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Is Industrial Energy Inefficiency Transient or Persistent? Evidence from Swedish Manufacturing

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Abstract

Energy inefficiency in production implies that the same level of goods and services could be produced using less energy. The potential energy inefficiency of a firm may be linked to long-term structural rigidities in the production process and/or systematic shortcomings in management (persistent inefficiency), or associated with temporary issues like misallocation of resources (transient inefficiency). Eliminating or mitigating different inefficiencies may require different policy measures. Studies measuring industrial energy inefficiency have mostly focused on overall inefficiencies and have paid little attention to distinctions between the types. The aim of this study was to assess whether energy inefficiency is *transient and/or persistent* in the Swedish manufacturing industry. I used a firm-level panel dataset covering fourteen industrial sectors from 1997–2008 and estimated a stochastic energy demand frontier model. The model included a four-component error term separating persistent and transient inefficiency from unobserved heterogeneity and random noise. I found that both transient and persistent energy inefficiencies exist in most sectors of the Swedish manufacturing industry. Overall, persistent energy inefficiency was larger than transient, but varied considerably in different manufacturing sectors. The results suggest that, generally, energy inefficiencies in the Swedish manufacturing industry were related to structural rigidities connected to technology and/or management practices.

JEL classification: D22, L60, Q40
Keywords: Stochastic energy demand frontier model, persistent and transient energy inefficiency, energy inefficiency.

1 Introduction

Greenhouse gas (GHG) emissions from human activities are the main driver of climate change that has been observed during last few decades (Intergovernmental Panel on Climate Change (IPCC), 2013). About two-thirds of these emissions are associated with energy use (International Energy Agency, 2020), and global attempts to reduce GHG emissions and combat climate change have aimed at reducing energy use. In a recent report, the United Nation Secretary General's Advisory Group on Energy and Climate Change demanded a reduction in global energy intensity by 40% by 2030 (AGECC, 2010). Sweden is a front-runner in these matters and has set ambitious energy and climate-related goals, including an aim of being 50% more efficient in energy use by 2030 than it was in 2005 (Government offices of Sweden, 2018). The target is expressed in terms of primary energy use in relation to gross domestic product and the intention is that overall energy intensity will be reduced.

Energy intensity is generally defined as energy use per unit of activity, such as output. Energy efficiency improves if the same level of goods and services are produced using less energy, or if more of goods and services are produced using the same level of energy. For a given level of output, energy efficiency is defined as the ratio of minimum-possible to observed energy use. Improving energy efficiency can change energy intensity for the better.

The industrial sectors (including manufacturing) generally contribute significantly to both energy use and GHG emissions. Industry generated more than 30% of total global GHG emissions in 2010 (Fischedick et al., 2014), and consumed about 36% of total global energy use in 2014 (United States Energy Information Administration, 2017). Hence, improving energy efficiency of the industrial sector is essential if energy and climate-related targets are to be realized.

Industrial energy inefficiency may exist for various reasons, such as lack of upgrades to the most energy efficient technology, or sub-optimal allocations of energy in production. Overall energy inefficiency can however be decomposed into two types, persistent and transient (see e.g. Kumbhakar et al., 2014). *Persistent energy inefficiency* reflects structural rigidities in production and/or systematic shortcomings in management over a long period. *Transient energy inefficiency* is due to temporary shortcomings, like acute management problems, and this type of inefficiency is more readily improved in the short run.

Recent studies on efficiency measurements have focused not only on overall efficiency measures, but have also distinguished between transient and persistent. The distinction between types of inefficiency may have important implications for choosing optimal energy policy aimed at mitigating inefficiency (Kumbhakar et al., 2014; Kumbhakar and Lien, 2017; Lai and Kumbhakar, 2018; Lien et al. 2018). While transient energy inefficiency might be addressed by policies affecting short-term performance, mitigating persistent inefficiency might require policies aimed at making structural changes. Hence, studies measuring overall energy inefficiency are potentially misleading for designing short- versus long-term energy policies.

The stochastic frontier analysis (SFA) framework allows for estimating both persistent and transient energy inefficiency. Currently, empirical estimates of these two types are limited to a few studies within the household and residential sectors (e.g. Alberini and Filippini, 2017), and most studies with a focus on industry estimate the overall energy inefficiency only (e.g., Buck and Young, 2007; Boyd, 2008; Lundgren et al., 2016). Clearly, it would be advantageous if analysis which estimates persistent and transient energy inefficiencies could also be applied for industries.

This study contributes to the empirical literature on frontier analysis by estimating persistent and transient energy inefficiencies for the Swedish manufacturing industry. The manufacturing industry is one of the major drivers of Swedish GDP, and covers about 45% of the total energy use in Sweden in 2008 (Statistics Sweden (SCB); cited in Martinez and Silveira, 2013). Hence, measuring transient and persistent energy inefficiencies is likely to have important implications for designing energy policies in both the long run and the short run. Furthermore, because the analyses in this study are performed at the sectoral level, the results are potentially interesting for the same sectors in other countries that have a similar industrial structure. Until now, the empirical evidence for this industry has been limited to a few studies that measured overall energy efficiency, e.g. Lundgren et al. (2016) and Zhang et al. (2016). This study is the first to measure transient and persistent energy inefficiency for the Swedish manufacturing industry.

The paper is organized as follows. Section 2 is an overview of the evolution of the four-component SFA model, presenting the four-component stochastic energy demand frontier derived for a cost minimizing firm as well as its estimation approaches, and the empirical specification. Section 3 provides a summary of the data, while section 4 presents the results. Finally, section 5 discusses the results and offers some conclusions.

