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E.ON Energy Research Center

RWTH AACHEN UNIVERSITY

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# Fueling the US economy: Energy as a production factor from the great depression until today*

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**Abstract**

We analyze the relationship between factor augmenting technical change and factor substitution through a nested CES function using capital, labor, and energy inputs. We use US aggregate data on output, factor use, and factor prices for the years 1929–2015 to show the interdependence and coevolution of the different input factors. We demonstrate the robustness of the system of equations approach for estimating such a production function. We find that the input factors are gross complements, and that in the time period considered, technical change was mostly labor saving, while the linear time trend of energy augmenting technical change was zero.

*JEL classification*: C13, C32, E23, O33, Q43

*Keywords*: aggregate production, technical change, multi-factor production, energy demand

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# I. Introduction

Energy consumption in the US is often portrayed to be more than a simple economic decision, it is a part of the American identity. Schurr and Netschert (1960) notes that firewood was so plentiful in the 19th century US that a roaring hearth was seen as a fundamental right. The average American used five times as much firewood compared to the average Englishman, as deforestation in Europe necessitated a substitution of wood with coal, which spurred the development of new ovens to avoid the noxious coal smoke. The paradigm of cheap and abundant energy was challenged by the oil crises of the 1970s, which put an end to the gas-guzzling V8 as a standard engine and led to energy saving efforts to curb the ballooning energy expenditures. Still, the US has enjoyed ready access to cheap energy for much of the 20th century, especially compared to other industrialized countries. The reality of climate change and the economical and ecological imperatives of depleting fossil fuel deposits raise the question of how an economy can adjust to these changing circumstances, and what this means for growth and the use of input factors like labor, capital, and energy.

In this paper, we analyze the long-term technical change and the substitution elasticities between labor, capital, and energy as production factors by using a nested CES production function. The interdependence of production factors as defined by their mutual elasticities of substitution and factor specific technical change requires a careful econometric methodology that is capable of identifying both components simultaneously. Using aggregate economic data on factor use from the years 1929–2015, we analyze the long-term trends for factor augmenting technical change and the possibilities of substituting the production factors. We find that the substitution elasticities are below unity, with an elasticity of substitution of around 0.6 to 0.7 between energy and labor or capital. We also demonstrate that the methodology is robust to a variety of specifications, making it a powerful tool for disentangling and scrutinizing the dynamics of substitution and technical change.

The question of how energy inputs are used in the economy has been tackled in a variety of ways. Some research has focused on the question of whether growth causes energy consumption or vice versa (Stern and Enflo, 2013), while others have focused on the role of technology (Hassler et al., 2012). Fossil fuels are a finite resource, and already in 1865 did Jevons ask the coal question and what impact efficiency and scarcity could have on the development of economic output in the UK. For Dasgupta and Heal (1974) the question reemerged after a period of abundant energy, and recently Acemoğlu et al. (2012) also incorporates the exhaustability of resources in a model of directed technical change. With our analysis of the long-run developments of energy use and technical change in the US economy, we aim at providing further context to the studies of the effect of the exhaustability of fossil fuel resources on the economic output and the development of capital stock.

The analysis also ties into an important question, debated by, among others, Hudson and Jorgenson (1974) and Berndt and Wood (1979): whether capital and energy are complements or substitutes. The evidence is mixed, insofar as time series analysis for single countries points to a complementarity of capital and energy, while pooled panel data across countries has shown evidence for subtitutability. However, there are few long-term studies such as the one by Stern and Enflo (2013), and an understanding of the timeframe necessary to meaningfully alter the trajectory of energy consumption within a country also crucially depends on this relationship (Apostolakis, 1990).

Research on the relationship between capital and energy has long been cognizant of the fact that energy consumption is tied to the engineering intrinsic in the capital stock, and that capital formation and energy use are tightly intertwined (see Prywes, 1986 or Ayres, 2007). However, most early studies rely on the translog function for estimating elasticities, which has stricter requirements on the data, and violations of concavity often proved to be big methodological barriers. It also severely limited how factor specific technical change can be modeled. The attractiveness of a CES specification with factor specific technical change lies in the fact that it is well suited to identifying technical change effects and substitution effects simultaneously.

By identifying technical change and the elasticity of substitution, we can deduce that in an environment where constraints for one factor, such as labor, are more binding, investment in machinery that enhances the productivity of labor is attractive. This can simultaneously represent an increase in the capital stock, which means a *ceteris paribus* substitution of labor for capital. The investment in capital stock that better utilizes scarce labor therefore leads to a substitution between labor and capital, and at the same time labor augmenting (and thus labor saving) technical change. The question becomes more complex when energy is introduced as a third production factor. However, for both labor and energy, the development of technical change embodied in new capital stock is a crucial vector that determines the trajectory of factor use and the substitution possibilities in the future.

The necessity of a robust estimation technique for multi-factor CES functions is underscored by the importance of the CES specification in modeling applications, in particular when energy and environmental models are used. We employ an estimation method that uses a system of equations, first developed by León-Ledesma et al. (2010) for two factors. An extension to three factors was first proposed by Frieling and Madlener (2016), and tested in a limited way with a 25 year sample of data for Germany. Kim et al. (2017) show the advantage of the CES function compared to functions with fixed elasticities, such as Cobb-Douglas or Leontief. However, they specify the CES function without nesting, which only allows identical elasticity parameters between the input factors. Papageorgiou et al. (2017) includes a Cobb-Douglas component into the CES function in order to alleviate some of the methodological concerns highlighted in Frieling and Madlener (2016).

In order to confirm the robustness of the system of equations approach, in the present study we first test 15 different specifications of a nested CES production function with factor specific technical change. The specifications differ in the assumed elasticity of substitution between capital and labor. The estimation results for the different specifications demonstrate that the system of equations approach gives very robust results for a wide range of reasonable specifications, while misspecifications lead to clearly implausible results, such as technical change on the order of a 40% yearly increase in productivity. We find that the elasticity between energy and the labor-capital aggregate lies robustly below unity, a clear indicator that energy is a complementary input factor to capital and labor, even over the very long run. Our estimation results over some 85 years are between 0.6 and 0.7, and are significantly higher than those obtained for Germany in Frieling and Madlener (2016) using data for 25 years, where the elasticity was only estimated to be around 0.18. This points to a substantially higher flexibility in factor use in the long term, while the capital stock in place limits the substitution possibilities in the medium and short term.

