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List of abbreviations

AC	Air conditioning
ADF	Augmented Dicky-Fuller
CHP	Combined Heat and Power
EQ	Electrical and ICT equipment
ESD	Energy Service Demand
ETSAP	Energy Technology Systems Analysis Program (Technology Collaboration Programme of the International Energy Agency)
EU	European Union
GVA	Gross Value Added
IFTP	Industry Food, Textile, Pulp and Paper
ICHM	Industry Chemicals
ICMN	Industry Cement and non-ferrous minerals
IBMT	Industry Basic metals (Iron and steel and non-ferrous metals)
IMMO	Industry Metal tools, machinery, other industries
ICNS	Industry Construction
LT	Lighting
LR	Long-run
MD	Mechanical drive
OECD	Organisation for Economic Co-operation and Development
ORC	Organic Rankine Cycle
OT	Others
PH	High temperature process heat
R&D	Research and Development
SH	Space heating
SR	Short-run
STEM	Swiss TIMES Energy systems Model
TIMES	The Integrated MARKAL EFOM System
WH	Water heating

1 Project goals

The objective of this project is 1) to conduct an empirical analysis of the price elasticities of natural gas and electricity consumption for Swiss industry (including sub-sectoral detail) based on historical time series, and 2) to investigate future long-term developments of the industry sector's energy demand patterns under different policy frameworks by considering demand elasticities, fuel and technology substitutions, and energy efficiency improvement measures.

2 Summary

In this project price elasticities of natural gas and electricity consumption for Swiss industry are investigated based on historic time series. In addition, future long-term developments of the Swiss industries' energy demands are analysed by employing an energy-econometric accounting framework combined with a techno-economic modelling approach. Therefore, a combination of the global macro-economic model E3ME and the Swiss energy system model STEM will be applied to conduct a multi-scenario analysis scoping on the Swiss industry.

3 Work undertaken and findings obtained

The project consists of two workpackages which are relatively independent from each other, and hence started both.

3.1 WP1: Empirical analysis of the price elasticities of energy consumption for the Swiss industry

The aim of the first work package is to estimate price demand elasticities for electricity and natural gas consumption by each industrial sub-sector for Switzerland (see Table 11 and Table 12 in the appendix).

The industrial energy price elasticities are key parameters for the modelling of future energy pathways for industry in Switzerland, to determine how industry is likely to respond following the introduction of market-based instruments, such as an energy tax, carbon tax or carbon price. In a simple modelling framework, increases in energy prices (e.g. due to a carbon tax) would have a direct impact on energy demand, as higher costs of energy would drive firms to invest in more energy-efficient equipment or to adopt more energy-efficient behaviors. Higher energy prices would also have indirect impacts, reducing the relative competitiveness of domestic industry, leading to a squeeze in production and a further knock-on impact on energy demand. Our combined E3ME-TIMES modelling approach captures both these direct and indirect channels by which energy prices impact on energy demand. The aim of this work package is to derive price elasticities of energy demand, that can ultimately be used in our combined modelling framework.

This report outlines our approach and results for estimated price elasticities in energy demand equations. Before estimating industrial energy demand equations, we undertake a literature review to inform our econometric specification and to compare previous estimates of energy price elasticities. In Section 3.1.2 a summary of price elasticity estimates from the literature is presented. In Section 3.1.3 we describe the data sources used for the estimation of Swiss energy demand and energy price elasticities. In Section 3.1.4 we explain our methodological approach and the specification of the econometric equations. Finally, in Section 3.1.5, we present the results from the econometric analysis and discuss the meaning of the results.

The text here will form the basis of Deliverable 1, which is a formal write-up of our econometric estimates of energy price elasticities.

3.1.1 Literature Review

The purpose of the literature review is twofold. Firstly, it informs our own econometric specification for energy demand equations and, secondly, it provides a robustness check for the elasticity estimates that we derive for Switzerland. The results from these studies can also be used for benchmarking our price elasticities estimates and, in particular, for comparing our top down macro level estimates to bottom up micro estimates.

There are a number of studies that have sought to estimate the price and income elasticities for household gas and electricity demand in Switzerland (see Filippini et al. (2015), Filippini (1999), Zweifel et al. (1997), Dennerlein (1990), Spierer (1988), Dennerlein and Flaig (1987)). However, we only identify one study by Mohler (2016) that has estimated price elasticities for industrial energy demand in Switzerland. There are large differences in the drivers of energy consumption among households versus industry, due to different time-preferences, energy service uses, consumption patterns and other related factors. Studies that focus on estimating price elasticities of energy demand in households are therefore not included in the scope of the literature review. Instead, we focus on studies that estimate industrial energy demand equations. Because there are limited analyses of industrial energy demand in Switzerland, we conduct a wider search for estimates of industry gas and electricity price elasticities across international sources of energy literature.

The energy studies identified use a variety of different econometric specifications, estimate over different time series, use different data sources and focus on different regions. There is also a difference in the granularity of the industrial energy demand data, with some studies using detailed firm-level data, whilst other studies estimate energy demand equations using data at a broader industry sector level. Drawing on results from the literature review, we can examine the extent to which identified price elasticities are analogous and we can begin to identify a plausible range of values for the price elasticity of industrial energy demand.

As highlighted by Madlener et al. (2011), there are surprisingly few econometric studies of industrial energy demand. Of those studies that do exist, the vast majority estimate energy demand at an aggregate industry sector level, rather than at the industrial sub-sectoral level. In fact, we only identify two studies that provide results for price elasticities at an industry sectoral level[1]. The studies that seek to estimate price elasticities of energy demand broadly fall into two groups:

- (i) studies that use logit and translog functions to estimate input factor and fuel substitution (often static in nature)
- (ii) studies that use time-series or panel data, to estimate long-run relationships between energy demand, economic activity and energy prices

3.1.1.1 Economic intuition

Most of the econometrically estimated energy demand equations include elasticity estimates with respect to economic activity and energy prices (relative to other factor costs).

Economic intuition suggests a positive relationship between economic activity and energy demand: industries will use more energy as production grows. With the existence of economies of scale and cost-efficiency improvements as industries expand, we would expect the magnitude of the elasticity on economic activity to be less than unity, implying that a scale-up in production is met by a less than proportional increase in energy consumption.

We would expect a negative relationship between real energy price and energy demand. If energy prices increase (relative to other factor inputs) then we would expect firms to respond by reducing energy inputs in favor of other factor inputs and to improve energy-efficiency through behavioral and

[1] Refer to industry-specific energy price elasticities estimated by Tamminen and Tuomaala (2012), and Madlener et al. (2011), which are presented in Table 13 and Table 14 in the Appendix, for convenience.

technological measures. The price elasticity for the aggregate energy demand equation effectively captures factor substitution effects. In those industries where it is easier to switch between factor inputs, we would expect the price elasticity of energy demand to be more elastic. In the case where fuel equations are estimated, the fuel price elasticity is dependent on the ease at which production

3.1.1.2 Energy price elasticities from the literature

The table below shows estimated price elasticities of industry energy demand, as identified in the energy literature. The interpretation of the price elasticities presented here is the percentage change in energy demand for a 1% increase in price. As shown in the table, there are a wide range of energy price elasticities that are estimated in the literature.

Table 1: Summary of findings from literature review

Study	Country	Energy carrier	Estimation method	Data	Own price elasticity estimates
L Mohler, 2016	Switzerland	All fuels	Linear logit and Translog	1997-2008	-1.03 to -0.56
Tamminen and Tuomaala, 2012	Finland	Electricity, other energy	Translog	2000-2009	Electricity: -0.98 to -1.3 Other energy: -0.83 to -1.0
Madlener et al. 2011	Germany	Electricity	Panel	1970-2007	LR: 0 to -0.5 SR: 0 to -0.57
Madlener et al. 2011	France, UK, Italy, Germany, Spain	Electricity, gas, oil	Translog	1978-2006	Various (many unintuitive)
Arnberg and Bjorner, 2007	Denmark	Electricity, other energy	Linear logit and Translog	1993, 1995-1997	Electricity: -0.19 to -0.21 Other energy: -0.23 to -0.45
Polemis, 2007	Greece	Electricity	Multivariate cointegration	1970–2004	LR: –0.85 SR: –0.35
G. Liu, 2006	OECD countries	Electricity	Dynamic panel	1978 to 1999	LR: -0.044 SR: -0.013
G. Liu, 2006	OECD countries	Natural gas	Dynamic panel	1978 to 1999	LR: -0.243* SR: -0.067*
Kamerschen & Porter, 2004	USA	Electricity	Simultaneous equations	1973–1998	–0.34 to–0.55
Bjørner et al. 2002	Denmark	Energy	Panel cointegration	1983-1997	-0.44
Beenstock et. al. 1999	Israel	Electricity	Cointegration	1975–1994	LR: –0.31 to –0.44
Bose & Shukla, 1999	India	Electricity	Pooled regression	1985/86–1993/94	–0.04 to –0.45

Madlender et al (2011) is one of the most comprehensive econometric studies of industry energy demand to date. In this study, electricity demand in Germany is estimated using a panel cointegrating approach, drawing on data over the period 1970-2007, disaggregated by industry sector. The estimated energy price elasticity for industry energy demand using this approach ranges between 0 and -0.57 in the long run (depending on the industry sector), implying that a 1% increase in energy prices could drive up to 0.57% reduction in electricity demand. To complement and compare to the panel econometric approach, Madelener (2011) also uses a translog function to estimate industry electricity, gas and oil demand at an aggregate industry level, across a selection of five EU Member States but, using the translog specification results are unintuitive and the author concludes that the results obtained from the cointegration analysis are more plausible and robust. For both estimation approaches, a specification is tested with a deterministic time trend to control for technological progress and structural changes and is found to be significant for some industry sectors.

In studies by Mohler (2016), Tamminen and Tuomaala (2012), and Arnberg and Bjorner (2007). translog functions are also used to estimate energy price elasticities and to examine the extent to which energy demand and other factor inputs are substitutes or complements. The Mohler (2016) study uses firm-level data covering manufacturing, services and retail sectors in Switzerland over the period 1997-2008. The study estimates a price elasticity of energy demand of -1.03 (for low energy intensity and high energy intensity firms) and an elasticity of -0.56 (for medium energy intensity firms). In Tamminen and Tuomaala (2012), firm-level data covering energy demand in Finland over the period 2000 to 2009 is used to estimate substitution elasticities for factor inputs across 71 sectors. The own-price elasticity of electricity demand is estimated in the range of -0.98 to -1.3, while the own-price elasticity of other energy demand is estimated to be in the range of -0.83 to -1.0 (dependent on sector). Arnberg and Bjorner (2007) use a linear logit specification to estimate price and substitution elasticities using data for 903 firms in Denmark in 1993 and over the period 1995-1997. They estimate own price elasticities in the range of -0.19 to -0.21 for electricity and in the range of -0.23 to -0.45 for other energy use.