2 The Evolution of Four-Component SFA Models

The methodology of SFA panel models has evolved from the early models proposed by e.g. Pitt and Lee (1981) to the more recent four-component error term model[1] (Kumbhakar et al., 2014; Colombi et al., 2014; Tsionas and Kumbhakar, 2014). In this model, the error term captures (i) unobservable unit-specific heterogeneity, (ii) transient inefficiency, (iii) persistent inefficiency, and (iv) random noise, each of which is separately identified given distributional assumptions (e.g. Kumbhakar et al., 2014). The earlier and simpler SFA models included some, but not all, four components at the same time. For instance, the earliest SFA panel models were designed to capture persistent inefficiency, but did not allow for unobserved heterogeneity of panel units nor for transient inefficiency (see Pitt and Lee, 1981; Schmidt and Sickles, 1984; Kumbhakar, 1987; Battese and Coelli, 1988). Models subsequently proposed by Kumbhakar and Hjalmarsson (1993) and Kumbhakar and Heshmati (1995) captured both transient and persistent inefficiencies, but confounded persistent inefficiency with unit effects, because they did not separate inefficiency from unobserved heterogeneity. The first models separating unobserved unit heterogeneity from inefficiency were the "true fixed effect" and the "true random effect" panel SFA models by Greene (2005). However, these models are not capable of separating persistent inefficiency, if it exists, from unit-specific effects.

The four-component error term SFA model improves upon the earlier models because it can separate unobserved heterogeneity from persistent inefficiency, and transient inefficiency from random noise. The model is more flexible in the sense that it allows for the inefficiency of a unit (e.g. firm) to be correlated with itself over time, and a unit may reduce part of its inefficiency over time by reducing short-term rigidities. In contrast, earlier SFA models generally assumed that inefficiency is independently distributed over time, which is a rather restrictive assumption (Lien et al, 2018). Other developments of the four-component error term SFA model allow identification of determinants of inefficiency (see e.g. Reifschneider and Stevenson (1991), Kumbhakar et al. (1991), Battese and Coelli (1995), Badunenko and Kumbhakar (2017), Lai and Kumbhakar (2018) and Lien et al. (2018) for more comprehensive descriptions). The determinants of the four component inefficiencies are not as such in the scope of this paper.

[1] The four-component model is also referred to as the generalized true random-effects model (GTRE) by Tsionas and Kumbhakar (2014).

2.1 A Stochastic Energy Demand Frontier Model for Panel Data

A technically energy efficient producer reaches the maximum level of output (as represented by the production frontier) given the technology at hand and the use of other inputs. As there are many different input combinations that may lead to the same level of frontier output, there is a concern about whether the observed combination of inputs is the best. A relevant criterion for determining the performance of producers should relate to production decisions such as cost minimization or profit maximization, under which allocative efficiency can be accommodated. The cost minimization criterion is generally used in empirical applications for evaluating allocative efficiency and identifies the least-cost input combination for producing a given level of output.[2] More precisely, for a cost-minimizing firm, a stochastic energy demand frontier represents the minimum level of energy required to produce a given level of output, given the available technology and the use of other inputs and their prices. The most energy efficient firms are located on (or close to) the frontier, while less efficient firms are located further below the frontier. The overall energy inefficiency score of a firm is measured as the deviation from the frontier, i.e. the difference between the observed energy use and the cost-minimizing level defined by the derived energy demand frontier. The score reveals the percentage by which a firm could reduce its energy use in relation to the frontier (i.e. a cost-minimizing energy use given technology available), while still producing the same level of output.

A firm's overall energy inefficiency may be persistent and/or transient due to technical inefficiency (the failure to operate at the production frontier), allocative inefficiency (the failure to minimize production costs), or a combination of both (Filippini and Hunt, 2012). As mentioned earlier, persistent inefficiency reflects structural problems in a firm's production process and/or systematic shortcomings in management, while transient reflects more temporary management problems.

A few studies have used SFA to measure industrial energy efficiency (e.g. Boyd (2008), Buck and Young (2007), Filippini and Hunt (2011), Zhou et al. (2012), and Lundgren et al. 2016).[3] The stochastic energy demand frontier model in this study is based on the cost-minimizing input demand equations derived in e.g. Schmidt and Lovell (1979) and further discussed in Kumbhakar and Lovell (2000). Adopting the framework proposed by Colombi et al. (2014), Kumbhakar et al. (2014) and Tsionas and Kumbhakar (2014), a four-component stochastic

[2] A firm is said to be "allocative efficient" (with respect to cost minimization) if there is no other bundle of inputs that can produce a given level of output at a lower cost.
[3] There are examples where Swedish industrial energy efficiency has been measured using approaches other than SFA, such as a study by Zhang et al. (2016) using data envelopment analysis (DEA), and a study by Pardo Martínez and Silveira (2013) using energy intensity as a measure of energy efficiency.

energy demand frontier allowing for unobserved heterogeneity, persistent and transient inefficiencies can be written as:

$$ln\,E_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j\, ln\,X_{jit} + \underbrace{\mu_i + \eta_i + u_{it} + v_{it}}_{error\ components} \quad (1)$$

where subscripts i and t represent firm and year, respectively. E is the actual energy use as a function of a vector of variables, $\boldsymbol{X}$, including e.g. the level of output and relative price of other inputs to energy price (more on this below).[4] $\boldsymbol{\beta}$ is a vector of j coefficients to be estimated. Unexplained energy use is reflected by the error terms μ_i, η_i, u_{it} and v_{it}.

