model (Vickrey, 1963) has become a key model for examining congestion effects in a network (Arnott *et al.*, 1993; Van Den Berg and Verhoef, 2011), as well as social-optimums via pricing (Chakirov, 2016) and pricing schemes (Laih, 1994). However, Arnott *et al.* (2001) note that traditional macroscopic models focus on link congestion, while ignoring or simplifying other elements of congestion such as modal congestion, parking, interactions with pedestrians and spill-back effects. In particular, the importance of value of time heterogeneity among individuals in road pricing models has been recognized by numerous researchers (Small and Yan, 2001; Verhoef and Small, 2004). Modern traffic microsimulation frameworks such as MATSim (Horni *et al.*, 2016b) are specifically designed to incorporate many of these various heterogeneities, making them useful for such modeling.

Fellendorf and Vortisch (2000) developed one of the first approaches for the microsimulation of pollutant emissions. A traffic flow model is used to calculate the speed and acceleration of each vehicle at a 1-second frequency, and available engine maps to calculate the emissions. More recently, Kraschl-Hirschmann *et al.* (2011) coupled the microscopic traffic flow simulator (VISSIM) with a microscopic emissions model (PHEM) to investigate the impact of traffic signaling on emissions. Ma *et al.* (2015) used the output from a travel-diary survey to build a microsimulation of Beijing, and estimated the CO_2 emissions and possible reductions.

Kaddoura and Kickhöfer (2014) developed an agent-based marginal-cost pricing approach for congestion and applied it successfully to a large-scale scenario of Greater Berlin (Kaddoura, 2015). When considering the internalization of congestion costs, a particular contribution of this work was to assign the external congestion costs to the causing agents. In particular, they note that it is simple to calculate the incurred time-loss through congestion for each agent, but much more challenging to map it back to the causing agents. The approach calculates each agent's contribution to the delays on traveled links using a queue-based node-link model including spillback.

In real networks, such an approach would require knowing the location and VTTS of every driver connected to a particular incident of congestion, to determine who was affected, and their resulting extra costs. This is clearly unrealistic as it would involve tracking a large proportion of the population.

MATSim and the Switzerland scenario

MATSim is a powerful tool for performing agent-based transport simulations. A population is represented by a set of agents who try to optimize their daily travel plan over repeated iterations of the model, through a process called re-planning. It can handle scenarios consisting of millions of agents traveling on a city, regional or national transport network. It is designed as a modular event-based framework, where the actions of agents, such as a departure, arrival, link entry or exit, are events which are passed around the framework.

This event-based design makes the traffic flow simulation framework, separate from the re-planning component, well suited for processing individual-level mobility data at the trip level. The traffic flow simulation is based on a first-in first-out queue model where each link is represented as a queue with three attributes: the non-congested (freespeed) travel time t_{free}, the flow capacity c_{flow} and the storage capacity of the link $c_{storage}$. The link queues are updated typically every second, and agents are moved from one link to the next if the freespeed travel time on the link has passed, enough time has passed since the last vehicle left the link (the inverse of c_{flow}), and there is enough capacity $c_{storage}$ on the following link. Importantly, an agent who leaves a link prevents all following agents from leaving that link for the time of $1/c_{flow}$, and the tracking of agents restricted by $c_{storage}$ on the incoming links allows the consideration of spillback on congestion.

The IVT Switzerland Scenario builds on the work of Bösch *et al.* (2016) to provide a MATSim scenario for all of Switzerland (Hörl, 2020) with a synthetic population for 2019. It represents a typical working day in Switzerland. As a MATSim scenario, the population consists of individual agents, each with daily travel plans (preferences) and social-demographic characteristics. These agents represent the entire population of Switzerland on a network generated from OpenStreetMap (Haklay and Weber, 2008). The scenario is available in 1%, 10% and 100% samples with respectively increasing runtimes (Hörl, 2020).

The simulations here are carried out using a discrete mode choice approach developed by Hörl *et al.* (2019). The initial travel demand, which comes from census data, is routed along the shortest path based on non-congested travel times. Then, at each iteration, a small fraction of agents are selected for re-planning. Each feasible mode alternative for each agent is routed along the shortest path based on the updated travel times from the previous iteration, and one is selected based on a discrete mode choice model. This process is repeated over several iterations until equilibrium.

Analysis of road transport externalities in Switzerland

Numerous sources are available for the analysis of external costs in Switzerland, including standards, government reports and databases. These sources guide and inform the evaluation of new and existing infrastructure projects. The Swiss Federal Office for Spatial Development (ARE) (Federal Office for Spatial Development, 2020) produced a report on the external costs and benefits of transport in Switzerland, built on the methodology developed by Ecoplan / Infras (2019). It presents the most recent external cost-benefit analysis for the Swiss transport system, primarily focusing on external environmental, health and accident-related costs. Specifically, external costs for 12 different cost categories are computed, differentiated according to three different perspectives: transport mode (road/rail/air/water, passenger/freight, vehicle type), transport user and heavy vehicles.

For the modeling of road transport pollutant emissions in Switzerland (and other European countries), emission factors are commonly taken from the Handbook Emission Factors for Road Transport (HBEFA) (De Haan and Keller, 2004; Keller *et al.*, 2017). The HBEFA database contains emission factors for a range of vehicle categories and traffic situations, differentiated by emission type, pollutant and year. The HBEFA is the standard for road pollutant analysis in Germany, Switzerland and Austria, and is supported by the European Commission.

The Swiss Federal Office for the Environment (FOEN) (Keller, 2010) also use the HBEFA to provide a detailed analysis of past and predicted future pollutant emissions, covering road transport in Switzerland from 1990 to 2035. Emissions values are calculated for three emissions types: emissions when the engine is in hot operating condition, cold-start emissions and evaporation emissions. The calculation of these values require both traffic volume data as well as the emissions factors from the HBEFA for each emission type. The report models the development of the vehicle fleet composition, vehicle specific mileage and emission standards trends, resulting in traffic volumes (mileage and start/stop processes) differentiated by vehicle category, emission standard and road category. These traffic volumes are then multiplied by the corresponding emissions factors (i.e. for road gradient and temperature) to obtain the final emissions values.

Concerning congestion specifically, Keller and Wüthrich estimate the external traffic delay costs for the years 2009 to 2014 (Keller and Wüthrich, 2016) and then again from 2015 to 2017 (Keller and Wüthrich, 2019). In this study, vehicle hours of delay for Switzerland were estimated and the proportion attributable to heavy vehicles determined. From 2013 onwards, this was achieved by combining and aligning INRIX traffic flow data and traffic demand data from the National Passenger Transport Model. The time lost per road section was calculated by subtracting the free-flow travel time from actual travel time, where traffic jams are considered to occur only when the actual speed is less than 65% of the free-flow speed. This approach only considers flow congestion, and not queuing delays. For the other years, online data from the Swiss Federal Roads Office (FEDRO) counting stations was used. A summary of their results is provided in Table E.1. The values provide a useful

estimate of delay costs in Switzerland. However, the use of an "at-least" approach will tend to underestimate the lost time and resulting associated delay costs (Keller and Wüthrich, 2016). This is particularly the case for non-motorway road segments, where long road lengths and imprecise speed data can influence results.