Liu (2006) uses a dynamic panel approach (based on Arellano and Bond, one-step GMM) to estimate price elasticities for electricity and natural as using data for OECD countries over the period 1978-1999. The results of the study indicate a long run price elasticity of –0.044 (in the electricity demand equation) and a long run price elasticity of -0.243 (in the gas demand equation). A deterministic time trend was tested as a proxy for technological change but was found to be insignificant. By contrast, Polemis (2007) models aggregate oil and electricity demand for industries in Greece using a multivariate cointegration technique and estimates a long run price elasticity of –0.85, and a short-run price elasticity of –0.35.

3.1.2 Data

The key data required for our analysis incudes energy demand, economic activity and energy price data for Switzerland. Aggregate energy demand across all industry sectors in Switzerland has remained relatively stable over recent decades, however, this steady trend in energy demand at the aggregate industry level masks more complex trends in energy demand and energy-using behavior at an industry sectoral level. To best capture sector-specific effects, we estimate econometric energy demand equations at an industry sub-sectoral level. This requires data for each of the variables in the regression at the industry sector level.

The quality of the data underpinning an econometric estimation is vital to ensure the reliability and robustness of the elasticity estimates. Before estimating the price and output elasticities for industry gas and electricity demand in Switzerland, we undertook a review of available data. We compared data from alternative sources to test its reliability and credibility.

As well as ensuring good data coverage across industry sectors at the national level for Switzerland, the available time series will also affect the robustness of the econometric estimation. A longer time series increases the sample size and improves the consistency of the elasticity estimates. However, by using data over many decades, we implicitly capture behavioral relationships from far back in history. This raises questions about the appropriateness of applying our estimated energy price elasticities for forward-looking analysis, given expected changes in the relationship between energy prices and demand, due to structural change, technological progress and new policies that target industry energy-using behavior. To mitigate this risk, we consider possible indicators to control for energy-saving technological progress and we test equations using both short and longer time series data. For the forward-looking scenario analysis (in Work Package 2), we apply a detailed bottom-up model to capture deployment of different energy-saving technologies and their subsequent impact on energy demand.

3.1.2.1 Energy demand data

To capture the sector-specific characteristics of industry energy demand in Switzerland, gas demand, electricity demand and total energy demand data is required at an industry sectoral level.

For gas and electricity demand data by industry sector, we identified three key data sources:

- Bundesamt für Energie (BfE), Schweizerische Gesamtenergiestatistik (2018): gas and electricity demand by industry sector over the period 1999-2016 (annual)
- Bundesamt für Energie (BfE), Kantonsstatistik (2018): electricity consumption by canton over the period 2011-2014 (monthly)
- International Energy Agency (IEA), World Energy Balance (2018): gas and electricity demand by industry sector over the period 1960-2015 (annual)

When considering which of these data sources to use, the IEA data has the advantage of a longer time series. The BfE data, however, is more current, including data up to 2016 and some of the data is available on a monthly basis.

The IEA and BFE are both internationally-recognized reputable sources, providing the most reliable energy demand data available for Switzerland. However, there are some differences in the sector-level energy demand trends. IEA and BfE gas and electricity consumption data was compared at the sectoral level and this analysis shows that, in most cases, the two data sources reflect the same trends in energy consumption at a sectoral level (see Annex A) but there are some key differences between the two data sources, which could be due to differences in the way these indicators are measured or in the industry classification.

For this study, we run two alternative regressions. One is a shorter time-series regression uses the full available series of BfE data (over 1999-2016). We also test a longer time-series regression which uses the IEA industry energy demand data to extend the series from BfE back over the period 1970-1999. By extending the time-series we increase the sample size and improve the consistency of the econometric estimates but also include in data from further back in history, which raises questions about its relevance for capturing current and future energy-using behaviors.

3.1.2.2 Gas and electricity price data

To estimate the price elasticity of energy demand at an aggregate level, we use a weighted average energy price[2]. The energy price term in the aggregate energy demand equation includes all tax, and so captures the final price faced by industrial end users. The price term used in the aggregate energy demand equation is in real terms, to remove distortionary effects of inflation. By using the real price of energy, it can be thought of as a measure of relative energy prices, implicitly capturing substitution effects between factor inputs. For the gas share equation, the price term reflects the price of gas relative to the weighted average price of all fuels. Similarly, for the electricity share equation, the price term reflects the price of electricity relative to the weighted average price of fuels. The purpose of using a relative fuel price is to capture fuel switching effects.

[2] Fuel price weights are calculated based on the share of each fuel in total energy demand.

It is noted that there are likely to be differences in gas and electricity prices faced by different firms and across different industry sectors: those plants that consume particularly large volumes of energy can typically negotiate better deals with energy suppliers. However, due to data limitations, we use the same average industry gas and electricity price series to estimate energy price elasticities for each industry sector. It is expected that, whilst the absolute price of energy might vary slightly across industry sectors, the prices faced at the industry sectoral level should follow similar trends (as they are determined by the same underlying drivers i.e. changes in wholesale prices, distribution costs and tax). Therefore, we do not expect that our use of 'industry average' electricity and gas prices to bias our estimated energy price elasticities.

We identified two sources of data for energy prices:

- Eidgenössische Elektrizitätskommission ElCom, Tarif-Rohdaten der schweizerischen Verteilnetzbetreiber (2018): electricity prices by consumption category and canton over the period 2009-2018 (annual)
- International Energy Agency (IEA), Energy prices and taxes series (2017): industry average gas and electricity prices (with and without tax included) over the period 1978-2016 (annual and quarterly)

In this study, we use the IEA data which covers both gas and electricity prices over a longer time period.

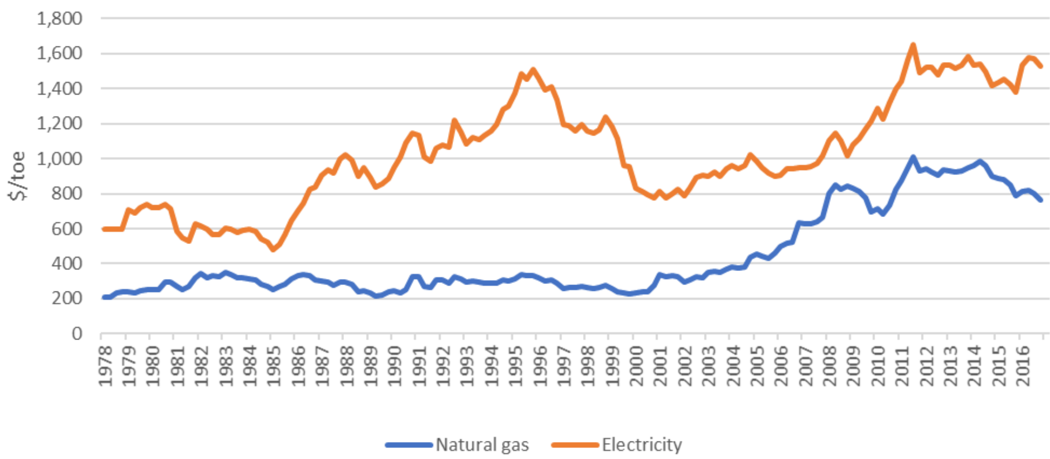


Figure 1: Swiss industry gas and electricity prices incl. tax (IEA, 2017)

3.1.2.3 Industry activity

An indicator for industrial activity captures and controls for the impact of increased level of industrial production on aggregate energy use. Two possible measures lend themselves to capturing industry activity: sectoral GVA and sectoral gross output. Each of these options for the economic activity indicator has strengths and weaknesses.

In the National Accounting System, gross output measures the total revenue of a particular sector, while GVA is defined as gross output net of intermediate costs and taxes (and so reflects the net contribution of each sector). The advantage of using GVA as an indicator of productive activity is that, unlike gross output, it does not reflect changes in the cost of other intermediate goods and services that may not impact on the energy requirements for the production process but would impact on the gross output measure of production. However, the issue with using GVA as an indicator of productive activity is that, if intermediate consumption of energy falls (e.g. due to energy efficiency improvements), then, by definition, GVA will increase, as the total cost of energy would be lower for the same level of output. This would lead to a bias in the results. To better isolate the impact of productive activity on energy demand we instead use gross output (in real terms).

We identified three data sources for industry output:

- Bundesamt für Statistik (BfS) (2018), Produktions-, Auftrags- und Umsatzstatistik im sekundären Sektor: Turnover by industry sector over the period 1991-2017 (quarterly data); GVA by industry sector over the period 2005-2017 (quarterly data)
- OECD (2018), STAN database, Value added in manufacturing over the period 1990-2016
- Eurostat: National Accounts Aggergates by Industry (*nama_10_a64)*

A combination of these sources is used to generate data over the required timeframe.

3.1.2.4 Technological progress

Increased deployment of energy-efficient technologies and industry structural changes are likely to be important drivers of future industry energy demand but are inherently difficult to capture in a top-down econometric equations. In previous studies (e.g see Madelner et al, 2011), a deterministic time trend has been included in the econometric specification as a proxy for energy saving technological progress, to capture, and control for, the effects of technological improvements and gradual changes in industry structure. An alternative approach for controlling for technological progress would be to include a measure of total spending on R&D and/or investment, which could be a good proxy for total investment in technologies and would form a quality adjusted measure of investment. Due to issues with data availability for spend on R&D and investment, we instead test a specification with a time trend as a proxy for technological progress.

3.1.2.5 Summary of data source

Table 2 below provides a summary of the key data sources and the time periods for which they are used.