Kumbhakar et al. (2014) showed that each of the four error terms can be identified given their respective distributions. The term μ_i captures unobservable heterogeneity among firms (i.e. firm effects), and is assumed to follow a standard-normal distribution (i.e. $\mu_i \sim i.i.d\ N(0, \sigma_\mu^2)$). For a firm that is not fully energy efficient, u_{it} and η_i measure the difference between actual and optimal energy use in the short and long run, respectively. Term η_i is a one-sided error capturing the level of underlying persistent or time-invariant energy inefficiency, and is assumed to follow a half-normal distribution (i.e. $\eta_i \sim i.i.d\ N^+(0, \sigma_\eta^2)$) with $E(\eta_i) = \sqrt{2/\pi}\,\sigma_\eta$. This part is only allowed to vary across firms i. Term u_{it} is a one-sided error capturing the level of underlying transient or time-varying energy inefficiency, also assumed to follow a half-normal distribution, (i.e. $u_{it} \sim i.i.d\ N^+(0, \sigma_u^2)$) with $E(u_{it}) = \sqrt{2/\pi}\,\sigma_u$. This part is allowed to vary both across firms i and over time t. Both inefficiency terms are assumed to be larger than or equal to zero, and to capture the technical and allocative inefficiency (Filippini and Hunt, 2012). Finally, v_{it} is a conventional symmetric random noise term and is assumed to be normally distributed (i.e.,$v_{it} \sim i.i.d\ N(0, \sigma_v^2)$).

The half-normal distributional assumption for the one-sided inefficiency terms η_i and u_{it} is most common in empirical studies. Alternative distributions exist, such as the truncated normal, exponential, and gamma distribution, and a key question is whether choice of distribution has any critical implications for the results. Greene (1990) compared average inefficiency levels across four main distributional specifications for the one-sided inefficiency term (half-normal, truncated normal, exponential, and gamma) and found that there is almost no difference in average inefficiency for 123 U.S. electric utility providers. Greene's finding motivates assuming a half-normal distribution for the inefficiency terms in this paper.

[4]This set of variables is included based on a derived stochastic energy demand frontier equation within a cost-minimizing framework. The empirical specification is presented in Section 2.3.

2.2 Estimation

There are different approaches for estimating the four-component error model. For instance, Colombi et al. (2014) proposed a single stage Maximum Likelihood (ML) estimation, and a closed form ML estimator is obtained assuming a skewed normal distribution for both the time variant and invariant random components of Eq. (1).[5]

This distribution is more general than the normal distribution and allows for an asymmetric error term (Azzalini, 1985). Kumbhakar et al. (2014) and Lien et al. (2018) suggested a three-step approach to estimate Eq. (1). As argued by Lien et al. (2018), the three-step approach has two advantages compared to the single-stage ML approach. First, $\boldsymbol{\beta}$ parameters estimated using a three-step approach are not affected by distributional assumptions on u_{it} and η_i since they are estimated prior to distributional assumptions. Second, the three-step procedure is more convenient to implement in practice (Filippini and Greene, 2016), because the one-step ML estimator is based on a nonlinear optimization and therefore may not converge while maximizing the log likelihood function. However, the one-step ML estimator is a more efficient estimator than the three-step approach, i.e. it has a smaller variance (Lien et al., 2018). The three-step approach proposed by Kumbhakar et al. (2014) and Lien et al. (2018) is used in this study and the steps are summarized below.

In step 1, Eq. (1) is transformed to a standard random effect panel model by adding and subtracting the expected values of η_i and u_{it} to and from Eq. (1) as follows:

$$ln\,E_{it} = \overbrace{[\beta_0 + E(\eta_i) + E(u_{it})]}^{h} + \sum_{j=1}\beta_j\, ln\, X_{jit} + \overbrace{[\mu_i + \eta_i - E(\eta_i)]}^{\alpha_i} + \underbrace{[u_{it} + v_{it} - E(u_{it})]}_{\varepsilon_{it}} = h + \sum_{j=1}\beta_j\, ln X_{jit} + \alpha_i + \varepsilon_{it} \quad (2)$$

Regardless of any initial distributional assumptions for the two components η_i and u_{it}, Eq. (2) is a transformation of Eq. (1) such that components α_i and ε_{it} have zero mean and constant variance. This equation follows the standard form of a random effect panel model (Baltagi, 2008; Hsiao, 2014) and is estimated by random effect regression.

In steps 2 and 3, firm specific effects and residuals obtained from the first step are used as dependent variables of two separate SFA models to estimate persistent and transient inefficiencies. In the second step, the predicted values of α_i are used as the dependent variable to estimate persistent inefficiency, while

[5] Colombi et al. (2014) assume that v_{it} and μ_i are independent and identically distributed (*i.i.d.*) with standard normal probability density function, and that u_{it} and η_i are *i.i.d.* with half normal probability density function.

ignoring the differences between the true and predicted values of α_i. The term α_i is decomposed as:

$$\alpha_i = -E(\eta_i) + \mu_i + \eta_i \tag{3}$$

Eq. (3) is estimated using a standard normal–half-normal SFA model. Firm-specific persistent energy inefficiency is obtained using the conditional mean estimator of η_i, i.e., $E = (\eta_i|\mu_i)$ proposed by Jondrow et al. (1982). The corresponding firm-specific persistent energy efficiency scores are then calculated by *exp* ($-\eta_i$). These scores take values between zero and one, where one indicates a fully energy efficient producer in long run, i.e., $\eta_i = 0$.