The paper proceeds as follows. We describe the model and the system estimation approach in Section II. A thorough explanation of the data is given in Section III, where some key developments in factor use are highlighted. We show the robustness of the method in Section IV and the implications of the results in Section V. Section VI concludes and gives an outline of further research possibilities.

## II. Production Function

The CES production function as defined by Solow (1957) and Arrow et al. (1961) has become a staple tool of macroeconomic analysis. It allows a nuanced modeling of different elasticities and factor-specific technical change, which sets it apart from the Cobb-Douglas function. In its standard functional form, however, it is difficult to estimate empirically, since its nonlinear form requires a numerical estimation of the parameters. León-Ledesma et al. (2010) and León-Ledesma et al. (2015) show how a robust estimation of the CES model is possible for two input factors. In a model with three factors, the estimation becomes even harder[1]. We employ the technique described in Frieling and Madlener (2016) to analyze the long-term elasticity of energy as a production factor in the US. The functional form of the CES production function is given by the following basic form

$$Y = \Gamma \left( \alpha \left( \Gamma_1 X_1 \right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha) \left( \Gamma_2 X_2 \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{1-\sigma}}, \tag{1}$$

where $Y$ denotes output, $X_1, X_2$ are the input factors, $\Gamma, \Gamma_1, \Gamma_2$ are a general (Solow residual) technical change parameter as well as factor specific technical change parameters. The parameter $\alpha \in \{0, 1\}$ is the factor share of input factor $X_1$ in cost terms. The elasticity of substitution is denoted by $\sigma$.

The model can be extended to three or more factors by 'nesting' additional CES-like functions in place of one or more of the input factors:

$$\begin{aligned} Y &= \Gamma \left( \alpha V_1^{\frac{(\sigma-1)\sigma_1}{(\sigma_1-1)\sigma}} + (1-\alpha) \Gamma_3 X_3^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \\ V_1 &= \alpha_1 \Gamma_1 X_1^{\frac{\sigma_1-1}{\sigma_1}} + (1-\alpha_1) \Gamma_2 X_2^{\frac{\sigma_1-1}{\sigma_1}}. \end{aligned} \tag{2}$$

Before the estimation, the functions should be normalized using the appropriate normalization factors. We follow Klump and Saam (2008) and use the geometric mean of output, capital, and labor as a normalization constant for these factors. The geometric mean is preferable to the simple arithmetic mean, because these factors exhibit percentage based growth, so that normalizing with the arithmetic mean would overweight later data points. For the factor share parameters and time, on the other hand, the arithmetic mean is used for normalization. For the production factors labor ($L$), capital ($K$), and energy ($E$), normalizing with the normalization constants $Y_0, L_0, K_0, E_0$, and specifying technical change with a linear time trend as $\Gamma_i = e^{\gamma_i (t-t_0)}$, we define the following production function:

$$\begin{aligned} \frac{Y}{Y_0} &= \psi \left( \alpha_V V^{\frac{(\sigma-1)\sigma_{KL}}{(\sigma_{KL}-1)\sigma}} + \alpha_E \left( e^{\gamma_E (t-t_0)} \frac{E}{E_0} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \\ \text{with } V &= \left[ \frac{\alpha_L}{\alpha_V} \left( e^{\gamma_L (t-t_0)} \frac{L}{L_0} \right)^{\frac{\sigma_{KL}-1}{\sigma_{KL}}} + (1 - \frac{\alpha_L}{\alpha_V}) \left( e^{\gamma_K (t-t_0)} \frac{K}{K_0} \right)^{\frac{\sigma_{KL}-1}{\sigma_{KL}}} \right]. \end{aligned} \tag{3}$$

Normalization has a number of beneficial side-effects that are useful for estimation. First, it renders all factor inputs unitless. This means that the choice of units or measurements cannot influence the estimation results. Secondly, and more importantly, it ensures that CES functions that only differ in

[1]For an extensive treatment of the different methodologies for estimating CES functions, see also Henningsen and Henningsen (2011, 2012).

their elasticities have a common benchmark point. This significantly improves the identification of factor-biased technical change and the elasticity (León-Ledesma et al., 2010). Since the elasticities in a CES function are principally point elasticities, a common benchmark as a point of normalization ensures the comparability of estimation results. This is important for testing the effectiveness of the approach suggested in Frieling and Madlener (2016) in a rigorous fashion in this new context. The factor $\psi$ has to be introduced in the normalized function to account for the fact that the data is subject to shocks and the production function is not linear. This means that the chosen normalization points might not lie exactly on the production function. However, $E[\psi] = 1$, which makes it a useful control variable for the estimation, when $\psi$ is estimated to be substantially different from unity. For the empirical estimation, we construct a system of equations from the normalized production function and the first order conditions:

$$\ln \frac{Y}{Y_0} = \ln \psi + \frac{\sigma}{(\sigma - 1)} \ln \left( \alpha_V V^{\frac{(\sigma-1)\sigma_{KL}}{(\sigma_{KL}-1)\sigma}} + \alpha_E \left( e^{\gamma_E (t-t_0)} \frac{E}{E_0} \right)^{\frac{\sigma-1}{\sigma}} \right) \tag{4a}$$

$$\begin{aligned} \ln w = {} & \frac{1}{\sigma} \ln \left( \frac{Y_t}{Y_0} \right) - \frac{1}{\sigma_{KL}} \ln \left( \frac{L_t}{L_0} \right) + \frac{\sigma_{KL} - 1}{\sigma_{KL}} \left( \gamma_L \left( t - t_0 \right) \right) + \frac{\sigma - 1}{\sigma} \ln \psi \\ & + \frac{\sigma - \sigma_{KL}}{\sigma(\sigma_{KL} - 1)} \ln V + \ln \frac{Y_0 \alpha_L}{L_0} \end{aligned} \tag{4b}$$