Table 2: Summary of data sources used for estimation of energy demand equations (short time series)

Data/ Literature	Time series used	Sources
Energy demand	Energy Demand Data available from BfE 1999 to 2016 Energy Demand Data available from IEA from 1970 to 1999 Data from Swiss Federal Office of Energy Sector Statistics extrapolated based on growth rates for energy demand in IEA data (1970:2016)	Swiss Fedetal Office of Energy Sector Statistics (BfE, 2016 Datatable) International Energy Agency (IEA) – World Energy Balance and Energy prices and taxes series
Energy prices	Energy Prices and taxes: from 1978:2016 from the IEA Extended back from 1978 to 1970 using data from E3ME at a more aggregate level.	International Energy Agency (IEA) – World Energy Balance and Energy prices and taxes series
Industry output by sector	Index of industry output by sector from 1999 to 2017, 2010 ==1 The growth rates from data included in E3ME – which is based on Eurostat data and other sources – is used to extrapolate BfS data from 1970 to 1999	Swiss Federal Statistical Office, 'Production, order and turnover statistics in the secondary sector - quarterly time series, Index of Gross output, (BfS, 2017b). OECD STAN database Eurostat: National Accounts Aggregates by Industry *nama_10_a64*

3.1.3 Econometric methodology

3.1.3.1 Functional form

Our approach to estimation of energy demand is consistent with the equation specification used in the E3ME global macro-econometric model (CE, 2014). First, an aggregate energy demand equation is estimated, which captures the causal relationship between output, energy prices and energy demand. The price elasticity in this equation implicitly captures both energy-saving behavior and substitution to other factor inputs, following an increase in energy prices. Gas and electricity share equations are then estimated to capture fuel switching effects. A time trend is tested in some specifications, as a proxy for energy-saving technological progress.

$$\textit{Total energy demand}_i = \beta_1 \textit{ Gross Output}_i + \beta_2 \textit{ Weighted Energy Price}_i \ (+\ \beta_3 \textit{Time Trend}) + u_i$$

$$\textit{Gas share in energy demand}_i = \beta_1 \textit{ Gross Output}_i + \beta_2 \textit{ Relative Fuel Price}_i \ (+\ \beta_3 \textit{Time Trend}) + u_i$$

$$\textit{Electricity share in energy demand}_i = \beta_1 \textit{ Gross Output}_i + \beta_2 \textit{ Relative Fuel Price}_i \ (+\ \beta_3 \textit{Time Trend}) + u_i$$

The framework allows for the distinction of price elasticities for each energy user and fuel type. Individual fuel share equations are estimated for gas and electricity. These equations are intended to capture substitution between energy carriers by users on the basis of relative prices, although overall fuel use and the activity are also allowed to affect the choice. As outlined above, regressions are tested both with and without the inclusion of a deterministic time trend. We take logarithms of each variable included in the regressions, so that the parameter estimates can be interpreted as elasticities.

3.1.3.2 Functional form

The existence of stochastic trends in most economic and energy data suggests that standard regression techniques will lead to spurious regression results. We therefore use a cointegrating econometric approach, with error-correction representation, to capture both the short term dynamic, relationship between variables, as well as the longer term relationships. The econometric equations are estimated using a two-step error-correction methodology Engle and Granger (1987)[3]. In brief, the process involves two stages. The first stage is a levels relationship, whereby an attempt is made to identify the existence of a cointegrating relationship between the chosen variables. The second stage regression, known as the error-correction representation, involves a dynamic, first-difference, regression of all the variables from the first stage, along with lags of the dependent variable, lagged differences of the exogenous variables, and the error-correction term (the lagged residual from the first stage regression). Stationarity tests on the residual from the levels equation are performed to check whether a cointegrating set is obtained.

We specify equations in Error Correction form:

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \beta_2 \Delta y_{t-1} + \beta_3 (y_{t-1} - \alpha_0 - \alpha_1 x_{t-1})$$

We then use the Engle-Granger 2-stage method to estimate

1. A long run equation: $y_t = \alpha_0 + \alpha_1 x_t + \varepsilon_t$
2. An error-correction term: $ECM_t = y_t - \alpha_0 - \alpha_1 x_t$
3. A dynamic equation: $\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \beta_2 \Delta y_{t-1} + \beta_3 ECM_{t-1}$

Cointegration analyses focus on long-run movements between variables. Using the error correction specification, we can estimate the initial response in the year or two following a shock or deviations, as well as the adjustment to the long run relationship. The coefficient on the error correction term determines speed and type of return to trend relationships following an external shock to the system.

3.1.4 Unit root and cointegration tests

If the model contains a stochastic trend and the underlying time series for the variables in the regression are non-stationary, standard regression analysis will result in spurious results. In this case, it may be possible to run a regression using first-differences of each variable in the model, to convert the underlying time series to stationary series. However, this approach would lose important long-run relationships between variables that we are most interested in capturing. Instead, a cointegrating analysis can be performed if the series are all integrated of the same order, and if it is found that a linear combination of the series is stationary. Stationary linear combinations of time series suggest that those series share a common stochastic drift and trend together in the long run. In this case, the variables are said to be cointegrated.

To test for these properties of the underlying time series data we first perform a test for unit roots and then, if it is found that all of the underlying series do contain a unit root, we perform a cointegrating test to test whether there is a long-run cointegrating relationship between the variables.

An Augmented Dicky-Fuller (ADF) test is used to check presence of a unit root. The ADF tests the null hypothesis that the variable being tested contains a unit root (is generated from a non-stationary process).

Table 4 below shows the results from the ADF test on energy demand. If the absolute value of the reported test statistic, Z(t), is lower than the absolute value of all critical values reported, then the null

[3] Granger Representation Theorem states that, if a cointegrating relationship exists, then we can represent these in an error-correction model.

hypothesis cannot be rejected, the variable being tested in the Augmented Dicky Fuller test contains a unit root and was generated by a non-stationary process. For ease of interpretation p-values are also reported in parentheses. The results of the ADF test shows that, in all cases (with the exception of energy demand and gross output in Chemicals) the p value is greater than 0.05, meaning that we fail to reject the null hypothesis (at the 5% level) - the underling series contain a unit root.

Table 3: Results from unit root test on energy demand

Sector	Energy demand	Gross output	Weighted average energy price
Iron and steel	-0.79 (0.82)	-2.47 (0.12)	-1.45 (0.55)
Non-ferrous metals	-1.63 (0.46)	-2.47 (0.12)	-2.39 (0.14)
Chemicals	-2.67(0.07)	-2.80 (0.05)	-2.02 (0.27)
Non-metallic minerals	-1.31 (0.62)	-0.16 (0.95)	-0.03 (0.95)
Food and drink	-0.37 (0.91)	-0.11 (0.94)	-1.40 (0.57)
Textiles and clothing	-0.31 (0.92)	-1.91 (0.32)	-2.11 (0.23)
Paper, Paper Products	-1.72 (0.41)	0.01 (0.96)	-1.83 (0.36)
Engineering	-1.87 (0.34)	-2.40 (0.14)	-1.95 (0.30)
Other Industry	-1.66 (0.45)	-0.93 (0.77)	-2.46 (0.12)

Note(s): The critical value for the test statistic at the 1% level is -3.63; at the 5% level is -2.95 and at the 10% level is -2.61. P-values are reported in parentheses.

After identifying the presence of unit roots in the underlying data series in the model, the next step is to test that the variables are cointegrated i.e. that they trend together in the long run. We perform a cointegrating test to test for the stationarity of the residual term in the log-run residuals in the estimated equation. The results of the test indicate that, in all cases, cointegrating relationships do exist between energy prices and energy demand.

3.1.5 Results and discussion

The econometric specification, which allows for the estimation of both a short-term dynamic equation and a long-term relationship produces interesting insights for energy use in Switzerland. Parameters capture the effect of changes in gross output and energy prices on energy demand.

We test equation specifications using a shorter time series (over 1999-2016) and a long time series (over 1970-2016). We also tested specifications both with and without a time trend as a proxy to capture technological progress and structural change. We found that, in most cases, the econometric equation that was estimated using the longer time series data (over the period 1970-2016) and which included a deterministic time trend performs best, with highest explanatory power and estimated parameters that are mostly intuitive and consistent with economic theory. There are some exceptions to this finding.

3.1.6 Aggregate energy demand

Table 4 and Table 5 below present the estimated parameters (in the long run and short run) from the aggregate energy demand equation. Table 4 presents the long run relationship between energy prices (which is of most relevance for our subsequent modelling work), while Table 5 presents the immediate short-term response following a shock. In many cases, the price elasticity in the dynamic equation is not statistically significant, suggesting that, in the short term, firms do not change their level of energy use following a deviation in energy prices. In fact, in the short-term equation, we only find a statistically significant effect in the 'Paper & pulp' and 'Food, drink & tobacco' sectors, which that there is only evidence of these sectors adjusting energy use immediately following a change in energy prices. The ECM term in the dynamic equation indicates the speed of adjustment to long-run relationships (with a value of -1 indicating an immediate return to long-run behaviour within the year following the energy price shock). Our estimates for the ECM term suggest that long-run relationships between energy prices are typically reached within 1-5 years following a disequilibrium.

The parameters in the long run equation reflect the relationship between energy prices and energy use in the long run (i.e. around 5 years after any initial shock). Overall, we find larger and more significant effects in the long run equation, suggesting that most industries take time to adjust their energy-using behaviour following a change in energy prices (i.e. it takes time to change manufacturing processes and procedures or to invest in more energy-efficient equipment). The results suggest considerable heterogeneity in estimated price elasticities among industry sectors. The sector that is least responsive to a change in energy prices is 'Iron & steel', where our estimates indicate a 0.14% reduction in energy demand in the long run for a 1% increase in energy prices. By contrast, in the 'Non-metallic minerals' and 'Paper and pulp' sectors, we find that energy demand in more elastic as firms in these sectors are more responsive to a change in energy price, with an estimated price elasticity of -0.7 implying that firms in these sectors, on average, will reduce energy demand by 0.7% for a 1% increase in relative energy prices. In 'Textiles' and 'Other industry', we find unintuitive results, with an estimated positive relationship between energy prices and energy demand. In the case of 'Textiles', our parameter estimate is insignificant and could be explained by the fact that 'Textiles' is a relatively small industry sector in Switzerland with few firms operating in it. In the case of 'Other industry', our parameter estimate is large in magnitude, statistically significant and positive. 'Other industry' is a very heterogenous sector, as a catch-all for industries that are not elsewhere classified. It is therefore highly likely that our unintuitive result for this sector is explained by factors and structural change within the sector that cannot be adequately controlled for in our estimated equation.