Similarly, in the third step, the predicted values of ε_{it} from step 1 are used to estimate the transient inefficiency u_{it} using a standard normal–half-normal SFA model. This procedure ignores the difference between the true values and the predicted values of ε_{it}. As defined in Eq. (2), ε_{it} is decomposed as:

$$\varepsilon_{it} = -E(u_{it}) + u_{it} + v_{it} \tag{4}$$

Like the second step, firm-specific transient energy inefficiency is obtained using the conditional mean estimator of u_{it}, i.e., $E = (u_{it}|v_{it})$, proposed by Jondrow et al. (1982). The corresponding firm-specific transient energy efficiency scores are then calculated by *exp* ($-u_{it}$). These scores also take values between zero and one, where one indicates a fully energy efficient producer in the short run. Overall efficiency is obtained as a product of the transient and persistent efficiency scores.

2.3 Empirical Specification

The empirical specification of the four-component stochastic energy demand frontier model in this study is based on a Cobb-Douglas production technology. This form is widely used in frontier analysis models because of its relative simplicity (see e.g. Kumbhakar and Lovell, 2000). Assuming firms minimize costs using the inputs labor, capital and energy, the frontier is formulated as:

$$\begin{aligned} lnE_{it} = \beta_0 + \beta_Y lnY_{it} + \beta_{RPCE} lnRPCE_{it} + \beta_{RPLE} lnRPLE_{it} + \beta_s \boldsymbol{D}_s + \beta_t t \\ + \underbrace{\mu_i + \eta_i + u_{it} + v_{it}}_{four-component\ error} \end{aligned} \tag{5}$$

As in previous equations, subscripts *i* and *t* represent firm and year, respectively. *E* is the actual energy use by each firm, modeled as a function of the level of output *Y*, the relative price of capital to energy *RPCE* and the relative price of labor to energy *RPLE*. Given the log-format, coefficients are interpreted as elasticities. A time trend variable t is added to account for changes in energy use over time.

Furthermore, product heterogeneity within each sector is controlled for by the set of sub-sector dummy variables $\boldsymbol{D_s}$. These dummies represent different groups of products produced within each sector and are constructed from official Swedish industry classifications. The inclusion is reasonable; within each sector, firms producing the same products are likely to be more similar to each other than to other firms.

3 Data

This study uses a firm-level (unbalanced) panel data set covering 14 sectors in the Swedish manufacturing industry for the period 1997–2008. The dataset was provided by Statistics Sweden and contains detailed annual information on costs and quantities related to different inputs and sales. In this section, I first provide summary statistics on inputs and their prices as well as output for an average firm and year within each of the 14 sectors. The next sub-section briefly reports the evolution of these variables over time for the whole manufacturing industry, while the final sub-section provides sector-level comparisons.

3.1 Descriptive Statistics for an Average Firm and Year

Descriptive statistics for an average firm and year are presented in Table 1, where all monetary values were normalized to the year 2008 price level in the Swedish currency, SEK.

The inputs were capital, labor, and energy. Capital stock was calculated by the perpetual inventory method using gross investment data (excluding investments in building). From the sum of gross fixed capital formation in previous years as well as the depreciation rate of capital (determining service life of the capital), this method provides an estimate of gross and net capital stock for a time series. The capital depreciation rate was set to 0.087 for all firms and sectors in this study as suggested by King and Fullerton (1984) and Bergman (1996). Labor was the number of full-time employees. Energy was the sum of electricity, district heating, wood fuel, coal, solid fuel, and gaseous fuel, which were all converted to energy equivalents (GWh) by Statistics Sweden using the same conversion rates for all industries. The output for each firm and year was calculated as the firm's final sales divided by its corresponding producer price index for a given sector and year. The price of capital was calculated based on national and sector-level indices (Lundgren, 2010; Brännlund and Lundgren, 2010). Unit prices of labor and energy were calculated as the ratio of input cost to quantity used. For instance, yearly salary (price of labor) for each firm and year was calculated by the ratio of total salaries paid to employees in that year to the number of employees. This implies that the salary variable does not reflect e.g. the amount of part-time salaries, but instead reflects the average amount paid to a full-time employee by an average firm in each year. Similarly, the energy price for each firm and year was calculated by the ratio of total costs of energy in that year by that firm to the quantity used.

Table 1. Descriptive statistics for an average firm and year over the period 1997–2008

Sector	Obs.	Capital (MSEK)	Labor (number)	Energy (GWh)	Output (MSEK)	Capital price (index)	Salary (TSEK)	Energy price (SEK/MWh)
Basic iron and steel	410	535 (1132)	528 (858)	676 (1967)	1148 (2062)	0.12 (0.07)	702 (235)	554 (219)
Chemical	1201	398 (1633)	276 (913)	88 (242)	627 (2336)	0.09 (0.03)	641 (166)	496 (196)
Electro	1227	79 (257)	376 (1570)	7 (20)	1333 (9258)	0.1 (0.03)	346 (362)	380 (207)
Fabricated metal products	2193	11 (19)	43 (153)	2 (6)	30 (62)	0.08 (0.02)	451 (134)	604 (247)
Food	2553	130 (371)	200 (504)	23 (74)	427 (1159)	0.1 (0.02)	450 (332)	498 (186)
Machinery	3506	58 (161)	179 (420)	7 (20)	266 (795)	0.09 (0.02)	460 (131)	520 (188)
Mining	288	566 (1899)	265 (692)	204 (657)	494 (1399)	0.12 (0.06)	663 (383)	614 (233)
Motor vehicles	1218	508 (2249)	590 (2089)	27 (96)	1601 (7533)	0.08 (0)	392 (72)	458 (184)
Printing	920	30 (62)	73 (111)	4 (8)	64 (131)	0.08 (0.01)	500 (401)	522 (183)
Pulp and paper	1019	722 (1337)	397 (619)	433 (875)	1001 (1726)	0.09 (0.02)	459 (97)	351 (174)
Rubber and plastic	1349	46 (81)	90 (122)	8 (16)	111 (186)	0.09 (0.02)	463 (118)	506 (165)
Stone and mineral	1019	75 (129)	151 (217)	56 (214)	178 (263)	0.08 (0.02)	538 (1962)	485 (197)
Textile	749	31 (81)	79 (169)	8 (17)	68 (100)	0.07 (0.01)	352 (82)	453 (178)
Wood	3131	50 (133)	78 (153)	25 (57)	191 (430)	0.12 (0.02)	407 (101)	300 (231)

*Column "Obs." is the number of observations over all years and firms.