Table E.1 – Estimated congestion costs for 2010-2017

	Congestion costs (M CHF/year)						
	Motorway		Non-motorway		All roads		
Year	LMV	HMV	LMV	HMV	LMV	HMV	Both
2010	608.7	61.4	449.9	17.0	1,058.6	78.4	1,137.0
2011	634.3	63.8	454.4	17.2	1,088.7	80.9	1,169.7
2012	672.2	67.8	458.8	17.3	1,131.0	85.1	1,216.0
2013	645.7	65.5	462.7	17.4	1,108.4	83.0	1,191.3
2014	690.6	70.4	466.6	17.6	1,157.1	87.9	1,245.1
2015	736.6	71.0	468.3	17.7	1,204.9	88.6	1,293.5
2016	780.9	76.9	471.4	17.8	1,252.3	94.7	1,347.0
2017	840.6	87.6	473.8	17.9	1,314.4	105.5	1,419.9

Estimated congestion costs for Light (LMV) and Heavy Motorized Vehicles (HMV), Keller and Wüthrich (2019), p.20

For the monetization of externalities, the Swiss Association of Road and Transportation Experts (VSS) has published a series of norms (SN 641 82* : Cost Benefit Analysis for Road Traffic) aimed at guiding the assessment of monetary effects and the cost benefit analysis of transport projects, policies and regulations. Norms SN 641 820 (Basic Standard), SN 641 822a (Travel Time Costs for Passenger Traffic) and SN 641 828 (External Costs) are of particular interest in the context of external cost evaluation. They provide standard values for time costs and willingness to pay per vehicle type and trip purposes as well as standard methods for evaluating the monetary impacts of air pollution and climate impacts.

Limitations of the aggregate values

The values from the Swiss standards are only available as CHF/km or CHF/h. Although some external costs are given under a urban/rural or motorway/non-motorway classification, there is no temporal or spatial variation. One hypothesis of this paper is the following: For private car travel, the variation in external costs is significant, and justifies a disaggregate approach to the calculation of external costs. In the following work, this is done for the calculation of private car emissions and congestion delays. For noise, this was found to be too computationally expensive to do on a national scale, and hence per-kilometer values from the norms are still used. Other researchers have previously identified the usefulness of disaggregate noise models (Kaddoura *et al.*, 2017; Kuehnel and Moeckel, 2020). However, their noise calculations were carried out only on a city level and are based on the German RLS-90 approach (Bundesminister für Verkehr, 1990; Forschungsgesellschaft für des Straßenverkehr, 1997), which differs from the norms used in Switzerland.

E.2 Methodology

The approach requires that the GPS data has already been segmented into trip-stages and labeled with the transport mode used. This can be done with one of many methods. For an overview, see (Zheng, 2015). In the case of this project, the data was segmented and labeled with the transport mode by the GPS tracking app 'Catch-my-Day', developed by Motiontag AG.

The methodology requires a few static data inputs for the calculation of various externalities. Reference values for both emitted air pollutants and caused congestion are required. For the calculation of emissions, the HBEFA database (version 3.3) is required (Rexeis *et al.*, 2013). For congestion, average hourly values per link for both the delay caused by a vehicle present on that link are calculated on a 10% sample from the 2015 MATSim scenario for

Switzerland (see Appendix E.1), assigned to the respective causing links, and scaled up to 100%. This is done using the approach of Kaddoura (2015), previously described in more detail in Appendix E.1.

A multistage pipeline has been developed for imputing car-based externalities on labeled GPS traces using the MATSim framework (Horni *et al.*, 2016b). MATSim is a powerful tool for performing agent-based transport simulations. A population is represented a set of agents who try to optimize their daily travel plan over repeated iterations of the model, through a process called re-planning. It can handle scenarios consisting of millions of agents on a city, regional or national transport networks. It is designed as a modular event-based framework, where the actions of agents, such as a departure, arrival, link entry/exit are events which are passed around the framework.

This event-based design makes the core framework, without the re-planning component, well suited for processing individual level travel data at the trip level, It is on top of this framework that the following pipeline has been developed, consisting of the following steps, described in more detail below.

1. Cleaning of GPS data
2. Map matching to the MATSim network using Graphhopper
3. Calculating link entry and exit times
4. Conversion to MATSim events
5. Imputation of externalities on MATSim events
6. Monetize the externalities

The pipeline can be divided into two stages: the first creates a series of MATSim events representing the map-matched path of the GPS traces; the second processes those events using the previously mentioned reference values to impute the generated emissions and delays.

Data cleaning

GPS data accuracy can vary considerably depending on the sensor used, the surrounding environment and even geographical location. Hence, any GPS points not within 200m of a segment of the Swiss road network are removed before map matching. This is sufficient, as the Hidden Markov Model method used by Graphhopper develops a list of candidate links for each point, and then chooses the best one.

Map matching with Graphhopper

To map trip legs to the the MATSim network, the Graphhopper (Karich and Schröder, 2014) map-matching library was modified to support matching to a MATSim network instead of OpenStreetMap. Graphhopper uses a Hidden Markov Model (Newson and Krumm, 2009) to identify candidate links for each GPS point, with a error radius, σ, which in our case was set to 200m - equivalent to the filtering distance used to exclude GPS points.

An unlimited distance between consecutive points is allowed. The Graphhopper routing engine then identifies the best route between the set of candidate links, where a minimum of two matched GPS points are required. However, the standard implementation of Graphhopper does not calculate the entry and exit timestamps for each link in the network, which are needed to calculate the time spent and average speed on each link. Additionally, in the absence of high-frequency GPS measurements or additional sensor information, there may be insufficient GPS measurements to pinpoint the entry and exit times for each link. The MATSim compatible version of Graphhopper was been extended to return the entry and exit times for each link, including links where few or no GPS measurements are available.

Calculation of link entry and exit times

A trip leg contains a sequence of links L with the set of GPS points $P(l)$ matched to each link l. For convenience, let the first and last GPS point on each link in the set L be $p_{l,s}$ and $p_{l,e}$ respectively. The start and end links of a trip leg always have at least one GPS point associated with them, while other links may have none or more GPS points. Hence, trip legs are divided into sets of consecutive links L', beginning at l'_1, where $l'_{2..k}$ have no GPS points. The GPS recorded travel time over the links in L' is then proportionally allocated based on the non-congested (freespeed) travel time of each link L' for which there are no measurements, where l_{k+1} is the next non-empty link.