Table 4: Estimated parameters in long run energy demand equation (specification including time trend)

	Gross Output	Weighted Average Fuel Price	2009 dummy variable	Time trend	Constant/ Intercept
Iron & steel	0.20**	-0.14**	-0.19**	0.02**	4.52**
Non-ferrous metals	-0.40**	-0.37*	-0.60**	-0.03**	9.89**
Chemicals	0.45**	-0.25**	-0.15*	-0.01	6.54**
Non-metallics nes	0.70**	-0.74**	0.09	0.01**	5.76**
Food, drink & tob.	0.94	-0.26	0.20	0.05**	1.04
Tex., cloth. & footw.	-0.81**	0.03	-0.28	-0.05**	9.17**
Paper & pulp	1.27**	-0.71**	-0.15	0.03**	3.47
Other industry	-2.74**	1.10**	0.02	0.03**	10.78**

** indicates statistically significant at 5% level
* indicates statistically significant at 10% level

Table 5: Estimated parameters in short run dynamic energy demand equation

	Gross Output	Weighted Average Fuel Price	2009 dummy variable	Lagged change in total energy demand	Lagged residual (ECM term)	Constant/ Intercept
Iron & steel	0.47**	0.05	-0.14**	0.05	-0.61**	0.02**
Non-ferrous metals	-0.40	-0.10	-0.34**	0.39**	-0.36**	-0.02
Chemicals	0.43**	-0.15	-0.10**	0.54**	-1.22**	-0.03
Non-metallics nes	-0.32	-0.04	0.22**	0.16	-0.32**	0.03
Food, drink & tob.	2.47	-0.60**	0.06	-0.10	-0.24**	0.04
Tex., cloth. & footw.	0.32	0.13	-0.08	-0.24	-0.09	-0.01
Paper & pulp	0.05	-0.42**	-0.20**	0.11	-0.52**	0.02
Other industry	0.06	0.04	0.01	0.09	-0.22*	0.01

** indicates statistically significant at 5% level
* indicates statistically significant at 10% level

In Table 6, we compare our estimated price elasticities to those in other studies and find that our estimates are in a similar range to those estimated for industry sectors in other regions, but typically towards the lower-end of the range.

Table 6: Estimated energy price elasticity from our study compared to other studies

	Weighted average fuel price (Switzerland- this study)	L. Mohler (2016) - Switzerland	Polemis (2007) - Greece	Bjoerner and Jensen (2002) - Denmark
Iron and steel	-0.14	Low energy intensity firms: -1.03* Medium energy intensity firms: -0.56 High energy intensity firms: -1.03	-0.85 to -0.35	Average energy price elasticity of -0.44
Non-ferrous metals	-0.37			
Chemicals	-0.25			
Non-metallic minerals	-0.74			
Food and drink	-0.28			
Textiles and clothing	0.03			
Paper and pulp	-0.71			
Other industry	1.10			

3.1.7 Fuel shares

In addition to the aggregate energy demand equation, we have also estimated equations for the share of (i) gas and (ii) electricity in total energy demand. In these cases, our estimated elasticities reflect the effect of changes in the price of gas (or electricity) relative to the price of other fuels. They therefore capture a fuel switching effect. We find our results for the fuel share equations are often insignificant or less intuitive and are harder to explain. This is particularly the case in the gas share equations.

In the electricity share equations, we estimate price elasticities that are statistically significant when using data for Germany with a long time-series and time trend included (as shown in Table 6, below). However, in this case, the magnitude of the elasticity estimate is quite low- between -0.1 to -0.3. Our results for Switzerland are typically insignificant (see Table 7), even when testing alternative specifications (i.e. with/without a time trend) and using different lengths of time-series data. The low elasticities estimated in the case of Germany, and insignificant results for many industries in Switzerland, suggests that there is little evidence of fuel switching following a change in the relative price of fuels.

Table 7: Estimated electricity price elasticities in Switzerland and Germany

	Electricity price elasticity - Switzerland	Specification	Electricity price elasticity - Germany	Specification
Iron and steel	0.00	LS/TT	-0.08	LS/TT
Non-ferrous metals	-0.01	LS/TT	-0.22*	LS/TT
Chemicals	0.20	LS/TT	-0.14	LS/TT
Non-metallic minerals	-0.39	LS/TT	-0.29*	LS/TT
Food and drink	0.00	LS/TT	-0.23*	LS/TT
Textiles and clothing	-0.13**	LS/TT	-0.28*	LS/TT
Paper and pulp	-0.22**	LS/TT	-0.23*	LS/TT
Other industry	-0.08*	LS/TT	x	LS/TT

Note(s): SS – 'Short time series'; LS – 'long time series'; TT- 'inclusion of time trend'
* indicates statistically significant at 5% level

3.2 WP2: Investigation of future long-term developments of the Swiss industrial energy demand

3.2.1 General overview and scope

In WP2, we conduct a forward-looking analysis (until 2050) for investigating long-term energy demand for the Swiss industrial sector, for which we improve and apply the Swiss TIMES Energy systems Model (STEM) (Kannan and Turton, 2014). STEM is a technology-rich bottom up energy systems model for Switzerland which operates under a cost-optimisation framework with a long-term perspective. For the analysis of the Swiss industrial energy technology developments, the representation of the industry sector in STEM has been improved within the scope of this project. Initially, STEM distinguishes six industrial subsectors with energy service demands (industrial energy usages) for each sub-sector.

We started with task 1 of WP2 which deals with advancements regarding the representation of the industry sector in STEM. The focus of the advancements are model re-calibration to recent energy/statistical data, further disaggregation of industrial sub-sectors and inclusion of new/emerging technologies specific to certain industrial subsectors. A first major step in 2018 was the recalibration of STEM, i.e. update the model input data according to latest available statistics, as well as improvement in technology parameters.

3.2.2 STEM model recalibration

Our re-calibration and re-analysis of industry sub-sectoral is based on the annual energy data from the Swiss Federal Office of Energy (BFE, 2016a; 2016b); and supplemented by the International Energy Agency's (IEA, 2017) publication on the sub-sectoral industry related energy consumption for Switzerland. For example, we use data from the IEA (2017) on the energy consumption in 13 industrial sub-sectors by fuel type in combination with statistical data on energy end-use based on BFE (2016a). The aim of the re-calibration is to better represent the recent trends in industrial energy use pattern[4]. For the model calibration, we disaggregate annual energy balances for the different industrial subsectors to derive energy service demand at sub-sectoral level. Year 2014 is the latest data year, for which a comprehensive set of required data are available[5]. In the BFE (2016b) data, the industrial sector is divided into 12 different branches with a division oriented to the NOGA classification - the official general classification of economic activities of the Swiss Federal Statistical Office (BFS). Information on the total amount of different fuels consumed by the industrial sector is taken from BfE (2016b), which provides data on the type of usage of fuel and electricity for end use application such as space heating or process heat. This source also entails data on how the final energy for each service demand is allocated to the industrial sub-sectors.

Accounting of cogeneration (or combined heat and power generation (CHP)) technologies is treated differently in the energy balances of IEA and BfE. We consider in our calibration and sectoral disaggregation, that for cogeneration, only the 'on-site' energy commodities used for generation of heat and electricity consumed are accounted as industrial energy usage as in BfE (2015a). Electricity generated by thermal applications in different industry sectors as well as the corresponding fuels consumed by cogeneration applications is derived from BfE (2015a). This source also provides data on the types of cogeneration units, an indication of their location (canton) and their capacities. We use this information to allocate the heat from cogeneration to the subsectoral level according to main industrial activities identified for the respective cantons. For further detailed cogeneration data we consider

[4] The re-calibration is not limited to the industrial sector, but other end use sectors and supply sectors have also been updated.
[5] Swiss energy consumption is available for 2017. However, some data are not yet available at sub-sectoral level or their application by end use.

insights from Rossi (2013) who analyzed CHP application in the Swiss industry and disaggregated process heat demand to different temperature levels.

In 2014, the industrial sector accounted for 19% (157 PJ) of the total final energy consumption in Switzerland. Natural gas (42%) and electricity (24%) together represent two thirds of the total fuel consumption in industry (Figure 2). Almost half of the total fuel consumption is used for the generation of process heat, as shown in Figure 2.

Compared to initial version of the STEM model (Kannan and Turton, 2014), now we reorganize the representation of industrial sub-sectors differently. For example, in the initial version of STEM, food, textile and pulp and paper sectors were lumped together as IFTP sector. Now food and pulp and paper are modelled as separate subsectors, while the textile subsector is merged with the other sub-sectoral category. Figure 3 shows the energy consumption based on our new industrial sectoral clustering, i.e. seven disaggregated industrial subsectors.

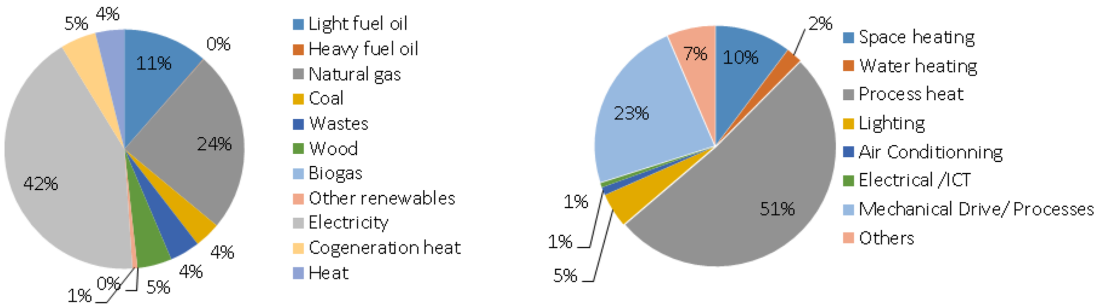


Figure 2: Final Energy consumption industry in 2014 by fuel (left) and by type of energy service demand (right)

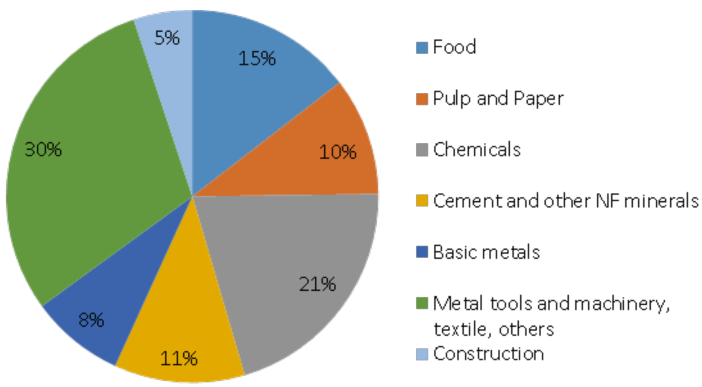
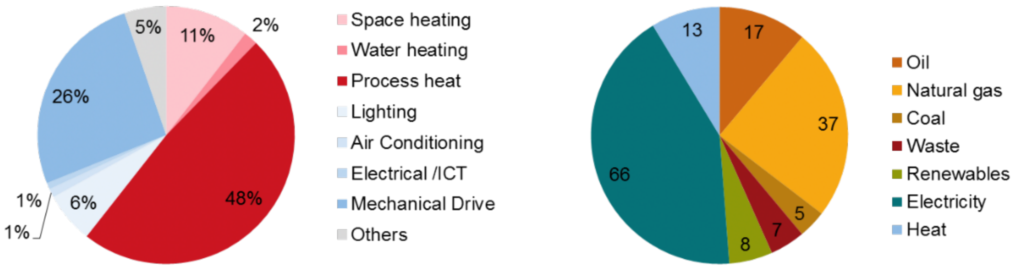


Figure 3: Final Energy consumption industry in 2014 by branches

Besides the aggregate of machinery, textile and other industries, which represents 30% of the total final consumption of the industry sector, chemical (21%) and food production (15%) are the second and third largest industry subsectors with respect to their share in final energy consumption. Each, the pulp and paper and cement & other nonferrous minerals subsectors has a share of about one-tenth of the industry sector's final energy consumption. The disaggregation of the industry sector in STEM depends on multiple factors, including available statistical indicators and figures as well as prospective data on demand developments, technology data, etc., which all will be taken into consideration for determining model further developments as envisaged in work package 2. In the following section, we describe the development of the industrial subsector in STEM within the framework of this project in 2018.