$$\begin{aligned} \ln r = {} & \frac{1}{\sigma} \ln \left( \frac{Y_t}{Y_0} \right) - \frac{1}{\sigma_{KL}} \ln \left( \frac{K_t}{K_0} \right) + \frac{\sigma_{KL} - 1}{\sigma_{KL}} \left( \gamma_K \left( t - t_0 \right) \right) + \frac{\sigma - 1}{\sigma} \ln \psi \\ & + \frac{\sigma - \sigma_{KL}}{\sigma(\sigma_{KL} - 1)} \ln V + \ln \frac{Y_0 (\alpha_V - \alpha_L)}{K_0} \end{aligned} \tag{4c}$$

$$\ln p = \frac{\sigma - 1}{\sigma} \left( \ln \psi + \gamma_E \left( t - t_0 \right) \right) + \frac{1}{\sigma} \ln \left( \frac{Y_t / Y_0}{E_t / E_0} \right) + \ln \frac{\alpha_E Y_0}{E_0}. \tag{4d}$$

Our identifying assumption is that factors are paid according to their marginal productivity in equilibrium, an assumption that seems less restrictive over the long-term data of 87 years employed by us, than in the short term, where deviations from the equilibrium are likely. One caveat is that this assumption might misrepresent the dynamics due to the often heavy-handed regulation of energy markets, a criticism pointed out by, among others, Papageorgiou et al. (2017). However, given that the decision to utilize energy inputs is made according to the real cost producers face and their capability of using the energy, as defined by the embodied capital stock and the elasticity of substitution, we judge the assumption as being less restrictive than it might seem at a first glance. The external costs of pollution or the price distortions of subsidies are incorporated into the decision to the extent that they are reflected in the factor costs faced by producers.

We assume that the yearly income is divided as factor payments according to the accounting identity:

$$Y \equiv wL + rK + pE. \tag{5}$$

The system of equations (4) is estimated simultaneously using different values for $\sigma_{KL}$. From the results reported in Frieling and Madlener (2016) we see that there is likely a band of probable values for $\sigma_{KL}$ that yields plausible results, and a number of values outside this band where the performance of the approach deteriorates. In order to test the robustness of the results, we therefore estimate the function using a grid of 15 values for $\sigma_{KL}$ with a SUR estimation approach[2]:

$\sigma_{KL} = (0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.99, 1.01, 1.2, 1.5, 3.0)$.

The values are chosen to examine behavior close to the discontinuities of the CES function around 0 and 1, as well as the results of more extreme values of $\sigma_{KL} > 1$. As shown by Chirinko (2008), and also in the analysis of Frieling and Madlener (2016), we expect the best performance to be somewhere between 0.6 and 0.8.

We expect to see how sensitive the estimated values of $\sigma$ are to the choice of $\sigma_{KL}$, by identifying which values fail to yield any results, where the results are nonsensical or extreme, by comparing estimation statistics and the residuals, as well as in comparison to existing studies on the subject.

## III. Data

For the analysis we use annual data from the US for the years 1929–2015. For this type of analysis, the size of the dataset is often limited. We rely on a variety of sources: The data on GDP (nominal and real), employment, employee compensation and net fixed capital is provided in the National Income and Product Accounts (NIPA) that are published by the Bureau of Economic Analysis (BEA). Data on prices and consumption of coal, natural gas, and petroleum inputs after 1949 are from the February 2017 monthly energy report provided by the US Energy Information Administration (EIA). Prices and consumption data before 1949 are from Schurr and Netschert (1960).

Where possible, we compare multiple sources in order to ensure the consistency of the data. An alternative source for oil prices dating back to 1850 can be found in the BP Energy Outlook. Prices

[2] The estimation procedure was implemented using the system estimation of EViews 8. Other estimation methods, such as FIML, 3SLS, and GMM do not provide qualitatively different results. The documented and easily customizable programs used for preparing the data with normalization and estimating the systems using any of the aforementioned estimation techniques is available from the authors upon request.

for oil, gas, and coal are cost averages of total expenditures on all forms of these energy sources. The different qualities and forms of extraction are not further disaggregated.

GDP is measured in billions of dollars. The base year for the calculation of real $ values is 2009. Employment numbers are measured in thousands of full-time equivalent jobs. Additionally, we account for the number of self-employed persons. Because we are interested in the factor costs of the production inputs, we use data on total employee compensation that includes employer contributions to social security and other payments. Due to the messy and imprecise separation of labor and capital income for self-employed persons in general, we use the employee compensation as a shadow price of labor, meaning that the total employee compensation is scaled up by the number of self-employed persons.

Table 1
*Variable description*

| Variable | Symbol | Description |
|---|---|---|
| Output (GDP) | $Y$ | Output as real GDP in bn. $, 2009 prices. |
| Labor | $L$ | Labor as full-time equivalent employees + self-employed, in 1000. |
| Capital | $K$ | Net capital stock in bn. $, 2009 prices. |
| Energy | $E$ | Sum of energy consumed per year in TJ. |
| Coal | | Annual coal consumption, converted from short tonnes to TJ. |
| Oil | | Annual crude oil consumption, converted from barrels to TJ. |
| Nat. Gas | | Annual natural gas consumption, converted from cubic feet to TJ. |
| Wages | $w$ | Total employee compensation in real $, 2009 prices. |
| Capital Cost | $r$ | Real user cost of capital derived from the accounting identity (5). |
| Energy Price | $p$ | Average real price in $ per TJ. |
| Coal Price | | Real coal price in $ per J. |
| Oil Price | | Real oil price in $ per J. |
| Nat. Gas Price | | Real gas price in $ per J. |
| Norm. Factor | $\psi$ | Factor with $E[\psi] = 1$ to account for the function's nonlinear nature. |
| Cost shares | $\alpha_i$ | The average factor share in cost terms of factor $i$ in eq. (5). |
| Tech. change | $\gamma_i$ | The linear time trend of factor augmenting technical change for $i$. |
| KL elasticity | $\sigma_{KL}$ | The elasticity parameter between capital and labor. |
| Energy elasticity | $\sigma$ | The elasticity parameter between energy and the KL aggregate. |

For capital inputs, we use the net fixed capital of the NIPA data in $ bn. Capital is evaluated at repurchasing cost, less depreciation. Capital costs are not measured directly, instead they are derived from the three-factor accounting identity (eq. (5)), which implies that we implicitly account for energy costs as a disaggregated part of capital costs. Note that this is analogous to Frieling and Madlener (2016). A comparison of the return series with data from Piketty and Zucman (2014) shows that our result is consistent.