**Standard deviations are given in parenthesis.

3.2 Aggregate Industrial-level Descriptive Statistics for 1997 – 2008

At the aggregate industry level, capital stock had an increasing and fairly constant trend over time from 183000 MSEK in 1997 to 333000 MSEK in 2008. Labor, i.e. the number of employees, showed no overall trend over the studied period. Energy increased from 1997 to 2000, while remaining relatively constant onwards. This aggregate trend was mainly driven by the two most energy consuming sectors, *Pulp and paper* and *Basic iron and steel*.

The aggregate output at industry level showed an overall increasing trend over time and the growth rate was relatively high between 1998 and 2000. This was mainly driven by two sectors, namely *Electro and Motor vehicles*, which were the sectors with the highest levels of output over the studied period. Price of capital, an index-based variable, had a decreasing trend on the aggregate level over the studied period. The average salary remained relatively constant over time at about 450 TSEK from 1997 to 2008. The average energy price increased at the aggregate level within the studied period from about 300 (SEK/MWh) to 630 (SEK/MWh).

3.3 Sector-level Descriptive Statistics for 1997 – 2008

Capital stock had an increasing trend over time within most of the industrial sectors. However, the growth rate of capital stock varied among the different sectors. The highest growth rates were seen in *Fabricated metal products* and *Basic iron and steel*, while *Electro* and *Printing* had the lowest growth rates. The sectors with the largest capital stocks were *Pulp and paper* (ranging from 45000 to 72000 MSEK) and *Motor vehicles* (36000 to 69000 MSEK).

Labor showed no overall trend within most of the industrial sectors over the studied period. The sector with the largest number of employees was *Motor vehicles* (ranging from 48000 to 68000 employees) followed by *Machinery* (ranging from 42000 to 68000 employees). As previously mentioned, *Pulp and paper* and *Basic iron and steel* were the two most energy intensive sectors within the manufacturing industry. The growth rate of energy varied among different sectors, with the highest growth rates in *Fabricated metal products* and *Basic iron and steel*. The largest negative rates were found in the *Textile* and *Printing* sectors.

The overall output growth rate varied among sectors. The highest positive growth rates were found in *Fabricated metal products* and *Motor vehicles*, while negative rates were found in *Printing* and *Textiles*. Capital prices decreased over time within different sectors, with converging trends except for *Electro* in which the price of capital increased over time. The largest negative rates were observed in *Basic iron and steel* and *Mining*.

The highest salary growth rates were seen in *Electro* and *Motor vehicles*, while the highest negative rates were found in *Basic iron and steel* and *Mining*. The highest average salaries were in *Basic iron and steel* until 2005. In 2008, the average salary in *Chemical* and *Mining* exceeded *Basic iron and steel*. In general, the data showed a converging trend in salaries between different sectors over the studied period. The highest growth rates in energy prices were found in *Electro* and *Textiles*, while the lowest growth rates were found in *Basic iron and steel* and *Mining*. The highest average energy prices until 2005 were in *Mining* and *Basic iron and steel*, after which *Fabricated metal products* and *Printing* had the highest prices for energy.

The variation in Table 1 is expressed by standard deviations (SD) in parentheses, indicating heterogeneity within sectors. As complementary descriptive statistics, the top two sectors with highest coefficient of variation (CV), i.e. the ratio of standard deviation to mean, are also indicated below.

Capital stock had the highest SD in *Motor vehicles* and *Mining*, while CV was highest in *Motor vehicles* and *Chemical*. Labor showed the highest SD in *Motor vehicles* and *Electro*, and the highest CV in *Electro* and *Fabricated metal products*. Energy had the highest SD in *Basic iron and steel* followed by *Pulp and paper*, and the CV was highest in *Stone and mineral* and *Motor vehicles*. Output showed the highest SD and CV in *Electro* and *Motor vehicles*.

The distributions of all inputs and output within all sectors were substantially skewed, and this skewness can be seen by comparing averages and median values for the different variables within each sector as presented in Table A.1 in the Appendix. This observation means that, within each sector, there are firms that are very large in comparison to the majority of firms.

4 Results

This section presents the results of the parameter estimates for the stochastic energy demand frontier model, as well as sector-level averages of the overall, persistent, and transient energy efficiency scores. A numerical example is then provided to illustrate the potential reduction in energy use by each sector if inefficiency is eliminated, in the context of the available technology.

4.1 Parameter Estimates for the Stochastic Energy Demand Frontier

Estimated coefficients of Eq. (5) are presented in Table 2. The results generally suggest that energy use is inelastic with respect to the level of output and to the relative prices of capital and labor to energy as their coefficient estimates are smaller than unity.

For all sectors in Swedish manufacturing, energy use increased with the level of output produced. The output coefficients, interpretable as elasticity values due to the log format, were all statistically significant and ranged from 0.57 for *Basic iron and steel* to 0.96 for *Pulp and paper*. The estimated elasticity of energy demand with respect to the relative price of capital to energy was also positive and, in most sectors, statistically significant, ranging from 0.2 in *Printing* to 0.5 in *Chemical*, suggesting that capital and energy are substitutable to some degree. The elasticity estimates for energy demand with respect to the relative price of labor to energy were statistically insignificant in most sectors, meaning that the level of substitutability between energy and labor is zero. However, for a few sectors, this elasticity was statistically significant but relatively small in size, and its sign differed, implying that labor and energy to be either substitutes or complements depending on the sector. Estimates of the time trend coefficient showed statistically significant positive effects on the energy use in most sectors, ranging from 1% to 7% on yearly average, suggesting that energy use increased over time.