Note: ICT: Information and communication technologies

Figure 4: Energy consumption in industry in 2014 (by energy service demand (left) and by fuel in PJ (right)

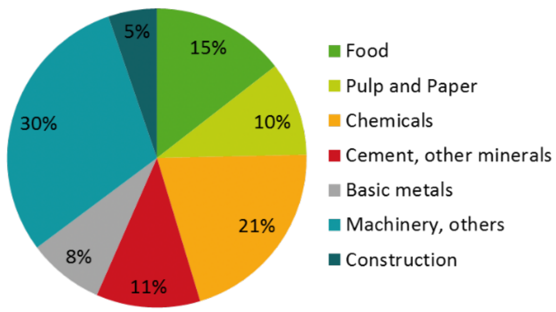


Figure 5: Share of industrial branches in end energy usage in 2014

3.2.3 Modelling the industrial subsectors

The branches of relevant are characterized in terms of their structure and relevant production properties. We refine the iteratively derived split of fuel consumption into different Energy Service Demands (ESDs) that we include in STEM for each branch. Furthermore, energy-related characteristics are incorporated in the model, e.g. temperature levels of process heat demand. We include new and emerging technologies that hold potential for being used in the respective branches. Other energy saving options such as the improvement of existing technologies and process-related measures are identified. For refining the industrial sector, we divide the industrial final energy demand into seven branches, as described in section 3.2.2. We use the 2014 data to orient the calibration year 2015.

3.2.3.1 Food industry

The food industry was the second largest consumer of the Swiss industrial energy in 2014 (Figure 3). Figure 6 shows the energy consumption in food industries (IEA, 2017). Process heat accounted for most final energy demand, followed by mechanical drives (Figure 8). Natural gas is the main energy carrier for process heat production, while the other energy demands were mainly satisfied using electricity. Overall, over 40% of the ESDs were satisfied by using electricity, while the usage of natural gas provided another 40% of the energy demand. Based on Hofer (1994), approximately 3% of the electricity in the food industry is used for process heat, for example in baking. Cooling in the food industry accounts for 28% of the electricity demand (Eichhammer et al., 2009), while another 30% is used for mechanical drives. The rest is split between process technology, pumps, ventilation and air compression. Based on this assumption, we estimated the ESDs in the food industry.

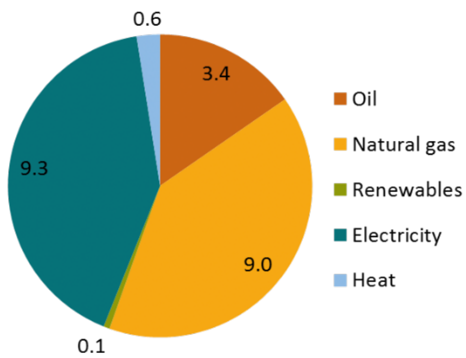


Figure 6: Final energy consumption of the food industry (PJ) (International Energy Agency, 2014), own calibration

Table 8 summarizes the key processes in the food industry and their temperature levels. We constrain our model in such a way that a realistic representation of the process heat demand is ensured, even though processes are not modeled explicitly. For example, the process heat demand over 140°C is mainly used for baking and therefore, must be provided with appropriate oven systems.

Process	Temperature [C°]
Drying	30 – 90
Washing	40 – 80
Pasteurizing	80 – 110
Boiling	95 – 105
Sterilizing	140 – 150
Heat treatment	40 – 60
Baking	150 – 300

Table 8: Temperature levels of main processes in food industry

In terms of end use application, a quarter of the heat demand in the food industry can be attributed to space heating (SH) and hot water (WH), while another 40% of the heat demand is process heat (PH) lower than 100°C (Figure 7). The remaining 35% of the heat demand accounts for process heat between 100 °C and 300 °C, of which only a small share occurs over 140 °C.

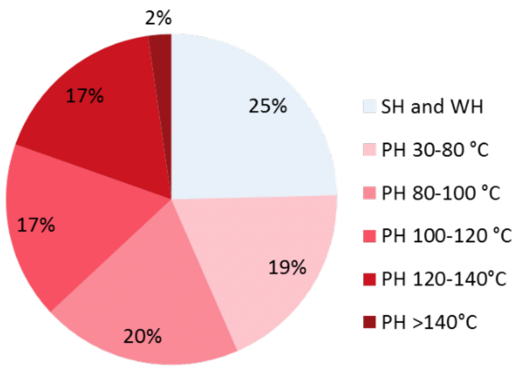


Figure 7: Temperature level of heat demands in the food industry (Rossi (2013); Rudolph and Wagner (2008)

Electric motors, compressors and refrigeration systems have potential to recover heat at temperatures between 30˚C to 70˚C. We consider a range of low temperature heat recovery technologies such as, heat pumps and organic Rankine cycles. Furthermore, the installation of absorption and adsorption chillers and the usage of solar energy for the generation of low temperature heat is enabled. A detailed description of technologies included in the analysis is provided in Section 3.2.4. Apart from the installation of waste heat recovery technologies and solar thermal systems, a promising measure is the usage of food processing residues as an energy resource. Based on the Federal Office of the Environment (2017a), food residuals in Switzerland accounted for 20% of the overall production, which is equivalent to 500,000 t/year. We derive a theoretically potential for waste energy based on methane yield.

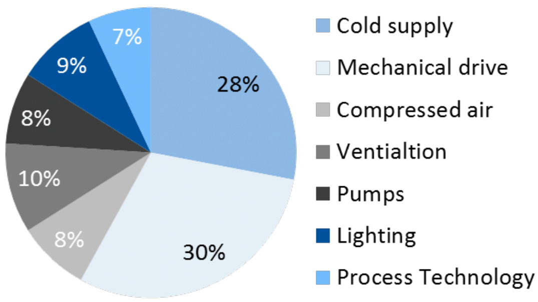


Figure 8: Share of technologies in electricity demand (Eichhammer et al., 2009)

3.2.3.2 Chemical industry

Based on final energy consumption, the chemical branch was one of the largest (21%) consumer in the industry sectors in 2014 (Figure 3). Due to the large variety of products output from chemical industries, identifying the main production processes like in the food branch is rather challenging. Furthermore, due to confidentiality, the production characteristics of the chemical branch are usually not publicly available. Over 60% of the final energy is used for process heat, and almost a quarter for mechanical drive (Figure 9). Most heat demand is provided by natural gas and heat from CHP (Figure 9). Overall, the consumed fuels are mainly natural gas, electricity and heat from CHP units.

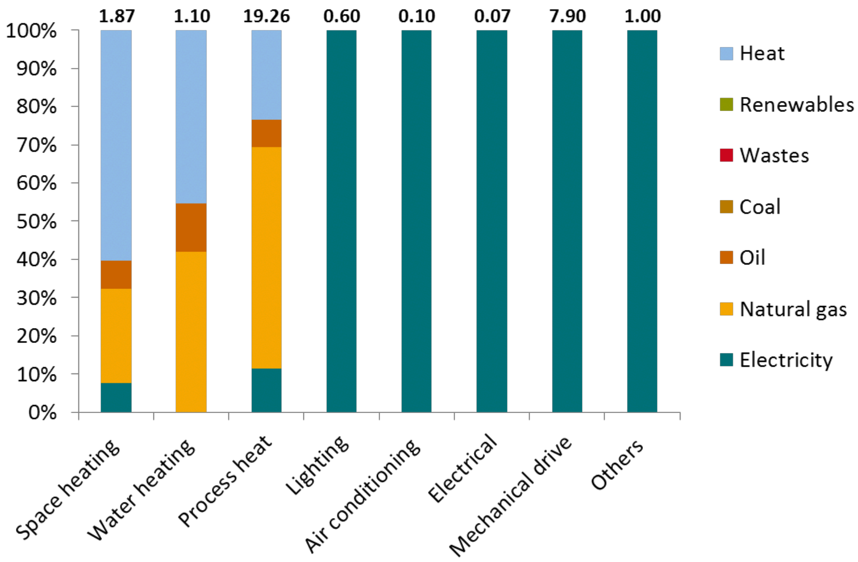


Figure 9: Final energy consumption of the chemical industry split into ESDs in 2014 (PJ) (Swiss Federal Office of Energy, 2016a,b; International Energy Agency, 2017)

We derive the temperature level of the heat demands based on Rossi (2013) and Arpagaus (2017). Due to the variety of different products, the process heat temperature is broader than in the food industry (Figure 10). Almost three quarters of the heat demand occur at temperatures over 240°C. For waste heat recovery, we assume that the maximum recoverable waste heat using heat recovery technologies is 15% of the final energy. Over 90% of this waste heat occurs at temperatures below 100°C. The description of the waste heat recovery technologies are given in Section 3.2.4.

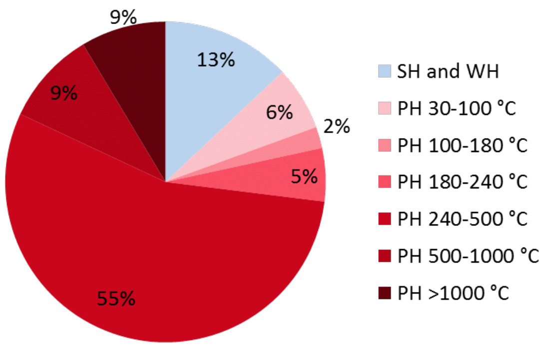


Figure 10: Temperature level of heat demand in the chemical industry (Rossi, 2013; Arpagaus, 2017)

3.2.3.3 Cement industry

Energy demand in cement and other non-ferrous minerals industries accounted for 11% of the industrial energy consumption (Figure 3). Though it has a small share of the total industrial energy, it is one of the energy intensive branches, with over 90% of the heat demand occurring at temperatures over 500°C. Thus, we investigated some of the key cement production process to assess the heat recovery and alternative technologies, which are elaborated in Granacher (2018).