Let the projection of GPS point $p_{l,i}$ onto link l be $p'_{l,i}$. $t(p)$ gives the time at point p. $t\_link(l)$ gives the travel time on link l, $t\_gps(a, b)$ gives the recorded time between two GPS points a and b and $t\_network(a, b)$ gives the summed travel time over a set of links in the network. A helper function $t\_between(a, b)$ returns the time needed to travel between projected points and the vertices of a link l, traveling at the freeflow speed for that link: for example, from $p'_{l,e}$ to the end of the link; or the start of the link to the first projected point on that link $p'_{l,s}$.

In MATSim, the assumptions hold that an agent always starts and ends somewhere on a link. Hence, only the exit time for the first link and the entry time for the last link need to be calculated. Additionally, $entry\_t(l_j) = exit\_t(l_{j-1}), \forall j = 1..n$. As such, the algorithm can be separated into two cases:

- **First Link** For the first link l_1, $exit\_time(l_1) = t(p'_{l_1,e}) + t\_between(p'_{l_1,e}, l_1)$
- **Other Links**
  $entry\_time(l_j) = exit\_time(l_{j-1})$
  if $P(l_j) = \emptyset$
  then $exit\_time(l_j) = entry\_time(l_j) + t\_gps(p'_{l_{j-1},e}, p'_{l_k,s}) \cdot \frac{t\_link(l_j)}{t\_network(\{i,...,j,...,k\})}$
  where l_i and l_k are the most recent and next link with $P(l_k) \neq \emptyset$, respectively
  else $exit\_t(l_j) = entry\_t(l_j) + t\_between(l_j, p'_{l_j,e})$

The sequence of links with entry and exit times are then converted to valid MATSim events for each person and date.

Estimation of emission externalities

To estimate the externalities of each trip leg, the generated events are processed using the MATSim framework, extended with two additional modules. The first, developed by Hülsmann *et al.* (2011) and Kickhöfer and Nagel (2016), applies the HBEFA factors to calculate the emitted pollutant amounts incurred on each link, based on the observed travel speed on that link. The emissions factors are taken from the HBEFA database (version 3.3). To this module a few extensions have also been made. The module was originally designed to work with simulation output from MATSim, where real world boundary conditions (speeding) and data artifacts are not present. Hence, average speeds on each link are now capped at the freespeed of the link. Furthermore, the road types for assigning emissions factors are extracted from OpenStreetMap, rather than a VISUM model, as was done in the original Berlin Scenario. These improvements have been contributed back to the MATSim codebase, in accordance with open-source principles of the MATSim framework.

The HBEFA provides four traffic states, free-flow, heavy, saturated and stop&go, while MATSim considers only two in its queuing model - free-flow or queuing (to exit the link). Hülsmann *et al.* (2011) align these by assigning the difference between the actual travel time and the free-flow travel time on a link (the congestion) to the HBEFA stop&go traffic state, and the rest to free-flow. In doing so they ignore the heavy and saturated states. However, in the original paper, they also suggest an alternative version, which accommodates all 4 HBEFA traffic states, using the average speeds of each traffic state provided in the HBEFA. In this project, we implement this method, allowing for all 4 HBEFA traffic states to be considered in the emissions model.

The emissions module outputs quantities in non-monetized terms. These are then con-

verted to monetary damages using the most current normative values for Switzerland derived from the "Nachhaltigkeits - Indikatoren für Strasseninfrastrukturprojekte" (NISTRA) (Federal Roads Office - ASTRA, 2017). For this work, the values were revised for the year 2019, and the values used are presented in Table 6. For PM_{10} emissions, distinct normative values were available for urban and rural areas. Links in the network were assigned the rural or urban classification based on the Swiss building codes (ARE, 2017). Links in unbuilt areas were assigned as rural, and all others as urban. The assignment was done based on the midpoint of the link.

The NISTRA does not specify whether its monetization values are average or marginal. However, it is widely recognized that for air pollution costs, the marginal costs are virtually the same as the average costs, as numerous epidemiological studies have shown that the relationship between pollutants and health effects are almost linear (Van Essen *et al.*, 2019).

Estimation of congestion externalities

The calculation of the experienced delay is a simple affair, if one makes the broad assumption that all delay is attributable to other users in the system, and not external causes such as signal control, rogue pedestrians and extraordinary events. However, calculating the true caused delay to other users in the network would require GPS traces for all users of the transport network. As such we use an average model of caused delay from the output of the MATSim scenario for Switzerland. This method gives the *average* marginal external cost for traveling on each link in a certain time window.

The approach of Kaddoura and Kickhöfer (2014) is used to calculate the caused congestion on each link by an agent. The approach has a number of diverging implementations, and in this project we apply version 3, where the delays caused to each agent are allocated to the agents ahead in the queue until the delay is fully internalized. For each link in the network, the entry and exit times of each simulated agent are stored as a queue of potential delay-causing agents. Each time an agent exits a link with a delay, this queue is iterated through, and each causing agent pays for $1/c_{flow}$, the delay they caused on that link, until the delay is internalized. If an agent exits a link without delay, the previously stored queue on that link is reset. Any remaining non-internalized delay is considered to be a result of $c_{storage}$, which is carried over to the next link closer to the bottleneck and then distributed to the stored queue for that link. In this manner, the delays caused by an agent to other agents on other links in the network can be accounted for. For a specific example of how this algorithm works, the reader is referred to Section 3.2 of (Kaddoura and Kickhöfer, 2014).

A 30-hour MATSim simulation period is used to allow all trips to conclude, and the average delay caused by a vehicle for each link in the network over a set of time windows covering an entire day (24 hours) is computed. Let $x_{l,t,a}$ be the delay caused on link l at time t by agent a to all other agents in the network which might have been affected on other links. $A_{l,t}$ is the number of agents who passed through link l in time period t. The average delay caused by traveling on link l at time t is then given by

$$x_{l,t} = \frac{\sum_a x_{l,t,a}}{A_{l,t}}$$

This gives a matrix of dimensions L x $(1440/T)$ where L is the number of links in the MATSim network, and T the size of the time period in minutes. The value of 1440 corresponds to 24 hours in minutes. For a trip matched to the MATSim network, it is then trivial to obtain the average caused marginal delay on each traversed link and calculate the average marginal delay caused by the trip. In an ideal world, the time loss caused to each agent in the simulation would be monetized individually based on the value of time (VOT) of the affected agent during that trip, before the aggregation was performed. However, as this information is not contained in the MATSim scenario, congestion externalities were monetized using the Swiss reference VOT, and the monetization factor can be applied to the aggregated values.