Energy data is converted from the different measurements to TJ using the conversion factors provided by the EIA. Likewise, the prices of coal, oil, and natural gas are converted into $/PJ. Prices before 1949 are derived from the reported expenditures measured in millions of $ in Schurr and Netschert (1960). Note that we deliberately deviate from the methodology of Kander and Stern (2014) and Frieling and Madlener (2016) of incorporating a quality index to show substantive qualitative changes in the total sum of heat units consumed. The reason is that the data scarcity for non-fossil fuel energy sources in the timeframe of our sample prevents us from accurately measuring renewable and nuclear energy. However, fossil fuel consumption makes up the vast majority of primary energy consumption in the US. In 1949 renewable sources accounted for only 9.3% of primary energy consumption, about half of which was hydropower and the other half from biomass. The share of nuclear and renewable energy together rose to around 18.3% in 2015. This, coupled with the very low natural gas prices in the US compared to other natural gas markets, leads to the quality index remaining very stable throughout the sample. In order to not unnecessarily obfuscate the analysis with the inclusion of unnecessary and uninformative parameters, the quality index is therefore omitted.

All prices are converted into real terms using the appropriate deflators. A short description of the different data variables and how they relate to the model in the system of equations (4) is provided in Table 1.

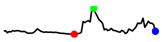
### III.1. Descriptive Statistics.

In the observed time period, real GDP has been recorded as low as $778.3 bn in 1933 to a maximum of $16397.2 bn in 2015. In the same time period, the total number of people active in the labor force grew from 37 million in 1932 to a high of 140 million in 2015. This means that annual real GDP growth was 3.20% in the observed time period, while the labor force increased by 1.30% per year. The cost of labor in the form of employee compensation went up, on average, by 4.84%. The capital stock evaluated in real $ grew, on average, by 3.29% each year, while the user cost of capital remained almost constant with an average yearly change of 0.10%. Over the time period considered the aggregate fossil fuel consumption in heat units increased by 1.44%[3] p.a., while the average yearly increase in energy expenditure was 3.19%. However, this masks the heterogeneity within the data. While many of the years between World War II and the first oil crisis of 1973 saw a higher increase in energy consumption than GDP, the growth rate of energy consumption exceeded that of GDP only in the years 1976, 1987, 1988, 2010, and 2013 after that time. This highlights the importance of long-term analysis. A study of the 25 years after WW II would show that energy consumption outpaces

[3]When nuclear and renewable sources are included, total primary energy consumption increased by 1.7% p.a.

the increase in output, while a study of the last 25 years would clearly show the opposite, where output growth left the increase in energy consumption behind. The relative increase of the labor and energy costs are also an indication that labor was the main constraining input factor, leading to a relative increase in the price of labor. The average unemployment in the years 1948–2015, as reported by the Bureau of Labor Statistics, was only 5.6%, further evidence that increasing labor inputs into production was often not possible.

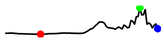
Table 2
*Economic summary statistics*

| | Value | Arithm. Mean | Geom. Mean | Min (Year) | Max (Year) | SD |
|---|---|---|---|---|---|---|
| GDP |  | 6413 | 4556.5 | 778.3 (1933) | 16397 (2015) | 4795.4 |
| Labor |  | 87339 | 81276 | 37043 (1932) | 140620 (2015) | 32276 |
| Capital |  | 18682 | 13253 | 2819.6 (1931) | 49167 (2015) | 14291 |
| Energy |  | 58355 | 52154 | 16491 (1932) | 90635 (2007) | 24327 |
| Wages |  | 38715 | 35048 | 14696 (1934) | 67213 (2015) | 16208 |
| Cap. cost |  | 11.84 | 11.693 | 6.1815 (1933) | 14.952 (1944) | 1.7468 |
| Labor share |  | 62.591 | 62.516 | 56.941 (2013) | 73.235 (1932) | 3.105 |
| Energy share |  | 3.2655 | 2.907 | 1.5338 (1969) | 9.8118 (1980) | 1.8082 |

When looking at the factor shares of labor and energy in cost terms as a percentage of GDP (see eq. (5)), we see a mean factor share of 62.6% for labor and 3.27% for energy. Especially the factor share of energy fluctuated heavily, reaching as high as 9.81% in the wake of the second oil crisis in 1979/1980. The labor share was highest in 1932 at 73.2% and reached its lowest point with just 56.9% in 2013. The decreasing labor share seems counterintuitive, considering that real wage growth far outpaced real GDP growth. However, the large increase in the capital stock over the observed time period already points to a culprit, namely increased output achieved through investment in machinery that increased the productivity of the available labor.

The effect of choosing the geometric mean instead of arithmetic mean for normalization of the factor inputs and output can be seen in Table 2, which also shows some other summary statistics. For easier comparison the series are also displayed as spark lines, with the minima, maxima, and endpoints highlighted. Key events like the great depression, the energy crises in the 1970s, and the financial crisis of 2007 are apparent in the time series and summary statistics. Interestingly, WW II does not seem to have had a very large effect of on economic output, however, our data does not allow us to specifically quantify the shift of private sector to public sector production that might have occurred. Overall, we see that the labor share has mostly declined within the sample, while the energy share was stable at a very low value in the first half of the sample, before it increased sharply with the rising energy prices during the oil crises, and since then has not returned to pre-crisis levels. The different energy sources have developed at least somewhat independently from each other (Table 3).