In Switzerland, there are six cement plants in which 94% of the clinker is produced in rotary dry kilns, the remaining 6% are produced in semi-wet kilns. The semi-dry kilns used in Switzerland are converted wet kilns which have approximately double the production output rate and consume 15 to 20% less fuel than wet kilns (Kogel et al., 2006).

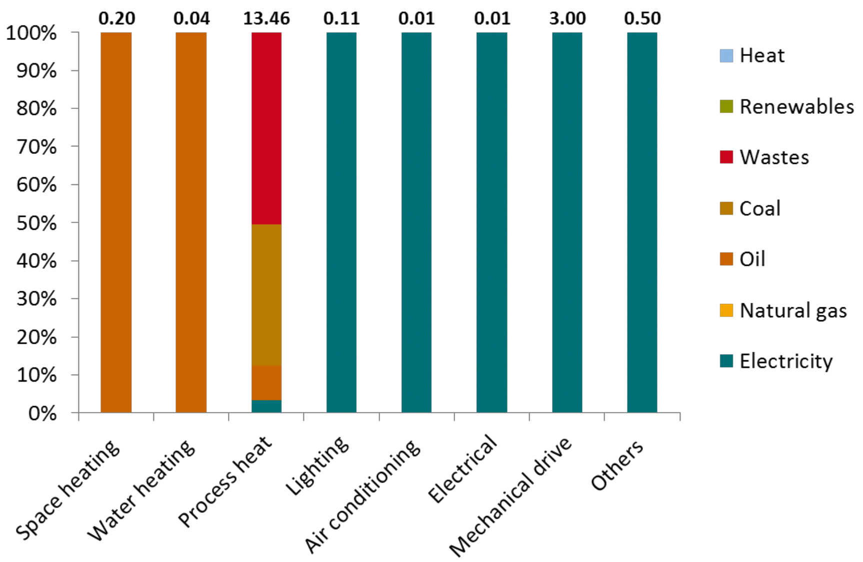


Figure 11: Final energy consumption of the cement industry split into ESDs in 2014 (PJ) (Swiss Federal Office of Energy, 2016a,b; International Energy Agency, 2017)

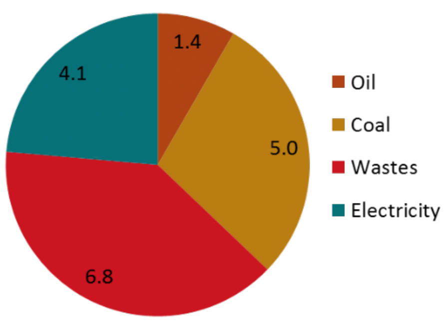


Figure 12: Final energy consumption of the cement industry in 2014 (PJ) (International Energy Agency, 2014; VSZ, 2017)

For this study, we assume that all of the process heat demand, which adds up to 84% of the total energy demand, accounts for the clinker production (Figure 11). The major part of the electricity demand is attributable to cement grinding, while a small share is used in other processes. For the estimation of ESDs, we use the data from BFE and the association of Swiss cement industries (VSZ, 2017) and estimate that 40% of the final energy consumption is industrial waste, 30% coal and 25% electricity (Figure 12).

In terms of energy efficiency, for a ton of clinker produced in Switzerland, 3.5 GJ of energy is used in 2015 (VSZ, 2017) while general (non-Swiss specific) literature data varies between 3.0 and 6.5 GJ (Blesl and Kessler, 2013). We consider the installation of new, more efficient clinker kilns as one measure for saving energy in addition to new milling process. Figure 13 summarizes the energy saving potential for Switzerland against its estimated costs based on Jibran et al. (2016). Besides the production of blended cement, cement plant upgrading with pre-heaters and pre-calciners provide a significant energy saving potential.

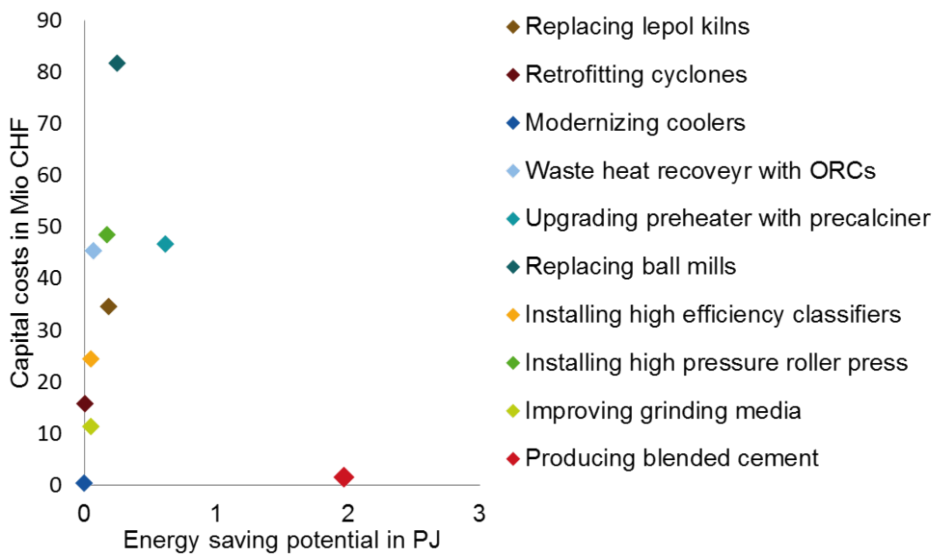


Figure 13: Measures considered for cement industry (Jibran et al., 2016)

3.2.4 New and advanced industrial energy technologies in STEM

This section gives an overview of heating and cooling technologies implemented in STEM. The main focus is on heat supply technologies for the food and the chemical branches.

3.2.4.1 Boilers, kilns and CHP

We consider a variety of boilers for the generation of process heat, space heat and hot water to be used in the industrial branches. Different fuel options such as natural gas, fuel oil, biogas, pellets, electricity, and industrial wastes are included. For the food industry, different ovens for baking are taken into account. Mostly tunnel and chamber ovens which run on electricity or fossil fuels are used today. In the cement industry, we consider new kilns for clinker production. CHP units generate heat and power simultaneously. Within the model, CHP units using natural gas, fuel oil, pellets, biogas and industrial waste are included.

Table 9: Thermal applications in the food, chemical and cement industry

Technology	Fuel	Branches
Boiler	Natural gas	Food, chemical
	Fuel oil	Food, chemical
	Pellets	Food, chemical
	Electricity	Food, chemical
	Industrial waste	Food, chemical
	Biogas	Food
Oven, Kiln	Electricty	Food
	Natural Gas [1]	Food, cement
	Fuel oil	Cement
	Coal	Cement
	Industrial waste	Cement
CHP unit	Industrial waste	Food, chemical
	Pellets	Food, chemical
	Nat. gas	Food, chemical
	Fuel oil	Food, chemical
	Biogas	Food

[1] Different kilns/ovens are considered for cement and food industry, see Tables A.1 and A.2

3.2.4.2 Heat pumps

Heat pumps are a promising technology when it comes to future industrial application. Their ability to transform low temperature heat to a higher temperature level is especially useful for waste heat recovery. For the future, thermo-acoustic heat pump represents one promising concept. The temperature level can be adjusted flexibly, and a high COP (Coefficient of performance) is yielded, compared to conventional heat pump technologies. However, the technology is still in a prototype-status. The first planned demo systems imply capacities of 700 kW and a maximum temperature level of 150°C (Wolf et al., 2017). We assume that the first commercially available systems will enter the market in between 2025 and 2030.

3.2.4.3 Solar thermal application

The usage of solar thermal energy in industrial production processes is limited to few applications today. Most of the solar systems currently in use in industry are deployed for drying processes in the food industry. Technologies for providing heat at up to 290°C are being developed (Weiss, 2005).

Different solar thermal collector types are available on the market. Within this work, flat plate collectors and evacuated tube collectors are considered for low temperature applications like space heating, hot water and suited shares of the process heat demand. For the application of solar devices, thermal storage units are crucial in order to make the heat accessible when it is needed. Therefore, thermal storage units are included in the model on a day-night level. In the food branch, the application of solar thermal components holds high potential, since over 60% of the heat demand occurs at temperatures below 100°C. The food industry implicates a lot of cleaning and washing processes, which occur at temperatures below 100°C and offer great potential for the usage of vacuum tube and flat plate collectors.

The alignment of industrial demands to seasonal and daily variations of solar radiation is only feasible to a restricted degree. Therefore, the installation of thermal storage units and the combination of solar systems with compensating technologies that can be used in winter is favorable when looking at solar heating systems in industry.

3.2.4.4 Organic Rankine cycle

An essential element of the detailed analysis is energy saving and waste heat recovery. Waste heat is considered all forms of heat escaping a system after provide its primary purpose. For example, sources of waste heat are furnaces, drying processes, refrigeration systems. The reduction of waste heat can generally be addressed by different approaches:

- Minimization of waste heat generation through efficiency measures such as insulation or process optimization
- Re-usage of waste heats within processes, for example in preheaters or drying processes
- Transformation of waste heat into other usable energy, for example temperature update or generation of electricity through heat pumps
- Transfer of waste heat to other consumers.

Currently, conversion of waste heat into usable forms of energy is considered and we explored the following three options:

- Transformation of heat into electricity using an organic Rankine cycle (ORC)
- Shifting of heat to higher temperature levels using heat pumps
- Direct utilization of heat.

Based on Bühler et al. (2014)technical wast heat recovery potential are about 30% of the theoretical waste heat. The reusable waste heat in the food and the chemical branch is assumed based on Hita et al. (2011) in combination with temperature levels of Bühler et al. (2017).

Organic Rankine cycles (ORC) are a promising technology for recovering waste heat. The process is based on a conventional turbine process, while an organic working fluid is used instead of water. Due to the low boiling point of the organic working fluid, low temperature heat can be transferred to electricity. Commercially available organic Rankine applications have an electric efficiency of 10-15% depending on the temperature of waste heat (Blesl and Kessler, 2013). Promising potential for ORC devices can be found in the cement industry, since waste heat occurs at high temperature levels. In the food industry, most waste heat occurs below 100°C, which limits the diffusion potential of organic Rankine cycles. The application of the technology in the chemical industry is estimated to be promising due to the higher temperature level of waste heat.