4.2 Estimated Levels of Energy Efficiency

Sector-level averages of transient, persistent and overall energy efficiency scores obtained from firm-level estimates are presented in Table 2. The results generally suggest that the main sources of overall inefficiency in Swedish manufacturing were persistent rather than transient. The average transient efficiency estimates range from about 80% to almost 100% across all sectors, while the average persistent efficiency estimates range from about 45% to almost 100%.

These results suggest that energy inefficiency within *Fabricated metal products*, *Food*, *Machinery*, and *Rubber and plastic* was nearly exclusively transient. On the other hand, energy inefficiency within *Chemical, Motor vehicles* and *Printing* was persistent. It is also possible to identify sectors that had both transient and persistent energy inefficiencies, such as *Basic iron and steel*, *Stone and mineral* and *Textile*. Finally, the results suggests that, given the contemporary technology, there was almost no room for efficiency improvement of any type in *Electro*, *Mining*, *Pulp and paper*, and *Wood*, implying that, in these sectors, firms performed close to the energy demand frontier (optimal performance) and were similar to each other in some ways.

Table 2 also shows the sectoral averages of firm-level energy efficiency scores divided into three types: overall, persistent, and transient. The firm-level energy efficiency scores were calculated using the density distribution of Jondrow et al. (1982) (illustrated in Figure A.1 in the Appendix for all sectors). These density distributions suggest that there were some sectors in which there was large variation between energy efficiency point estimates.

I also investigated whether each sector had differences in the average of energy efficiency scores among firms producing different product groups, which can be readily evaluated because, within each sector, firms' different products are grouped by Swedish Standard Industrial Classification. For instance, according to the standard 5-digit classification code[6], firms in *Basic iron and steel* produced six different groups of products. To address this question, a descriptive analysis was performed (results presented in Table A.2 in the Appendix). Some sectors had large variation in the average of point estimates of overall and persistent energy efficiency scores between groups of firms producing different products, such as *Chemical*, *Stone and mineral*, *Textile*, and *Printing*. This variation implies that there was heterogeneity among firms with respect to their potentials for EEI in these sectors. Given limited resources for promoting energy efficiency, this type of analysis can generally be used to effectively target relatively inefficient sub-sectors with more room for EEI.

[6]Information on Swedish Standard Industrial Classification and lists of product groups within each sector can be found at the homepage of Statistics Sweden.

Table 2. Estimated coefficients and sector average energy efficiency scores

	Variable	Basic iron and steel	Chemical	Electro	Fabricated metal products	Food	Machinery	Mining	Motor vehicles	Printing	Pulp and paper	Rubber and plastic	Stone and mineral	Textile	Wood
Frontier	*lnY*	0.57***	0.64***	0.69***	0.71***	0.69***	0.66***	0.58***	0.71***	0.90***	0.96***	0.75***	0.63***	0.63***	0.73***
	lnRPCE	0.03	0.50***	0.21***	0.38***	0.42***	0.23***	0.25*	0.37***	0.20***	0.23***	0.26***	0.45***	0.12	0.49***
	lnRPLE	0.23**	0.01	-0.07	-0.16**	0.01	-0.01	-0.13	-0.07	-0.04	0.07	-0.09	0.21***	0.01	0.00
	D_s	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
	t	0.02	0.07***	0.04***	0.03***	0.04***	0.00	0.01	-0.01	0.05***	0.01**	0.03***	0.01	-0.01	0.03***
	_cons	7.67***	6.23***	5.14***	4.42***	4.73***	4.89***	4.33***	5.14***	2.78***	6.55***	5.53***	6.91***	5.30***	5.33***
Energy efficiency (%)	*Transient efficiency*	85.10 (30-96)	99.98 (99-99)	99.97 (99-99)	80.85 (10-96)	83.81 (29-96)	90.09 (64-97)	99.97 (99-99)	99.99 (99-99)	99.98 (99-99)	99.99 (99-99)	89.59 (58-97)	79.67 (23-94)	85.64 (51-96)	99.96 (99-99)
	Persistent efficiency	49.42 (16-73)	44.84 (3-89)	99.88 (99-99)	99.93 (99-99)	99.90 (99-99)	99.86 (99-99)	99.87 (99-99)	60.65 (22-87)	67.46 (23-89)	99.87 (99-99)	99.91 (99-99)	56.87 (19-89)	49.02 (6-85)	99.91 (99-99)
	Overall efficiency	42.05 (13-69)	44.83 (3-89)	99.85 (99-99)	80.79 (10-96)	83.72 (29-96)	89.97 (64-97)	99.83 (99-99)	60.65 (22-87)	67.44 (23-89)	99.86 (99-99)	89.51 (58-97)	45.38 (14-77)	42.07 (4-77)	99.88 (99-99)
	Number of firms	69	218	381	703	606	850	72	260	390	148	340	209	198	698
	Obs.	408	1195	1214	2175	2538	3475	287	1207	912	1018	1344	1014	747	3085

Minimum and maximum point estimates of each efficiency type are presented in parentheses.
***, **, and * indicate 1%, 5% and 10% significance levels, respectively.
"Yes" indicates inclusion. Some of these dummies in each sector become statistically significant.
Some observations are dropped in the first step of estimation (random effect regression).