TABLE 3
*Descriptive energy statistics*

| | Value | Arithm. Mean | Geom. Mean | Min (Year) | Max (Year) | SD |
|---|---|---|---|---|---|---|
| Energy |  | 58355 | 52154 | 16491 (1932) | 90635 (2007) | 24327 |
| E. Price |  | 3.3737 | 2.5397 | 0.95303 (1931) | 11.289 (2008) | 2.6993 |
| Coal |  | 16141 | 15552 | 9837.8 (1932) | 24053 (2005) | 4424.5 |
| Coal price |  | 1.6253 | 1.5052 | 0.80552 (1929) | 4.6344 (2008) | 0.68814 |
| Oil |  | 26321 | 22178 | 5012.8 (1932) | 42524 (2005) | 12496 |
| Oil price |  | 5.1821 | 3.74 | 1.2385 (1931) | 18.857 (2011) | 4.6256 |
| Gas |  | 15893 | 11927 | 1640.7 (1932) | 29750 (2015) | 8867.6 |
| Gas price |  | 2.0592 | 1.3643 | 0.40344 (1949) | 9.0523 (2005) | 1.9445 |
| GDP |  | 6413 | 4556.5 | 778.3 (1933) | 16397 (2015) | 4795.4 |

The effective energy price peaked in 2008, same as the oil price, while the energy consumption did so in 2007. The consumption of natural gas at the beginning of the sample was only a tenth of total consumption (in PJ terms), and at its cheapest, in 1949, natural gas was only half the price of oil at its cheapest. Natural gas was the only energy source whose consumption increased after the financial crisis and it now makes up a third of total fossil fuel consumption. In general, after the financial crisis the relation between energy consumption and output started to decouple slightly. Peak fossil fuel consumption was in 2007 with 90635 PJ of fossil fuels consumed, and, while there has been a steady growth in output in the recovery since then, energy consumption has stagnated.

As a major natural gas and oil producer, the US experiences very low energy prices compared to most other industrialized countries, both in nominal and real terms. The mean real German energy price found by Frieling and Madlener (2016) in the period 1990-2015 was 6268.43 €/GJ. In the US this came to 5543.30 $/GJ.

## IV. Robustness of the Method

The estimation was performed using 15 different values of $\sigma_{KL}$, in order to test the robustness of the methodology to misspecified elasticity. As is evident from the overview given in Tables 4 and 5, the elasticity estimates for $\sigma$ show consistent results for a wide range of values of $\sigma_{KL}$, around 0.63 to 0.71. Previous econometric studies have shown that the long-run elasticity between capital and labor is likely less than unity (Chirinko, 2008). León-Ledesma et al. (2015), in their analysis with only two factors, also use US data, and find an elasticity between 0.439 and 0.721. We see from Table 4 that regardless of which of those values one assumes to be closest to the true value, our system estimation method yields robust results in the expansion to three production factors.

The result is surprising in just how robust the methodology is for identifying $\sigma$ and the technical change parameters. We expected the range of values that produce plausible results to be much narrower, with a more gradual and less abrupt differentiation to the more extreme possible tested values. Instead of only being reliable in a narrow band, the methodology produces robust results even if there is uncertainty about the exact value of $\sigma_{KL}$. This has the drawback that a precise identification of $\sigma_{KL}$ simultaneously with $\sigma$ is not feasible using this method, especially for larger samples, where the robustness that makes the method reliable renders the elimination of wrong specifications harder. However, it means that the system approach can be combined with a flexible technical change specification for modeling applications, or when the variable of interest is the elasticity between the different CES processes, rather than within a given process.

TABLE 4
*Estimation results, part 1*

| $\sigma_{KL}$ | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 |
|---|---|---|---|---|---|
| $\psi$ | 1.0231 | 1.0280 | 1.0317 | 1.0349 | 1.0398 |
| s.e. | 0.0059 | 0.0057 | 0.0055 | 0.0054 | 0.0056 |
| $\sigma$ | 0.6348 | 0.6381 | 0.6469 | 0.6621 | 0.7074 |
| s.e. | 0.0267 | 0.0256 | 0.0246 | 0.0241 | 0.0246 |
| $\gamma_L$ | 0.0131 | 0.0136 | 0.0142 | 0.0150 | 0.0162 |
| s.e. | 0.0004 | 0.0003 | 0.0003 | 0.0004 | 0.0004 |
| $\gamma_K$ | -0.0034 | -0.0027 | -0.0020 | -0.0015 | -0.0016 |
| s.e. | 0.0003 | 0.0003 | 0.0003 | 0.0003 | 0.0003 |
| $\gamma_E$ | 0.0031 | 0.0025 | 0.0017 | 0.0005 | -0.0027 |
| s.e. | 0.0034 | 0.0035 | 0.0036 | 0.0039 | 0.0048 |
| D.R.C. | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| (4b) $R^2$ | 0.6635 | 0.6651 | 0.6665 | 0.6680 | 0.6703 |
| (4c) $R^2$ | 0.5874 | 0.8091 | 0.8756 | 0.8922 | 0.8857 |
| (4d) $R^2$ | 0.9519 | 0.9659 | 0.9722 | 0.9762 | 0.9814 |

The results consistently show that most of the technical change was labor-augmenting, with $\gamma_L$ equal to a rate of 1.3 – 1.6% per year, while capital specific technical change ($\gamma_K$) was slightly negative, with -0.2% – -0.3%. The linear time trend of energy augmenting technical change ($\gamma_E$) is not statistically significant, and the null hypothesis cannot be rejected for the values of $\sigma_{KL}$ that give plausible results.

Table 4 shows that the normalization parameter $\psi$ is very close to unity for $\sigma_{KL} \in \{0.3, 0.8\}$. This means that our normalization points are well chosen. Only outside this band does $\psi$ fluctuate more, specifically when $\sigma_{KL}$ is very close to unity or very large (see Table 5). This is another indicator that there is some leeway for the specification of $\sigma_{KL}$, but that extreme values cause the parameter estimates to deteriorate. The comparison of the estimation statistics in Tables 4 and 5 also shows this effect.