3.2.4.5 Process cooling

Most cooling applications currently used in the industry are compression chillers. They operate in the same principle as heat pumps, while using the heat sink for cooling applications. Temperatures from 30°C to −100°C can be reached (Blesl and Kessler, 2013). Absorption chillers are the most common thermal chiller systems currently used. As in absorption heat pumps, the compression process is realized thermally by using waste heat. In adsorption chillers, temperatures of −10°C can be reached (Blesl and Kessler, 2013). Compared to compression chillers, absorption chillers offer the following advantages:

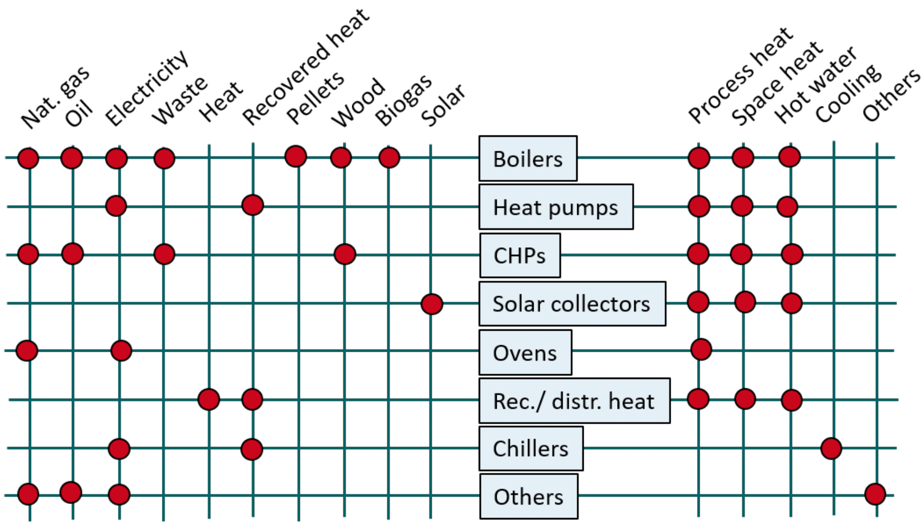
• Recovery of waste heat
• No rotating/ moving components
• Low maintenance
• High life time
• High performance in part load behavior

Table 10: Cooling technology for industrial applications

Technology	Branches
Compression chiller Absorption chillers Adsorption chillers	Food

4.7 Summary of the modeling approach of industrial sector

For the food, the cement and the chemical industry, we incorporated a range of new technologies. Furthermore, the properties of the individual industrial branches including process heat temperature levels and waste heat potential as described are included. For the food industry, we incorporate constraints that ensure the representation of the sub-sectors' characteristics with regards to their production processes and necessary temperature levels and technologies. For example, the process heat demand of the baking industry needs to be provided by ovens. Since the disaggregation of production processes in the chemical sector is very complex, no product-specific characteristics are considered. For the cement industry, we include a specific set of energy-saving measures. For the food and the chemical industry, the resulting energy system for providing the demands is presented in Figure 14.



Note: Rec: recovered, distr: district, Chillers are only modeled explicitly for food industry

Figure 14: Energy system for chemical and food industry

For both industrial branches, process heat can be provided by a set of different boilers, kilns, heat pumps and CHP units. Furthermore, recovered heat or district heat can be used for providing process heat, but only in line with feasible temperature levels of the demand. Heat recovery is directly linked to the activity of heat generating devices that produce waste heat. Using solar thermal for process heat demand, warm water and space heating is enabled. Solar radiation is modeled on an hourly resolution, so that hourly and seasonal variations in availability are considered. Cooling demand in the food branch is provided by either compression, adsorption or absorption chillers. In the chemical industry, the cooling demand is not modeled explicitly and is therefore included in the ESDs for mechanical drive and air conditioning. For the branches that are not elaborated further in this study, a generic set of demand-providing technologies is included for all ESDs.

4 National cooperation

The energy system modelling work of this project links to several modelling activities performed under the Swiss Competence Centres for Energy Research (SCCER), in particular to the SCCER Joint Activity *Scenarios and Modelling* in which STEM model is applied to perform an integrated system analysis. This SCCER Joint Acitivity joins forces of all eight SCCERs with allows for synergies of industry sector focused model development as envisaged in SWIDEM with the research undertaken in SCCER Efficiency of Industrial Processes (EIP). Contact has been made with the team of University of Geneva and EPFL and further exchange on potential collaboration is planned for 2019. Moreover, there is cooperation with the project team of the SCCER Joint Activity *White Paper Power-to-X*, where electricity-based hydrogen and related products are also investigated for the industry sector. Spillovers from this project are expected for the SWIDEM project as well.

5 International cooperation

The project team itself, with PSI and Cambridge Econometrics as partners, represents an international cooperation. In addition, both research teams are involved in different international cooperations based on other on-going research projects related to energy commodity elasticity analysis (CE) or related to energy systems modelling (PSI as member organisation of IEA-ETSAP).

Cooperation directly related to this project, in particular concerning the exchange of common data sources, is envisaged with the research group of the Centre for European Economic Research (ZEW) in Mannheim (Germany) that works on the SFOE funded research project on “Empirical Estimation of Electricity Demand Elasticities for Different Customer Groups in Switzerland and Implications for Energy Policies”. The first year project progress review was held jointly in October 2019 in Zürich.

6 Evaluation 2018 and outlook for 2019

The first annual project review meeting was held in September 2018. Work on both work packages has been performed according to schedule. For 2018, the main work was the empirical analysis of the price elasticities (work package 1), and to advance the STEM model with a more disaggregated representation of the industry in the model (work package 2). The milestones envisaged for 2018 have been achieved.

Further refinement of the macro-econometric analysis is to be performed in Q4 2018 /Q1 2019 including the documentation of the analysis. In view of joint scenario modelling, a draft for the definition of two scenarios will be provided to SFOE by the end of 2018 followed by preliminary test results from the energy system model in Q1/2019.

In 2019, the mapping of STEM model to the macro-econometric model E3ME will be established in order to conduct a joint scenario analysis as planned for 2019.

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Appendix

Table 11: Overview of the new composition of the industrial sub-sectors in STEM

Industry sectors	Industrial energy usage
IFOO -- Food	SH - Space heating
IPUP -- Pulp and Paper	WH - Water heating
ICHM -- Chemicals	PH - High temperature process heat
ICMN -- Cement and non-ferrous minerals	LT - Lighting
IBMT -- Basic metals (Iron and steel and non-ferrous metals)	AC - Air conditioning
IMMO -- Metal tools, machinery, textile, other industries	EQ - Electrical and ICT equipment
ICNS -- Construction	MD - Mechanical drive
	OT – Others

Table 12 Energy sectors (Fuel Users) covered in E3ME (industry sectors are highlighted in red)

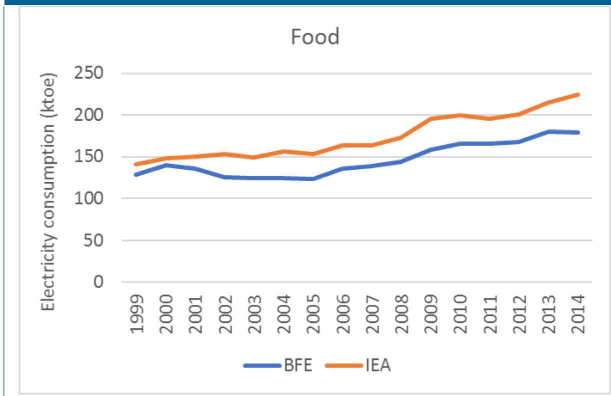
1 Power own use & transformation	12 Other industry
2 Other energy own use & transformation	13 Construction
3 Iron and steel	14 Rail transport
4 Non-ferrous metals	15 Road transport
5 Chemicals	16 Air transport
6 Non-metallic minerals	17 Other transport services
7 Ore-extraction (non-energy)	18 Households
8 Food, drink and tobacco	19 Agriculture, forestry, etc
9 Textiles, clothing & footwear	20 Fishing
10 Paper and pulp	21 Other final use
11 Engineering etc	22 Non-energy use

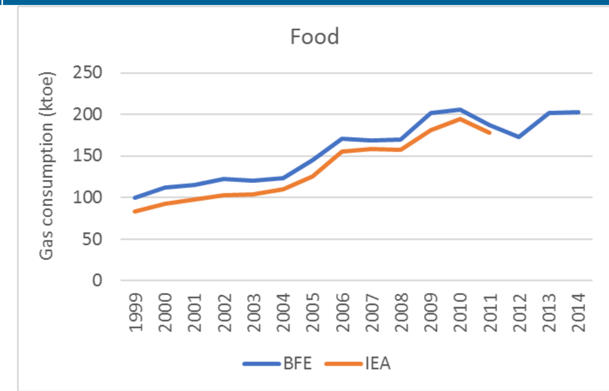
Comaprison of data on industry energy consumption

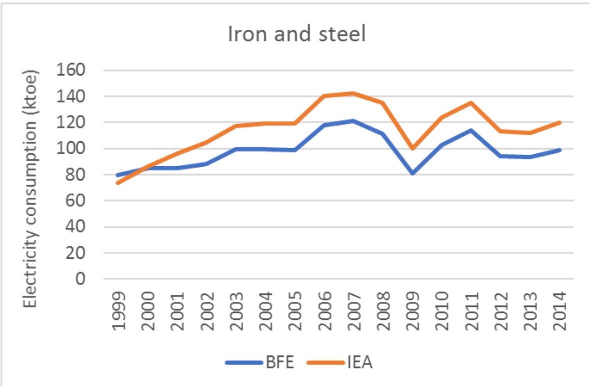
Figure 15: Gas and electricity consumption by industry sector: comparison between IEA and BFE data

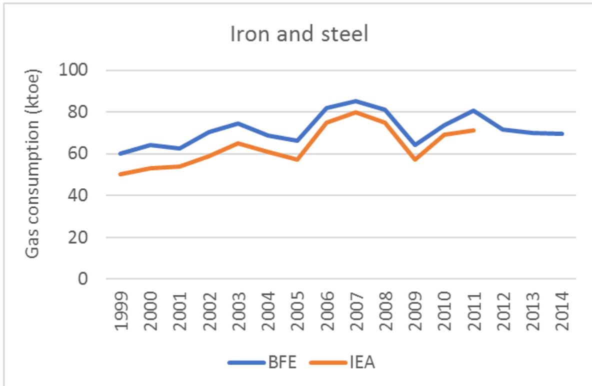
Electricity consumption data by industry sector	Gas consumption data by industry sector

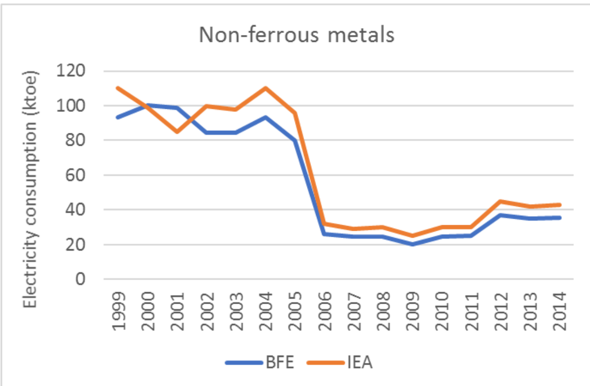
Electricity consumption data by industry sector	Gas consumption data by industry sector