Other external costs

Where monetization by discrete link based quantities is not implemented or possible, externalities are calculated directly using available CHF/km values. Ideally, noise emissions from car travel would be calculated based on the surrounding population, other noise emitters and the presence of noise reduction features. The Swiss norms (SN 641 828) provide decibel thresholds, above which health-related costs for the affected persons are to be considered. Using the MATSim scenario for Switzerland in a manner analogous to congestion, noise cost values per link per time could be calculated. However, it was unfeasible within the scope of this project to develop and integrate a nation-wide noise model. Instead, a normative value for noise emissions in CHF/km (differentiated by mode) is used. An in-depth spatially and temporally variant consideration of noise for all motorized modes is left as future work to improve the described methodology.

For walking and cycling modes, there are no pollutants or significant congestion externalities to calculate (at least in Switzerland, and excluding E-bikes). Hence, health benefits and damages are calculated in the pipeline on a CHF/km basis.

The pipeline is designed to support the marginal external cost calculations for other modes for which only per-kilometer values are available. Furthermore, the pipeline is adaptable to support the mapping of public transit trips to links in a MATSim transit network. This would enable the calculation of link-level congestion externalities on public transport, if data on crowding was available. Maibach *et al.* (2008) estimate crowding externalities to be roughly 50% of the VOT. However, they also note that the VOT varies greatly by transport mode, trip purpose and travel distance. The externality would also depend on the definition of "crowding".

Calibration of the congestion model

Congestion externalities were computed using the MATSim framework, as described in Appendix E.1. A 10% scenario for Switzerland for 2019 was first simulated for 40 iterations such as to reach equilibrium in terms of mode shares. Since MATSim is a stochastic simulation, this equilibrium is one within a distribution of possible outcomes. Therefore, the average caused congestion per link per time was computed as described in Appendix E.2 over a further 30 iterations, where the agents could only reroute their trips during re-planning. Delays only contribute to the average congestion if the corresponding travel speed was less than 65% of the free-flow travel speed on that link, consistent with the methodology used by Keller and Wüthrich (2016).

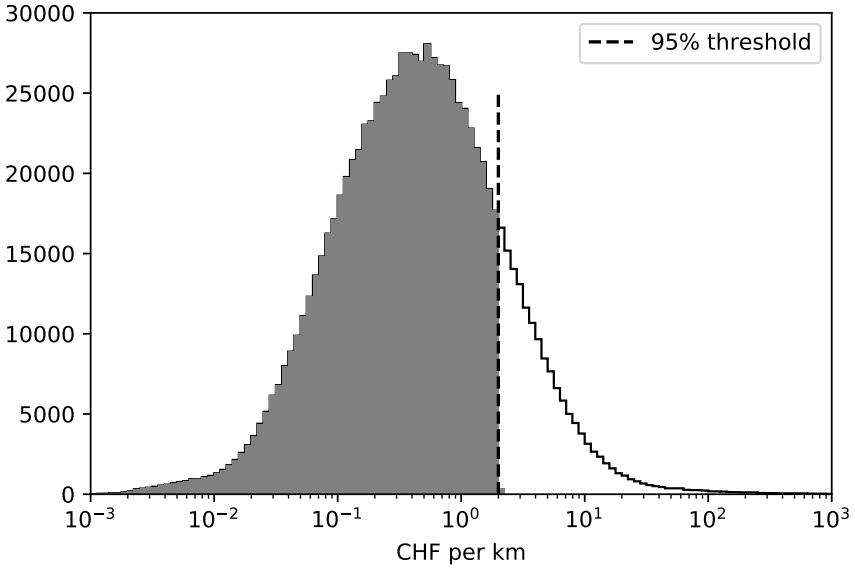
The median congestion across these additional 30 iterations was then computed and converted to a per-kilometer cost (Fig. E.1). During each additional MATSim iteration, 10% of agents are allowed to modify their chosen routes. This occasionally results in multiple agents simultaneously choosing to travel on previously non-congested links in the next iteration, and if this number of agents is large, it might take several iterations before they are randomly selected and routed along other less-congested paths. Thus, these oscillations in route choice can still result in high median congestion costs on a few links at certain times; in the current case, the maximum median cost per kilometer is nearly CHF 4,500. Therefore, the congestion costs per kilometer were capped to the 95 percentile value of the distribution, corresponding to a maximum cost per kilometer of just under CHF 2. After capping, the average cost per kilometer over all links exhibiting congestion is 0.22 CHF/km. A comparison of different capping thresholds is presented in Section E.3.

Software Architecture

To enable compatibility with both MATSim and Graphhopper, the pipeline has been built to run on the JAVA virtual machine. Java version 1.8 or above is required. MATSim version 11.0 and Graphhopper 0.12.0 are used. A script has been developed to divide the run into multiple instances of the pipeline to allow computation in parallel, allowing the expedient generation of results from the pipeline.

The input and output stages of the pipeline are also modular, meaning that data can be read or written from either a database or JSON files, allowing for the integration with different data

Figure E.1 – Distribution of per-kilometer congestion costs in the MATSim scenario with 95% threshold (log-scaled horizontal axis).



sources and other models.

The externalities pipeline described in this project takes advantage of the event-based framework in MATSim. Each module is designed as an *EventHandler* in a event-listener framework, where a function is called when certain events are fired, such as when a vehicle enters or exits a link. Sequences of these events are used to determine values such as travel times and average speeds on links. These handlers in turn generate new events such as a *WarmEmissionEvent*, containing the amounts of various pollutants produced by an agent traveling on a link.

On receiving a link-exit event, the congestion module determines the estimated congestion caused on that link based on the link id and exit time. The monetization module processes arrival events - which denote the end of a trip - to tally up all the produced externalities, and compute the monetary damages. All externalities are available on a trip leg level.

E.3 Results

Using the output of the Swiss MATSim scenario, which represents a simulated day for a synthetic population of Switzerland, the externalities pipeline is first validated by comparing the computed externalities with emission and congestion estimates from previous Swiss external cost reports. The pipeline is then applied to GPS tracking data collected within the course of the MOBIS transport pricing study (Molloy *et al.*, 2021) to demonstrate the heterogeneity in external costs that can be observed in the data.

Emissions

To validate the estimation of pollution externalities using MATSim, the total emissions are calculated using a 10% MATSim scenario for Switzerland and compared to the reference values available in the literature. To accommodate the new vehicle registration statistics according to Blessing and Burgener (2013) and Bianchetti *et al.* (2016), the personal vehicle fleet composition was adjusted to match the mileage-weighted fleet composition projected by the Swiss Federal Office for the Environment (FOEN) (Keller, 2010) for 2020 (Table E.2).