Table 5
*Estimation results, part 2*

| $\sigma_{KL}$ | 0.01 | 0.1 | 0.2 | 0.8 | 0.9 | 0.99 | 1.01 | 1.2 | 1.5 | 3.0 |
|---|---|---|---|---|---|---|---|---|---|---|
| $\psi$ | 1.004 | 0.978 | 1.012 | 0.9964 | 0.967 | 1.099 | 1.057 | 0.989 | 0.977 | 0.946 |
| s.e. | 0.010 | 0.006 | 0.006 | 0.0097 | 0.005 | 0.005 | 0.007 | 0.011 | 0.012 | 0.012 |
| $\sigma$ | 12553.830 | 0.546 | 0.633 | 1.0024 | 1.698 | 0.724 | 0.983 | 0.999 | 1.003 | 1.009 |
| s.e. | 40734.810 | 0.028 | 0.027 | 0.0036 | 0.108 | 0.011 | 0.005 | 0.003 | 0.004 | 0.004 |
| $\gamma_L$ | 0.020 | 0.015 | 0.013 | 0.0083 | 0.023 | 0.122 | -0.029 | -0.002 | 0.000 | 0.001 |
| s.e. | 0.000 | 0.000 | 0.000 | 0.0009 | 0.001 | 0.003 | 0.004 | 0.001 | 0.000 | 0.000 |
| $\gamma_K$ | -0.000 | -0.004 | -0.004 | -0.0134 | -0.006 | -0.184 | 0.155 | 0.003 | -0.001 | -0.002 |
| s.e. | 0.000 | 0.000 | 0.000 | 0.0011 | 0.001 | 0.006 | 0.015 | 0.001 | 0.000 | 0.000 |
| $\gamma_E$ | 0.025 | 0.006 | 0.004 | 0.4007 | 0.039 | 0.003 | -0.642 | 0.445 | 0.426 | 0.412 |
| s.e. | 0.002 | 0.002 | 0.003 | 0.0305 | 0.005 | 0.004 | 0.126 | 0.030 | 0.016 | 0.015 |
| D.R.C. | 116.967 | 0.000 | 0.000 | 0.0000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| (4b) $R^2$ | 0.675 | 0.641 | 0.660 | 0.6080 | 0.683 | 0.666 | 0.664 | 0.583 | 0.616 | 0.648 |
| (4c) $R^2$ | -73521.698 | -6.094 | -0.270 | 0.7930 | 0.673 | 0.868 | 0.791 | 0.747 | 0.724 | 0.664 |
| (4d) $R^2$ | -9217.896 | 0.563 | 0.905 | 0.9923 | 0.993 | 0.992 | 0.993 | 0.993 | 0.993 | 0.994 |

For $\sigma_{KL} \leq 0.2$, we see that the $R^2$ of eq. (4c) is negative, while it is between 0.58 and 0.91 for other values. For eqs. (4a), (4b), and (4d), we have high $R^2$ for all specifications. The only case that failed to converge during estimation was near the Leontief edge-case with $\sigma_{KL} = 0.01$ when using a GMM estimator, and produces extreme parameter estimates when using a SUR estimator.

The results in Table 4 show the robustness of the estimated parameters. For $\sigma_{KL} \in \{0.3, 0.7\}$, we see that the coefficients as well as standard errors are very similar. The $R^2$ values are also very close to each other. In comparison to the estimation results presented in Table 5, we see that outside of the band of likely values, other coefficients have to compensate for the misspecification. This results in technical change parameters with implausible values, such as $\gamma_K$ when $\sigma_{KL} = 0.99$ or $\gamma_E$ when $\sigma_{KL} \in \{0.8, 1.01, 1.2, 1.5, 3.0\}$. For very small values of $\sigma_{KL}$, the negative $R^2$ point to a possible misspecification.

For three-factor models, the definition of the elasticity of substitution between factors is less straightforward than in the two-factor case. Blackorby and Russell (1981, 1989) highlight the usefulness of the Morishima elasticity when thinking about the adjustment behavior between more than two fac-

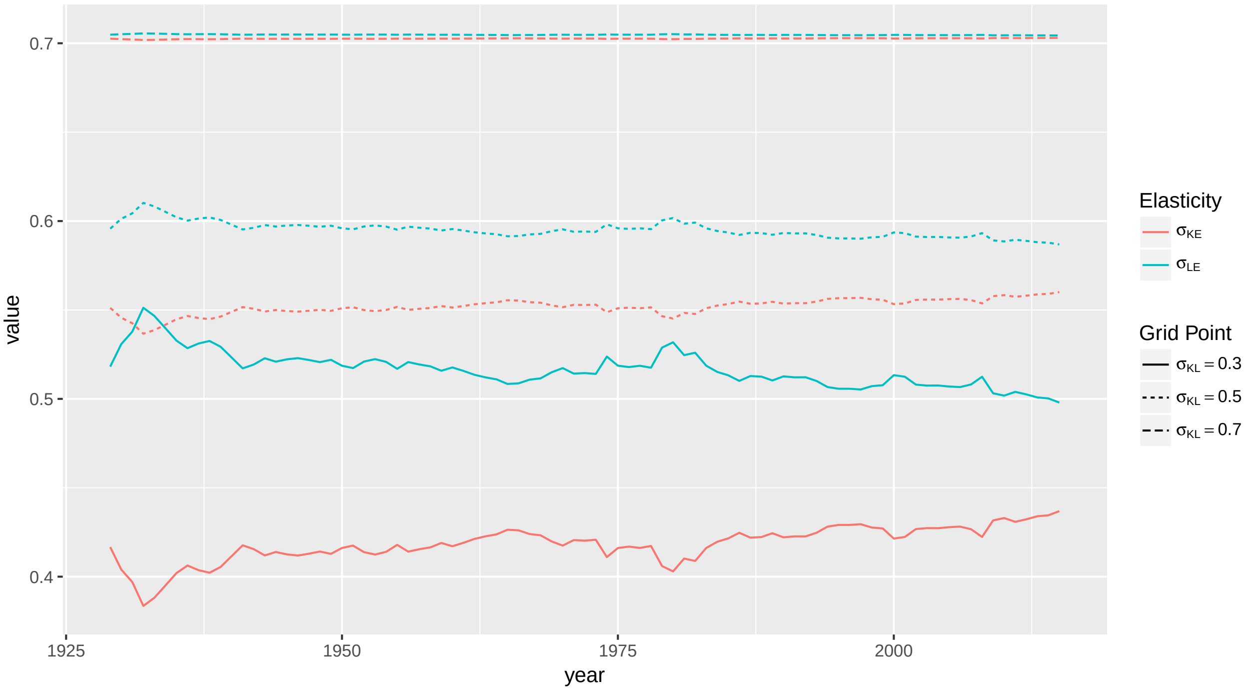



FIGURE 1
*Morishima elasticies for different values of $\sigma_{KL}$*

tors[4]. Since the Morishima elasticity in a CES production function is a function of the relative factor shares and the outer and inner elasticity parameters $\sigma$ and $\sigma_{KL}$, changing $\sigma_{KL}$ for the estimation also changes the Morishima elasticity. The Morishima elasticities for the nested CES function are defined by Anderson and Moroney (1993) as follows:

$$\sigma_{KL} = \sigma_{LK} \tag{6a}$$

$$\sigma_{EL} = \sigma_{EK} = \sigma \tag{6b}$$

$$\sigma_{LE} = \alpha_L \sigma_{KL} + (1 - \alpha_L)\sigma \tag{6c}$$

$$\sigma_{KE} = (1 - \alpha_L)\sigma_{KL} + \alpha_L \sigma \tag{6d}$$

Figure 1 shows the Morishima elasticities for labor and energy and capital and energy over the sample period for $\sigma_{KL}$ values of $0.3, 0.5$, and $0.7$[5]. In the case of $\sigma_{KL} = 0.7$ the Morishima elasticity is practically constant, since the estimation result gives us a coefficient of 0.7074 for $\sigma$. It also means that the Morishima elasticities $\sigma_{LE}$ and $\sigma_{KE}$ are almost identical.

Figure 1 also shows that the fact that Morishima elasticities are variable with the factor shares has very little influence on an aggregate level. Even when we assume a relatively extreme value of 0.3

[4] A more in-depth explanation of the usefulness of Morishima elasticities in the framework of a multifactor CES function is also found in Frieling and Madlener (2016).

[5] $\sigma_{KL} = 0.4 \vee 0.6$ omitted for clarity.


FIGURE 2
*Residuals of the four equations for different values of $\sigma_{KL}$*

for $\sigma_{KL}$, the variations in $\sigma_{KE}$ and $\sigma_{LE}$ are hard to distinguish from statistical noise.

Due to the interdependence of the parameters given by the cross-equation restrictions, it cannot be predicted how the misspecification of $\sigma_{KL}$ affects the estimation results. This means that, when using this method, the results should always be checked for plausibility. The numerical mechanics of nonlinear optimization can make the solvers get stuck in areas near the discontinuities of the production function (Henningsen and Henningsen, 2012). This is evident for cases where $\sigma$ is estimated to be very close to unity. Here we see that other factors have to compensate, leading to extreme estimates of energy specific technical change.

The residuals of the regression for the $\sigma_{KL}$ values of 0.3, 0.5, and 0.7 are plotted in Figure 2. As is obvious from the residual plots, the biggest difference for the levels of $\sigma_{KL}$ is in the wage and capital cost series, in particular the latter shows a pronounced lag of the residuals for the mean reversion when $\sigma_{KL} = 0.3$ compared to $\sigma_{KL} = 0.7$. Since the specifications have very similar parameter estimates, the only variation can be due to the change in $\sigma_{KL}$, which explains why we see the largest divergence of the residuals in the equations for wages and capital costs. However, all the specifications have very similar developments for the residuals of the output series and the energy price series. The residuals show the largest deviation in the energy price series. This might be due to the fact that energy price is partially exogenous, as manifested during the oil crises. At the same time, energy prices are more volatile than wages, which are mostly negotiated long-term and fixed in the short run. The residual plots also show that there is substantial serial correlation in the residuals.

## V. Interpreting the Results

The parameter estimates of between 0.6 and 0.7 for $\sigma$ obtained for the specifications $\sigma_{KL}$ is between 0.3 and 0.7 are significantly higher than the ones observed in Frieling and Madlener (2016), where only a 25 year sample was analyzed (for Germany) and an elasticity of around 0.18 was found. However, they are very much in line with the one by Kander and Stern (2014), where a 150 year sample of Swedish data was used. This is further evidence that there is a qualitative difference between long-run and medium-run substitutability of energy in the production process. It indicates that substitution possibilities are limited even over very long periods, but that some upper limit is approached some time after 25 years. In particular, since energy utilizing capabilities are embodied within the capital stock, the fact that the elasticity parameter of energy in a CES production function seems to rise with the sample size is not so surprising. As long as machinery is not replaced, the possibility to adjust energy consumption at a given output level is likely tightly constrained. This implies that the flexibility to adjust to changing economic circumstances or a different energy environment might be very limited in the short run. The energy share in the economy was highest shortly after the second oil crisis of 1979/1980, and in the following adjustment period growth remained anemic. Between the end of WW II up until 1970, the energy share of GDP never even reached 2%, leading to a firm belief in abundant and cheap energy. After a period where the energy share hovered between 5.0 and 9.8%, energy expenditures fell again, sometimes to only 2% of GDP. However, the knowledge of possible energy spikes and a generally more volatile energy market prepared producers to account for energy efficiency and substitution possibilities. Before the oil crises, the constrained labor inputs could be addressed with increased energy consumption and capital investment that enabled higher labor productivity. After the oil crises producers faced a double constraint in the labor and energy sector, both of which have to be addressed simultaneously through factor *saving* technical change, the vector of which is investment in capital stock that enables these productivity increases.

When it comes to modeling factor specific technical change and energy as a production factor, getting the elasticity between capital and labor exactly right matters less than expected. As long as the value of $\sigma_{KL}$ is chosen with consideration of existing prior information, the interaction between the production factors can be modeled quite well using the system approach for three production factors. The estimated technical change factors also agree with the observed changes in the variables: While GDP grew by 3.20% p.a. in the observed time period, the labor force only grew by about 1.30%

p.a., and while the capital stock growth even outpaced GDP growth and showed a yearly increase of 3.29%, energy consumption grew by 1.44% p.a. The coefficient estimates for technical change are statistically insignificant in the case of energy ($\gamma_E$), and slightly negative for capital ($\gamma_K$), while labor augmenting technical change is estimated to be between 1.31% when $\sigma_{KL} = .3$ and 1.62% when $\sigma_{KL} = .7$.