4.3 Quantifying Potential Energy Savings

A numerical example is provided to illustrate the potential reductions in energy use that could have been realized from eliminating overall, transient, and persistent energy inefficiency given the technology available at the time. The calculation is based on the sector-average transient, persistent and overall energy efficiencies and the yearly average energy uses seen in each sector over the period 1997–2008. The sectors are listed by yearly average energy use from highest to lowest in Table 3. *Pulp and paper* and *Printing* had the highest and lowest energy uses of about 37,000 and 200 GWh per year respectively.

Table 3. Potential yearly reductions in energy use from eliminating energy inefficiency

	Potential EEI (%)			Energy demand (GWh	Potential energy saving (GWh)		
Sector	Transient	Persistent	Overall		Transient	Persistent	Overall
Pulp and paper	0.01	0.13	0.14	36 745	3.87	46.55	50.42
Basic iron and steel	14.90	50.58	57.95	23 096	3441.45	9940.84	13382.29
Chemical	0.02	55.16	55.17	8 786	2.04	4845.39	4847.43
Wood	0.04	0.09	0.12	6 493	2.29	5.77	8.06
Food	16.19	0.10	16.28	4 994	808.66	4.24	812.90
Mining	0.03	0.13	0.17	4 888	1.66	6.58	8.23
Stone and mineral	20.33	43.13	54.62	4 769	969.56	1638.76	2608.32
Motor vehicles	0.01	39.35	39.35	2 060	0.22	810.52	810.74
Machinery	9.91	0.14	10.03	2 008	198.94	2.46	201.40
Rubber and plastic	10.41	0.09	10.49	934	97.28	0.77	98.05
Electro	0.03	0.12	0.15	729	0.19	0.90	1.08
Textile	14.36	50.98	57.93	492	70.73	214.95	285.68
Fabricated metal products	19.15	0.07	19.21	379	72.59	0.22	72.81
Printing	0.02	32.54	32.56	201	0.04	65.46	65.50

Potential EEI (%) = 100 – (Energy Efficiency %)

For the overall energy use in absolute terms (GWh per year), the largest overall potentials for energy savings were to be found in the second largest sector in terms of energy use *Basic iron and steel* (13,382), followed by *Chemical* (4,847) and *Stone and mineral* (2,608). In relative terms, large energy inefficiencies were found in *Basic iron and steel* (58%), *Textile* (58%), *Chemical* (55%), *Stone and mineral* (55%), *Motor vehicles* (39%), and *Printing* (33%), while very small overall potentials for EEI were found in *Pulp and paper*, *Mining*, *Wood* and *Electro*.

For transient inefficiencies, the largest potential energy savings in absolute terms (GWh per year) were to be found in *Basic iron and steel* (3,441), *Stone and mineral* (969), and *Food* (808). In relative terms, *Stone and mineral*, *Fabricated metal products*, *Food*, *Basic iron and steel*, and *Textile* had the largest potentials for EEI. For persistent inefficiencies, the largest potential energy savings in GWh per year were in *Basic iron and steel*, *Chemical*, *Stone and mineral* and *Motor vehicles*, while in relative terms, *Chemical*, *Textile*, *Basic iron and steel*, and *Stone and mineral* had high potentials for EEI. Table 3 also shows that the potential for EEI (%) and energy savings (GWh per year) were, in general, larger for persistent inefficiency. Finally, it is worth mentioning that the potential savings in Table 3 do not in any way reflect costs required to eliminate these inefficiencies.

5 Discussion and Conclusions

Industrial energy inefficiency may exist for various reasons such as lack of upgrades to the most energy efficient technology and/or sub-optimal allocations of energy in production due to factors unrelated to energy use *per se*, like e.g. poor management. Regardless of the reason, inefficiency may exist for short periods and be explained by temporary shortcomings (transient inefficiency), or for it may exist for longer periods, indicating structural rigidities (persistent inefficiency).

The Swedish manufacturing industry contributes a large proportion of overall production and economic growth in Sweden. Manufacturing's total energy use was about 45% of the total final energy used in Sweden in 2008 (Statistics Sweden (SCB); cited in Martinez and Silveira, 2013). Hence, identifying transient and persistent energy inefficiencies may have important implications for designing energy policies in both the short run and the long run, and may play an important role for overall industrial energy efficiency.

This study contributes to our knowledge of industrial energy efficiency by estimating and identifying persistent and transient energy inefficiency in the Swedish manufacturing sectors. Within the studied sectors, the results suggest that persistent energy inefficiency is notably larger than transient energy inefficiency. The implication of this finding is that conventional estimates of overall energy inefficiency, which do not distinguish between persistent and transient inefficiencies, mainly capture persistent inefficiency (at least for these sectors). However, the proportions of transient and/or persistent energy inefficiency varies both among and within the different manufacturing sectors.

The distinction between persistent and transient inefficiencies is potentially useful for policies targeting energy intensity, and guidelines that do not take this distinction into account could propose the wrong solutions. For instance, one of the largest overall energy inefficiencies (larger than 50%) is found in *Chemical*. However, the results of this study imply that policies that only improve short-term performances in this sector would be ineffective, because this sector is already efficient in terms of transient efficiency. Instead, policy makers interested in improving short-term inefficiencies might instead target *Fabricated metal products* and *Food*. These two sectors are not among the sectors with the largest overall energy inefficiencies, and would not necessarily be identified as particularly important based on conventional overall energy efficiency measures. However, they have the second and third largest transient energy inefficiencies, and policies that improve short-term energy performance might have relatively greater impacts on these sectors than others.