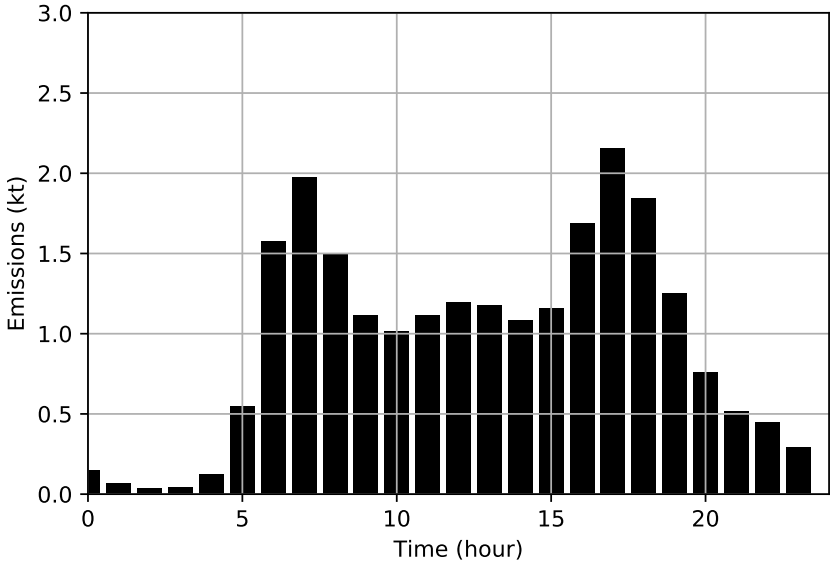
Emission values are estimated for the following pollutants: CO_2, CH_4, N_2O, PM_{10} (exhaust and non-exhaust) and NO_x. Figure E.2 shows hourly CO_2 emissions estimated from the

Table E.2 – Passenger vehicle fleet composition by emission standard (Keller, 2010)

Emission level	Mileage-weighted share Petrol	Diesel
Euro-0	0.00	0.00
Euro-1	0.00	0.00
Euro-2	0.02	0.00
Euro-3	0.03	0.01
Euro-4	0.13	0.07
Euro-5	0.13	0.11
Euro-6	0.26	0.23

MATSim scenario. As expected, these correlate with typical commuter patterns: two distinct peaks during the morning and evening rush-hour, low emissions in the morning and at night and higher values around noon.

Figure E.2 – Hourly CO_2 emissions for Switzerland



Hourly CO_2 emission values for Switzerland in kilotons (metric). Pollutants other than total CO_2 are omitted as their values are negligible in comparison.

The MATSim computed emissions values are then compared to those estimated by FOEN for 2020. Since MATSim simulates a single workday, the MATSim emissions values are scaled such as to match the total yearly travel distance by car reported by FOEN for 2020. Table E.3 compares the total estimated emissions values for both MATSim and FOEN in metric tons per year. Deviations are likely due to the fact that emissions factors depend on the exact type of petrol or diesel engine.

Congestion

Contrary to emissions, congestion caused cannot directly be estimated and assigned to the causers from GPS traces alone, since information on how many other drivers were present on the road at that given moment is lacking. Hence, MATSim is used to estimate the marginal congestion externalities during a typical workday.

To assess the suitability of this approach, we compare the total calculated congestion costs

Table E.3 – MATSim and FOEN estimated emission totals comparison

Pollutant	FOEN (tons/year)	MATSim (tons/year)	Ratio (MATSim/FOEN)
CO_2	10,167,283	8,740,076	0.86
CH_4	380	361	0.95
N_2O	159	103	0.65
PM_{10} (exhaust)	234	218	0.93
PM_{10} (non-exhaust)	2,381	2,638	1.11
NO_x	12,344	12,045	0.98

over the course of a 10% simulation of the MATSim scenario with those computed by Keller and Wüthrich (2019). As a calibration step to account for unresolved oscillation effects in the MATSim scenario, the per-kilometer congestion costs are limited to the 95% percentile (see Section E.2). The total congestion costs from the scenario are scaled to be equivalent to the total yearly travel distance reported by Keller and Wüthrich, for motorways and non-motorways respectively. The comparison between the congestion costs in the MATSim scenario for Switzerland and the reference values is presented in Table E.4 for different percentile thresholds, with the 95% percentile threshold in bold font. The corresponding per-kilometer congestion cost for each threshold is also reported.

The total yearly congestion values and thus the resulting costs estimated in MATSim for motorway and non-motorway road segments are lower respectively higher than those estimated by Keller and Wüthrich. This may be due to several factors. On the MATSim side, the model simulates passengers vehicles as well as trucks during a typical workday, and therefore does not account for seasonal variations in travel demand nor extraordinary circumstances such as large events, accidents and holiday traffic which also impact yearly congestion. Unlike emissions, which mainly depend on the total distance traveled, congestion is highly dependent on the actual demand patterns, road infrastructure and travel behavior. Thus, any deviations in the mode shares, route choice or road capacities affect the computed congestion values. In addition, the grouping of the MATSim estimates by road segment type is based on OSM data, which might differ from the classification used by Keller and Wüthrich. Finally, Keller and Wüthrich state that they have taken an "at-least" approach in estimating delays and that the values for non-motorway segments are highly underestimated. A combination of these effects likely contributes to the underlying cause of the deviation between the estimates.

Table E.4 – Comparison between reference congestion totals (M CHF) (Keller and Wüthrich, 2019) and estimates with MATSim for different per-kilometer thresholds. Ratio between MATSim and reference values in parentheses.

Road Type	MATSim						Reference
	90%	92.5%	**95%**	97.5%	99%	100%	
Motorway	245.3	284.9	**332.3**	398.0	461.5	595.3	840.6
	(0.29)	(0.34)	(0.40)	(0.47)	(0.55)	(0.71)	
Non-motorway	788.7	924.4	**1,090.0**	1,326.3	1,580.9	3,169.5	473.8
	(1.66)	(1.95)	(2.30)	(2.80)	(3.34)	(6.69)	
Total	1,034.0	1,209.3	**1,422.3**	1,724.3	2,042.4	3,764.8	1,314.4
	(0.79)	(0.92)	(1.08)	(1.31)	(1.55)	(2.86)	
Max (CHF/km)	0.84	1.23	**1.94**	3.73	7.69	4,476.58	

Sensitivity analysis

Taking the 95% percentile provides a good calibration against the overall total costs calculated by Keller and Wüthrich. However, the MATSim congestion cost estimates are sensitive to the chosen threshold. The sensitivity is evident for both motorway and non-motorway road types. We propose that this sensitivity stems from the long tail in the distribution of the per-kilometer congestion cost values (see Fig. E.1), caused at certain bottlenecks in the MATSim network for Switzerland, where route-choice oscillations result in an *all-or-nothing* switching behavior between routes. This oscillatory behavior remains an open problem. It may be that once this is solved, the thresholds are no longer needed. The sensitivity analysis suggests that before applying this methodological approach in other study regions, individual characteristics of the scenario and network need to be taken into account through a calibration step as was performed above.