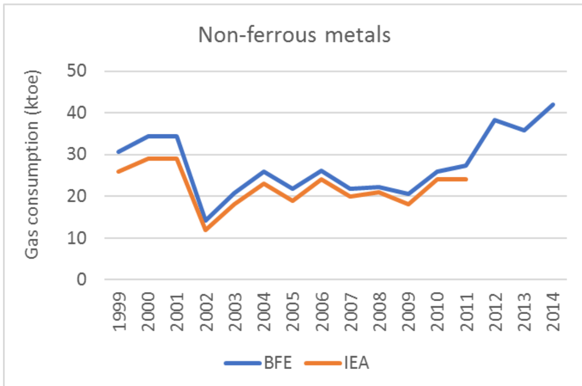


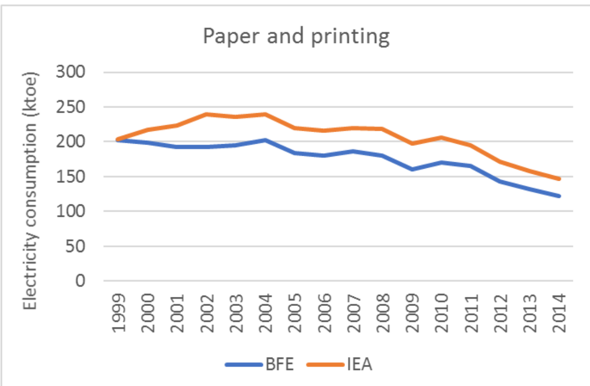


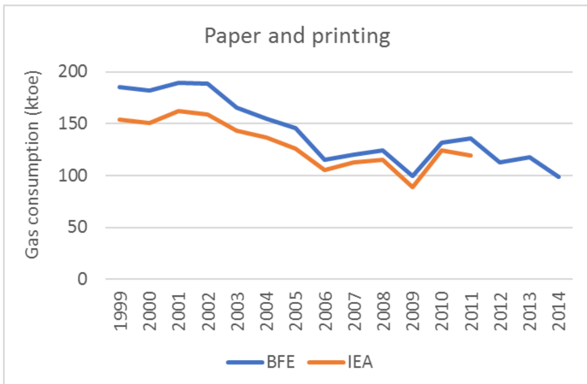


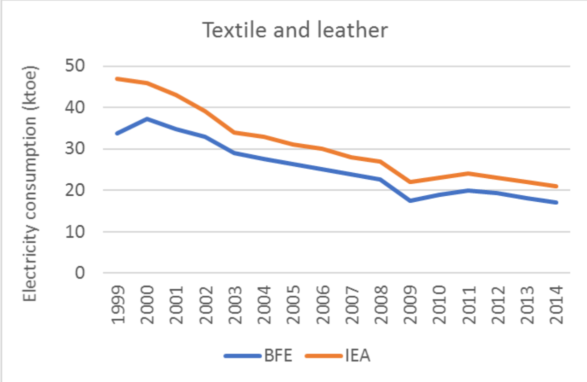
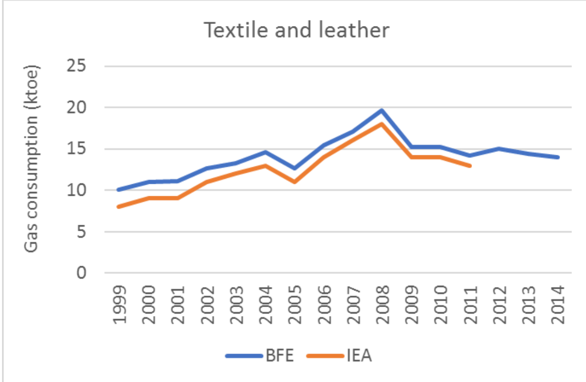
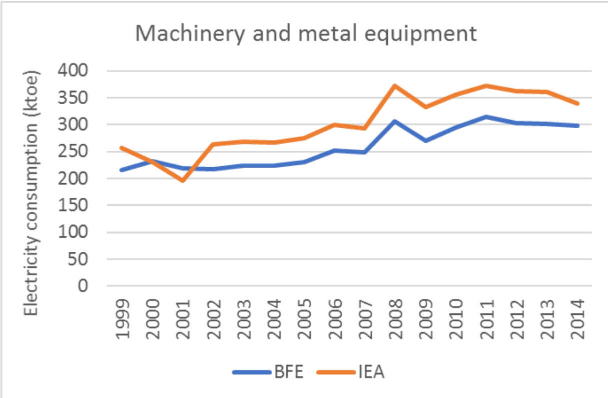
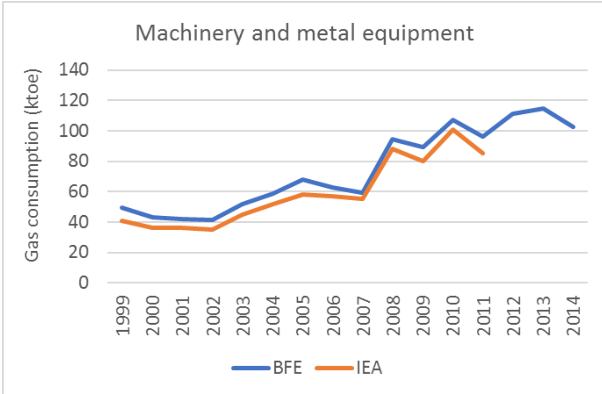
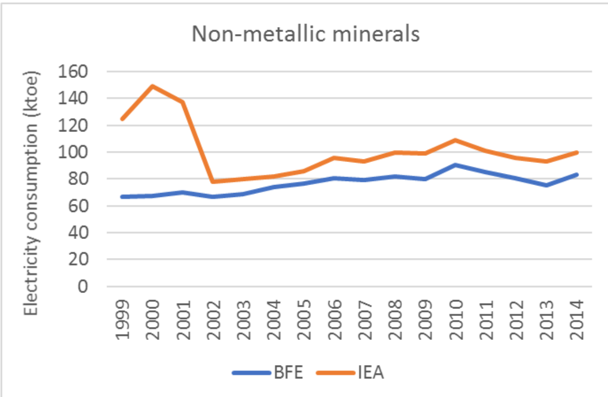
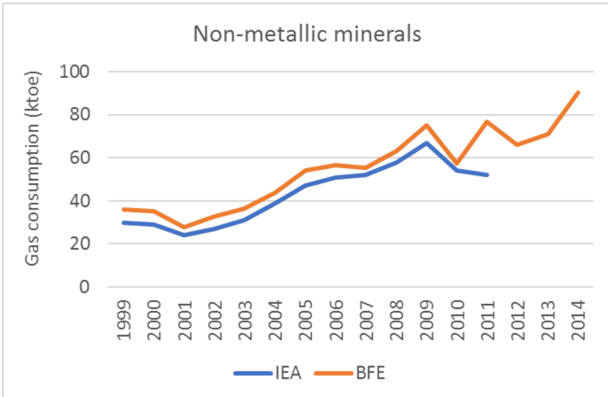










Electricity consumption data by industry sector	Gas consumption data by industry sector
	
	
	

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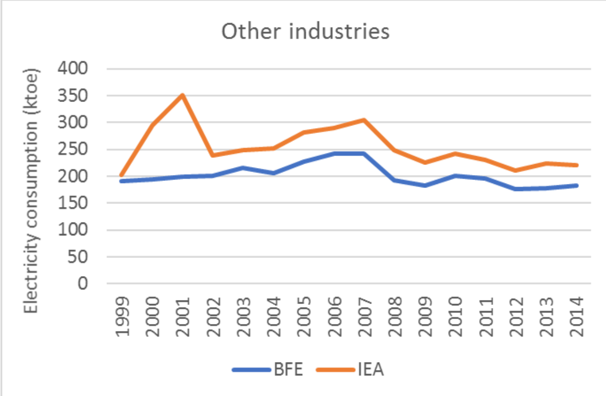	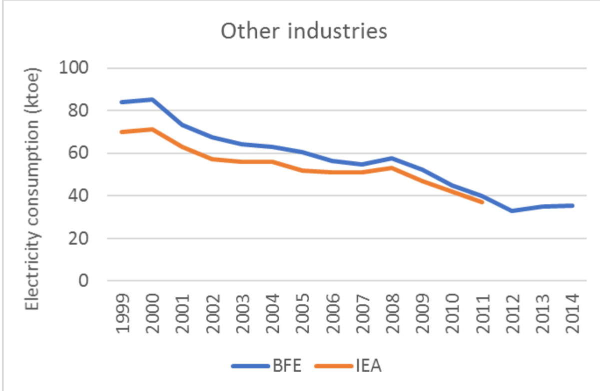

Sector-specific elasticity estimates in energy demand studies

Table 13 Results from 'Econometric Estimation of Energy Demand Elasticities' (Madlener et al. 2011) - uses sector-level electricity data for Germany from 1970-2007 and cointegrating econometric approach

Sector	**Economic activity**	**Price elasticity (electricity)**	**Significant time trend?**
1: Food & Tobacco	SR: 0.17 LR: 0.7	SR: 0 LR: 0	yes (positive)
4: Pulp & Paper	SR: 1.02 LR: 1.9	SR: 0 LR: -0.52	no
5: Chemicals	SR: 0.74 LR: 1.11	SR: 0 LR: 0	yes (negative)
6: Non-metallic Minerals	SR: 0.51 LR: 1.01	SR: -0.57 LR: -0.3	yes (positive)
8: Transport Equipment	SR: 0.48 LR: 1	SR: -0.31 LR: -0.3	no

Table 14 Results from 'Variation in price and substitution elasticities between sectors – A microdata analysis' (Tamminen and Tuomaala, 2012) - Uses firm-level data for Finland from 2000-2009 and cointegrating econometric approach

	Price elasticity (electricity)	**Price elasticity (other energy)**	**Shadow elasticity of substitution (all energy inputs)**
24: Manufacture of chemicals	-0.98*	-0.98*	1.57*
25: Manufacture of rubber and plastic products	-1.00*		

26: Manufacture of glass and ceramic products	-1.30*	-0.95	6.01
28: Manufacture of metal products	-1.00*		
156: Manufacture of food products, beverages and tobacco	-0.2		
271: Manufacture of iron and steel	-0.98*	-1.00*	0.23*
2725: Manufacture of processed iron and steel products	-1.29*	-1.00*	0.96*
21121: Manufacture of pulp, paper and paperboard	-0.97	0.83*	1.0*

Note: * indicates estimates are significant at the 5% level