These results show that there is a potential for reducing energy use through eliminating energy inefficiencies, which also implies a potential for decreasing energy intensity (defined as the ratio of energy to output) through energy efficiency improvements (EEI). This means that energy intensity targets can be addressed without decreasing output levels or compensating in other ways by increasing input. In terms of GWh per year, the largest total energy savings are to be found in *Basic iron and steel*, which is the second largest sector in terms of total energy use. Given its high level of energy use and large energy inefficiency, the potential for energy savings in this sector is larger than for all other 13 sectors put together. However, it should be noted that these results might be driven to some extent by the high degree of heterogeneity in the use of inputs (e.g. energy) in this sector (as indicated by the standard deviations in Table 1).

Based on these results, further research could, for example, focus on *Basic iron and steel* to identify the drivers of inefficiency, and to explore what sort of policy measures could be used to mitigate these inefficiencies. However, it should be noted that the relatively large estimates of energy inefficiency may also have been driven by difficulties in fully controlling for firm heterogeneity within product groups when adopting the framework of a four-component SFA model.

There are some differences between the results of this study and two earlier studies measuring energy efficiency for the Swedish manufacturing industry using SFA. This study showed that four sectors were almost fully energy efficient given the technology available to them at the time. This result to some extent differs to the findings Lundgren et al. (2016) and Amjadi et al. (2018), which estimated fuel and electricity efficiencies. The differences could be explained by the choice of different SFA models. The present study used the four-component SFA model, which is capable of decomposing overall inefficiency into its persistent and transient parts and of separating firm effects from inefficiency and noise. In contrast, Lundgren et al. (2016) applied True Random Effect model of Greene (2005), which did not separate persistent efficiency from firm heterogeneity, while the model used by Amjadi et al. (2018) did not fully control for firm-effects nor separate persistent and transient components of overall inefficiency. Furthermore, Lundgren et al. (2016) and Amjadi et al. (2018) estimated fuel and electricity efficiency separately for a shorter time period, i.e., 2000–2008. Taken together, these differences in data and analytical procedures could potentially explain the differences in results.

In general, policies promoting EEI should optimally target sectors based on where the marginal cost-effectiveness is highest. Identifying policy measures at the sector-level for improving persistent and transient energy efficiencies for the Swedish manufacturing industry in order to meet energy and climate related targets remains an interesting topic for future research.

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Appendix

Table A.1. Descriptive statistics for average and median firms and years over the period 1997–2008

Sector	Obs.	Capital (MSEK)	Labor (number)	Energy (GWh)	Output (MSEK)	Capital price (index)	Salary (TSEK)	Energy price (SEK/MWh)
Basic iron and steel	410	535 (104)	528 (192)	676 (58)	1148 (390)	0.12 (0.11)	702 (667)	554 (519)
Chemical	1201	398 (50)	276 (78)	88 (8)	627 (137)	0.09 (0.09)	641 (626)	496 (468)
Electro	1227	79 (10)	376 (64)	7 (1)	1333 (92)	0.1 (0.10)	346 (317)	380 (318)
Fabricated metal products	2193	11 (5)	43 (20)	2 (1)	30 (13)	0.08 (0.07)	451 (441)	604 (575)
Food	2553	130 (25)	200 (49)	23 (4)	427 (91)	0.1 (0.01)	450 (426)	498 (464)
Machinery	3506	58 (11)	179 (52)	7 (1)	266 (54)	0.09 (0.08)	460 (450)	520 (487)
Mining	288	566 (35)	265 (42)	204 (5)	494 (46)	0.12 (0.09)	663 (577)	614 (564)
Motor vehicles	1218	508 (18)	590 (84)	27 (3)	1601 (88)	0.08 (0.08)	392 (383)	458 (423)
Printing	920	30 (10)	73 (32)	4 (1)	64 (24)	0.08 (0.07)	500 (476)	522 (472)
Pulp and paper	1019	722 (132)	397 (186)	433 (44)	1001 (328)	0.09 (0.09)	459 (451)	351 (314)
Rubber and plastic	1349	46 (17)	90 (47)	8 (2)	111 (50)	0.09 (0.08)	463 (452)	506 (481)
Stone and mineral	1019	75 (23)	151 (65)	56 (5)	178 (67)	0.08 (0.08)	538 (451)	485 (476)
Textile	749	31 (9)	79 (36)	8 (1)	68 (33)	0.07 (0.07)	352 (341)	453 (410)
Wood	3131	50 (14)	78 (34)	25 (4)	191 (74)	0.12 (0.12)	407 (401)	300 (242)

*Column “Number of observations” is the number of observations over years and firms.

**Medians are provided in parenthesis.

Table A.2. Range of average overall, persistent and transient energy efficiency scores between firms producing different product groups (1997–2008)

Sector	Transient Efficiency	Persistent Efficiency	Overall Efficiency
Basic iron and steel	82–86	46–54	40–45
Chemical	100–100	25–65	25–65
Electro	100–100	100–100	100–100
Fabricatef metal products	81–81	100–100	81–81
Food	83–84	100–100	83–84
Machinery	90–90	100–100	90–90
Mining	100–100	100–100	100–100
Motor vehicles	100–100	56–63	56–63
Printing	100–100	57–73	57–73
Pulp and paper	100–100	100–100	100–100
Rubber and plastic	89–90	100–100	89–90
Stone and mineral	78–80	29–63	24–50
Textile	82–86	16–64	13–54
Wood	100–100	100–100	100–100

*Note: numbers are rounded, and 100 represents a number close to, but not exactly, 100.
** Product groups are based on the Swedish standard 5-digit classification codes.

Figure A.1.Density Distribution of Jondrow et al. (1982)' Energy Efficiency Scores(EE) for 1997–2008