Capturing the heterogeneity in external costs

As noted in the introduction, is it important to capture both the temporal, spatial, and individual variation in external costs when assessing the policy implications of proposed measures to tackle emissions and congestion. Using a set of over 1.6 million car trips collected from 3,680 participants during the MOBIS study, the external costs for each trip were calculated using the methodology presented in this section.

Fig. E.3 demonstrates the heterogeneity in external costs observed in the GPS data, as opposed to the available average per-kilometer reference values taken from Table E.5. The range of the external costs is smaller for pollution emissions than for congestion. The mean values are still consistent with the reference values. Using the map-matching computed with Graphhopper, the motorway-share of the trip is computed to allow the application of values for highway and non-highway kilometers separately, rather than just an average.

Table E.5 – Average monetization values

External cost	Value (CHF/km)
Congestion (average) [a]	0.00939
Highway	0.0206
Non-highway	0.0015
Emissions [b]	
CO_2	0.0233
PM_{10}	0.0388
NO_x	0.00939

[a] Keller and Wüthrich (2016, 2019), [b] Federal Roads Office - ASTRA (2017); Rexeis *et al.* (2013)

In Fig. E.4, the hourly variation between the two methods is compared on a trip level. In subplot (a), a roughly constant split between highway and non-highway travel throughout the day results in a nearly constant average hourly external cost with the ARE method, even during the middle of the night. On the other hand, average values with the MATSim method vary between 0 and 0.05 CHF/km depending on the time of day. Subplot (b) shows the total externalities caused over the observation period. Hence, the increase in traffic during the peak-hours does lead to some temporal variation in the total emissions with the ARE method, but much less than with the MATSim method.

In Table E.6, a summary of the external costs for different periods of the day are presented for the MATSim method. The morning and evening peaks cover 7:30am to 9:30am and 4:30pm to 7:30pm respectively. Here one can see that while the maximum marginal external costs are high (i.e. 15 CHF for one trip in the evening peak), the 95% percentile is much lower. The average external cost per kilometer in the morning peak is 1.63 times higher than the daily off-peak average, and the evening peak is 2.22 times higher. The per-trip values have similar ratios. The minimum values are not shown, being zero for all time periods.

Figure E.3 – External cost (CHF/km) by trip. The ARE congestion distribution applies a highway/non-highway classification, and hence still requires map matching to a network.

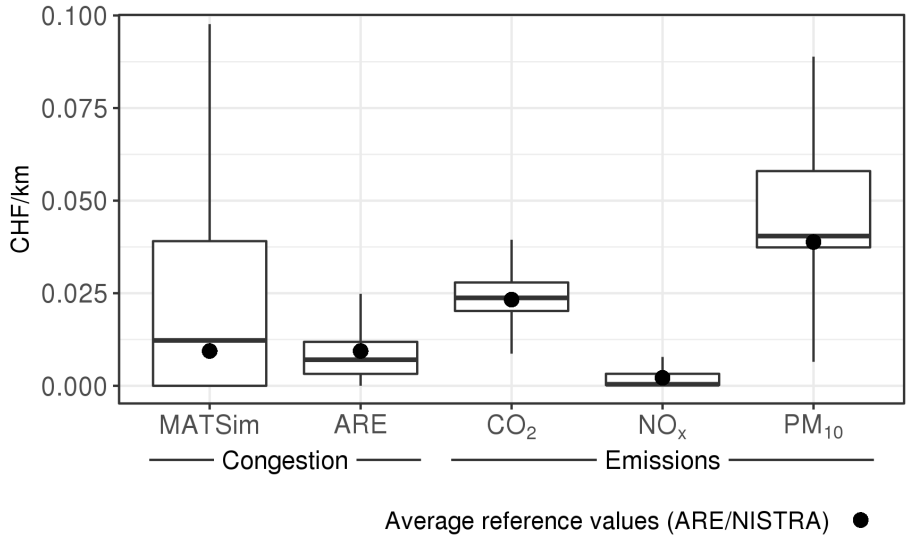


Figure E.4 – Total external cost by time of day (15 minute resolution). a) the average cost per trip at the starting time of the trip. b) The total external cost of trips starting at that time.

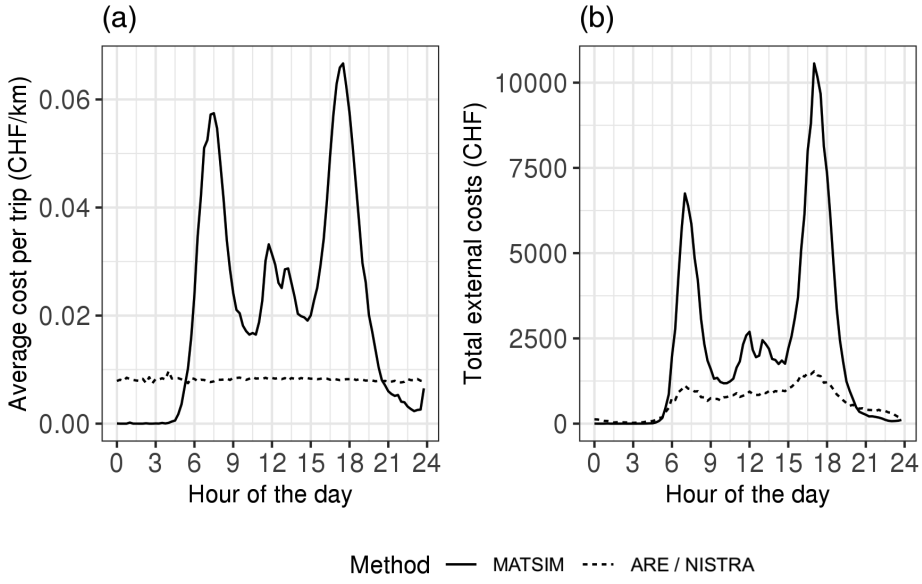


Table E.6 – Summary of congestion externalities for the MATSim-based method

	Per-Kilometer				Per-Trip			
Period	Median	Mean	95%	Max	Median	Mean	95%	Max
Morning peak	0.016	0.036	0.140	0.937	0.197	0.434	1.699	8.059
Day off-peak	0.011	0.022	0.083	0.769	0.129	0.275	1.060	13.858
Evening peak	0.029	0.049	0.169	1.056	0.328	0.652	2.384	15.363
Night off-peak	0.004	0.019	0.091	0.625	0.049	0.297	1.493	9.554

Discussion

As Verhoef (2002) stipulates, it is important to consider external costs on an individual level. Not only is this important in understanding the spatial and temporal distribution of the external costs within a transport network, it is also an important step towards understanding the potential impact of pricing policies. The method presented here shows how an agent-based transport microsimulation can be applied to real-world trip data to calculate external costs at an individual trip level. This approach captures much more variation than the use of average values.