The results are very much in line with those of León-Ledesma et al. (2015), who only looked at capital and labor as production factors. Given that we use slightly different data and their model incorporates an assumed markup factor if 10%, our results point in the same direction. One interesting point found by León-Ledesma et al. (2015) is that ignoring the technical change parameters for capital had an outsized influence on the estimation results, despite of the fact that they also found only very small capital augmenting technical change, whereas we even find a slightly negative effect. Since even small changes in productivity can accumulate over time, it seems sensible to prefer estimation methodologies that are able to *a-priori* incorporate flexible technical change specifications.

Because we find mostly labor augmenting technical change, it is unsurprising that the labor share has decreased in the observed timeframe. As wages increase and additional labor inputs are unavailable, productivity increases can come from investments in capital stock that allow the more effective use of the scarce labor and energy resources. Labor augmenting technical change can therefore also have a labor saving effect (c.f. León-Ledesma et al., 2010). The presence of gross complementary factor inputs, as we find in our analysis with all elasticities below unity, leads to technical change aimed at augmenting the most constrained factor. This can lead to an overall decrease of the cost share of this factor, because technical change responds endogenously to the relative price constraints of factors in the long run (Acemoğlu et al., 2012). This means that for the US economy a relative labor shortage and increasing labor productivity actually led to a rising capital share, since the more productive labor force was partially caused by the availability of a sufficient and advanced capital stock. During the time period analyzed in the sample, we see prolonged periods of very low unemployment, while energy and capital where readily available. We find that energy consumption is constrained by cost only in the second half of the sample.

At the same time, energy use increased disproportionally compared to output, as long as energy prices were not a constraining factor. Once the energy crises of the 1970s changed the expectation of continued cheap and abundant energy, we see that increases in energy consumption lag behind output growth. Over the observed timeframe this means that the linear time trend for factor productivity is essentially flat.

The fact that the capital specific technical change parameter is negative should also be explained. Due to the complementarity of capital and labor inputs and the comparative lack of flexibility for capital, once capital stock is in place it is hard to change. This means that in periods of contraction, the labor force decreases more than output, whereas in periods of economic growth and very low unemployment rates, labor augmenting investment in advanced capital goods is the only source of productivity increases and growth outside of population increases.

The results can also be interpreted in light of the hypothesis of Grossman and Krueger (1995) and Acemoğlu et al. (2012). Both argue, the former from an empirical point of view, the latter as a consequence of an endogenous growth model, that the effective price constraint and limited short-term substitutability of energy lead to more abatement and conservation efforts as a society grows richer. And while the US has been an economic superpower during the time period we analyze, many of the advances in energy efficiency and conservation efforts came only after the exhaustability of energy sources was made plain by severe price shocks. Papageorgiou et al. (2017) see a similar result, and importantly, they identify a high elasticity between clean and dirty energy inputs. This makes green growth possible. Kander and Stern (2014) also find that energy inputs are substitutes in their examination of the use of modern energy sources compared to animal and wood derived energy.

## VI. Conclusions

We find that the substitution as well as the implementation of technical change for energy and labor mostly takes place through changes in the capital stock. In the years after the great depression this mostly meant labor saving technical change. However, the development of output and energy share after the oil crises point towards an increasing relative investment in energy augmenting technical change. The fundamental limitations of substitution between the production factors mean that the relative scarcity of the production factors determines the prioritization of technical change investments. This leads to some important implications with respect to the spread and implementation of energy saving technology.

When it comes to the long-term projections about energy use, especially for the developing world, more information about the role of energy inputs is important. Wolfram et al. (2012) describes why the developing world will account for most of the future increases in energy consumption, mainly through the increased formation of energy using capital, not only in a production sector but also in the form of consumer goods, such as refrigerators, air-conditioning, television, and personal transportation. It is therefore helpful to understand the trajectory that developed countries took in their energy consumption. Since there is a strong path dependency in capital formation, it is likely that currently developing countries will not go through a period of such excess energy consumption as the US economy went. However, many developing countries subsidize energy consumption for households and firms out of a desire to shield them from the fluctuations and vagaries of the international energy markets. In light of the results of our analysis for the US economy, it seems likely that this desire may backfire in the long run, when outdated capital stock that relies on cheap and plentiful energy inputs has to be replaced before it is fully depreciated, just because the operating costs become too burdensome. Furthermore, capital replacement might be unusually easy for the US economy. Cuba still relies on pre-revolutionary cars not out of nostalgia, but because the constraints on capital formation are more restrictive than those on labor and energy. As energy becomes more scarce and expensive the luxury of a roaring and inefficient open hearth turns into a liability when woodlands are cleared and firewood becomes expensive. The low mileage of the typical US car built in the 1950s and 1960s becomes a significant burden on households when fuel prices spike. Additionally, government funds that are used to subsidize energy consumption are missing elsewhere, and subsidized energy crowds out the incentives to innovate within the countries (Acemoğlu et al., 2012). Due to leapfrogging, countries are never far from the production technology frontier. When subsidized energy categorically disincentivizes clean energy investments, it delays necessary adjustments which ultimately harms the citizens which the subsidies are designed to help.

From a methodological perspective, we showed that, with the appropriate technique, it is possible to estimate a multi-factor CES function without having to restrict the factor productivity specifications to factor neutral technical change. This allows a better understanding of the development of the factor shares, a question that has received increased attention since Piketty and Zucman (2014) proposed his theory of real capital returns outpacing growth. We find evidence that most technical change is labor augmenting. However, further analysis with a more refined technical change specification could yield a more nuanced picture of factor productivity developments over time.

We find that the energy price shocks of the 1970s have led to a profound reorganization of the US economy and capital stock. It is therefore important for developing nations to phase out energy subsidies, in order to protect themselves from misdirected investments in energy inefficient capital stock which overuses underpriced resources to the detriment of the environment and the fiscal situation. This is arguably doubly true when countries are constrained in how freely they can replace their capital stock, because the path dependency of energy consumption is even stronger. Future research should address the question of how the substitution possibilities develop over different time horizons, which could help to shed some more light over the pace of technological replacement.

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