The validation of the model in Appendix E.3 identifies some discrepancies between the reference values and the output of the proposed method, resulting from the various limitations of both approaches. However, an exploration of the trip-level heterogeneity on the real-world data indicates that the mean per-kilometer averages for both congestion and emissions are very close to the reference averages. The main insights follow from an exploration of the temporal variation captured by the congestion model. The mean values hide much of the temporal variation in external costs, and there are implications for policy analysis and transport planning. While average external cost values for congestion and emissions are currently used for the cost-benefit-analysis of new transport projects in Switzerland, the analysis in this paper shows that the respective total societal congestion costs and benefits would be distorted for policies aiming at reducing peak-hour congestion. One such policy might be a transport pricing scheme, in which using average congestion values would lead either to an ineffective price structure or the benefits of the scheme being undervalued.

The influence of the emissions model on the variation in external costs is less pronounced, but an effect is still evident. In particular, the external costs of PM_{10} emissions are a large component of the estimated externalities, and these vary greatly depending on the age, size and engine type of the vehicle (Rexeis *et al.*, 2013). These effects could be considered using the vehicle data reported by the study participants. The results indicate that reliance on the average per-kilometer values of external costs neglects the large variation around the average values, which undervalues the use of more efficient vehicles.

There are some limitations to the approach used. The performance of the map-matching step is reliant on the quality of the GPS input, the segmentation and mode detection. In a small minority of cases, the map matching is not consistent with the route chosen, which may lead to an over- or underestimation of the external costs. The assumption is also made that the owner used their reported vehicle, and not another one. Additionally, the MATSim model used to estimate the link-level external costs does not take into account other variations in demand that may affect the delay caused by a driver. These include accidents, changes in road conditions, and day-to-day variation in traffic. The external cost of scheduling delays is also not incorporated into the calculation of external costs, though this would be possible using the MATSim framework. As Arnott *et al.* (1990) note, the scheduling delay costs can be equal to the costs from congestion delays. The model also relies on the assumption that the MATSim scenario accurately reflects average conditions on the network, although thresholds were needed to account for outliers resulting from the oscillating behavior in the scenario. In future work, observed travel times and delays from real-world GPS data could be used to make link-level adjustments to the model on a day-to-day basis to account for these variations.

Projektabschluss

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Eidgenössisches Departement für
Umwelt, Verkehr, Energie und Kommunikation UVEK
Bundesamt für Strassen ASTRA

FORSCHUNG IM STRASSENWESEN DES UVEK

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Grunddaten

Projekt-Nr.:	ASTRA2017/006
Projekttitel:	Empirical Analysis of Mobility Behavior in the Presence of Pigovian Transport Pricing
Enddatum:	31.3.2021

Texte

Zusammenfassung der Projektresultate:

Die vorliegende Studie untersucht und analysiert die Wirkung eines Pigovian Transport Pricings in der Schweiz, d.h. die personalisierte Bepreisung aller externer Kosten im Verkehr. Der Kern des Projekts ist ein virtuelles Transport Pricing auf der Grundlage des beobachteten Verkehrsverhaltens der Teilnehmer des Experiments. Die empirischen Arbeiten des Projekts wurden von der ETH Zürich, der Universität Basel und der ZHAW von September 2019 bis Januar 2020 durchgeführt. Das Projekt wurde vom Swiss Competence Center for Energy Research (SCCER CREST-Mobility Joint Activity), dem Bundesamt für Strassen und dem Bundesamt für Verkehr finanziert.

Pigovian Transport Pricing ist eine fast 100-jährige Idee (Pigou, 1920; Vickrey, 1963), um die externen Kosten des Verkehrs auf ein volkswirtschaftliches Optimum zu reduzieren. Die externen Kosten sind alle gesellschaftlichen Lasten, welche nicht von den Nutzern selbst getragen werden. Im Idealfall berücksichtigt Transport Pricing alle externen Kosten: Emissionen von Schadstoffen, Lärm und Treibhausgasen, Sicherheitsrisiken und Gesundheitseffekte, Sitzplatzmangel im öffentlichen Verkehr und Stau auf den Strassen, aber auch die Betriebs- und Unterhaltskosten für die Verkehrsinfrastruktur. Die Umsetzung der Idee war technologisch lange nicht praktikabel, aber diese Hürde ist durch die Digitalisierung der letzten Jahre gefallen. Partielle Implementierungen von Transport Pricing nehmen weltweit zu, z.B. in der Form von Congestion Pricing in Singapur, London, Stockholm oder als Road Pricing auf deutschen oder französischen Autobahnen.

In der Schweiz sind bisher erst Befragungen und Verkehrsmodellstudien durchgeführt worden (Vrtic et al., 2010). Die MOBIS Studie geht einen Schritt weiter und testet die Wirkung von Pigovian Transport Pricing in einem Experiment mit 3'700 Teilnehmern in den Ballungsräumen der Romandie und der Deutschschweiz. Es ist das bis anhin grösste und umfassendste Transport Pricing Experiment im Verkehrssektor und erlaubt eine robuste Schätzung der Effektgrösse für die Agglomerationsräume in der Schweiz.

Das Design der Mobis-Studie baut einem "randomized control trial" auf. Der Kern des Experiments sind die vier Wochen, in denen die zugeteilten Informationen und Preise ihre Wirkung auf je ein Drittel der Teilnehmer entwickeln. Die Teilnehmer wurden zufällig den Interventionen ``Pricing'' und ``Information'' sowie einer Kontrollgruppe zugeteilt. Vorab wurden alle Teilnehmer vier Wochen beobachtet, sodass die Studie die Wirkung durch einen Difference-in-Differences-Ansatz unabhängig von saisonalen und anderen Einflüssen messen konnte. Geeignete Teilnehmer wurden im Rahmen einer ersten repräsentativen Befragung identifiziert und eingeladen. Die regelmässige Nutzung eines Autos (an mindestens zwei Tagen pro Woche) war eine Bedingung für die Teilnahme an der Studie. Am Ende der Studie wurde den Teilnehmern eine Anreizzahlung von CHF 100 überwiesen.

Nach der vierwöchigen Beobachtungsphase erhielt die Informations-Gruppe regelmässige Rückmeldungen über die Menge der externen Kosten, die ihr Verhalten verursacht hatte. Diese externen Kosten wurden in Geld umgerechnet und präsentiert, aber die Teilnehmer mussten nicht für diese Kosten bezahlen. Die Pricing-Gruppe erhielt für die 2. Phase es Experiments dieselben Informationen und zusätzlich ein Budget, von dem die verursachten externen Kosten abzogen wurden. Die Höhe dieses personalisierten Budgets entsprach etwas mehr als den externen Kosten der einzelnen Probanden während den ersten vier Wochen der Studie. Als Anreiz die externen Kosten ihres Verkehrsverhaltens zu senken, durfte diese Gruppe den nicht ausgegebenen Teil des Budgets behalten. In diesem Sinne wurde für diese Gruppe ein Pigovian Transport Pricing implementiert.

Das Kernergebnis der Studie ist die signifikante Reduktion der externen Kosten, welche für die Probanden in der Pricing-Gruppe beobachtet wurde. Die Teilnehmer änderten ihr Verhalten messbar durch Verschiebungen in der Routenwahl, der Wahl der Abfahrtszeit und der Verkehrsmittelwahl. Es sind insbesondere die Personen, die das Konzept der externen Kosten im Experiment verstanden hatten, welche für die Reduktion verantwortlich sind. Die kurzfristige Preiselastizität liegt bei -0.31 und damit in der Grössenordnung von Benzinpreiserhöhungen. Die Teilnehmer der Informationsgruppe zeigten ebenfalls Reduktionen, aber nicht in einem statistisch signifikanten Ausmass. Die Ergebnisse wurde in einer Reihe von Tests auf ihre Robustheit geprüft und bestätigt.

Die MOBIS Studie zeigt, dass Pigovian Transport Pricing in der Schweiz die beabsichtigten Wirkungen hätte, und dass diese durch gezielte Informationen verstärkt werden könnten. Es erscheint auch plausibel, dass längerfristige Anpassungen im Verhalten, welche in diesem Experiment nicht getestet werden konnten, zu einer verstärkten Wirkung führen würden.

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Zielerreichung:

Die Studie erreichte ihre Ziele vollständig, in dem sie mit einem grossangelegten Experiment erfolgreich zeigen konnte, dass Pigou-Preise das Verkehrsverhalten der Schweizer Bevölkerung verändern sollten. Die Grössenorderung der Veränderungen ist mit denen von Benzinpreisveränderungen vergleichbar.

Folgerungen und Empfehlungen:

Die Studie legt nahe Realexperimente in der Schweiz durchzuführen, z.B. Strassengebühren für eine Grossstadt, öV-Rabatte für Nebenzeiten auf hochausgelasteten Strecken, oder umfassende "Mobility Pricing" Ansätze. Systematische Auswertungen der vorhandenen Erfahrungen mit Preissignalen, wie z.B. Sparbillete, räumlich differenzierten Parkplatzpreisen wären wünschenswert, um die Datenbasis für die Schweizer Verkehrspolitik zu erhöhen.

Die Wirkung der Wissensunterschiede legt Informationskampagnen zur Idee der Externalität nahe, um die Mechanismen im Bewusstsein der Bevölkerung zu verankern. Es bietet sich, hier möglichst viele verschiedene Formate zu verwenden. Auch liegt es nahe mit lokalen und regionalen Experimenten zu beginnen.

Publikationen:

Die eigentlichen Ergebnisse wurden noch nicht veröffentlicht, aber befragungsmethodische und Datenerzeugungsaufsätze sind verfügbar:

Molloy, J., C. Tchervenkov and K.W. Axhausen (2018) Estimating the externalities of a sustainable mobility platform using GPS traces, paper presented at the Mobil.TUM 2018, Munich, June 2018.
Tchervenkov, C., J. Molloy, A. Castro Fernández and K.W. Axhausen (2020) MOBIS study: A review of common reported issues, paper presented at the 20th Swiss Transport Research Conference, online, May 2020
Molloy, J., A. Castro Fernández, T. Götschi, B. Schoeman, C. Tchervenkov, U. Tomic, B. Hintermann and K.W. Axhausen (2021) A national-scale mobility pricing experiment using GPS tracking and online surveys in Switzerland: Response rates and survey method results, paper presented at the 100th Annual Meeting of the Transportation Research Board, online, January 2021
Gao, Q., J. Molloy and K.W. Axhausen (2020) Trip purpose imputation using GPS trajectories with machine learning, Arbeitsberichte Verkehrs- und Raumplanung, 1574, IVT, ETH Zurich, Zurich
Molloy, J., C. Tchervenkov, Christopher and K.W. Axhausen (2021) Estimating the external costs of travel on GPS tracks, Transportation Research Part D: Transport and Environment, 95, 102842.

Der Projektleiter/die Projektleiterin:

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Unterschrift des Projektleiters/der Projektleiterin:



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FORSCHUNG IM STRASSENWESEN DES UVEK

Formular Nr. 3: Projektabschluss

Beurteilung der Begleitkommission:

Beurteilung:

MOBIS untersuchte und analysierte die Wirkungen eines Pigovian Transport Pricing in der Schweiz, d. h. die Wirkung der personalisierten Bepreisung externer Kosten auf das Verkehrsverhalten. Die Studie gilt als Meilenstein, denn sie ist die erste multimodale, randomisierte, kontrollierte Forschungsarbeit zu einer Mobilitätspreis-Intervention. Die Studie zeigt, dass Pigovian Transport Pricing funktioniert und die erwarteten Wirkungen hätte, die durch Aufklärungsarbeit verstärkt werden könnte, respektive durch eine stärkere Lokalisierung der Preise der Externalitäten, gerade auch für den öV. Das Projekt hat die Erwartungen hinsichtlich der Resultate vollumfänglich erfüllt.

Umsetzung:

Die Ergebnisse sind eine empirisch und methodisch gut abgesicherte Basis für die weitere verkehrspolitische Diskussion in der Schweiz, insbesondere für angedachte Experimente auf kantonaler oder kommunaler Ebene.

Die Analyse und Veröffentlichung der vorhandenen Daten, z. B. der SBB Sparbillette, wäre hilfreich.

weitergehender Forschungsbedarf:

Räumlich besser definierte grosse Experimente mit räumlich-zeitlich differenzierten Preisen wäre der logische nächste Schritt. Solche Experimente könnten Teil der erhofften kantonalen oder kommunalen Experimente sein.

Einfluss auf Normenwerk:

Keinen

Der Präsident/die Präsidentin der Begleitkommission:

Name: Kästli Vorname: Raphael

Amt, Firma, Institut: Bundesamt für Strassen ASTRA, Strategie und Forschung

Unterschrift des Präsidenten/der Präsidentin der Begleitkommission:

R. Kästli