TFP change and its components for Swedish manufacturing firms during the 2008–2009 financial crisis

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Abstract

A driving force of economic development is growth in total factor productivity (TFP). Manufactured goods are, to a large extent, exports, and represent an important part of the economy for many developed countries. Additionally, a slowdown in labour productivity has been observed in many OECD countries since the financial crisis of 2008–2009. This study investigates TFP change and its components for the Swedish manufacturing industry, compared with the private service sector, during the years 1997–2013, centering on the financial crisis. Stochastic frontier analysis (SFA) is used to disentangle persistent and transient efficiency from firm heterogeneity and random noise, respectively. In addition, technical change (TC), returns to scale (RTS) and a scale change (SC) component are also identified. Along with the empirical analysis, an elaborative discussion regarding TC in SFA is provided. The persistent part for manufacturing (service) is 0.796 (0.754) and the transient part is 0.787 (0.762), indicating improvement potentials. Furthermore, TFP change is substantially lower between the years 2007–2013, compared to 1997–2007. This occurs due to a lower technological progress. Policy should, therefore, target interventions that enhance technology. However, care needs to be taken so that policies do not sustain low-productive firms that otherwise would exit the market.

Keywords Financial crisis · Manufacturing · Persistent and transient efficiency · Technical change · Total factor productivity

JEL classification C23 · D24 · O14 · L25 · L60 · L80

1 Introduction

Total factor productivity (TFP) is the major determinant of economic growth (Krugman 1997) and particularly important for export-dependent countries. The reason for this essentiality is that high operation efficiency and technology development are necessary for competitiveness in an international market. A slowdown in labor productivity growth can be observed in a large share of the industrialized countries and Sweden performed worse than other OECD countries after 2007 (OECD 2015). Moreover, the productivity difference within sectors has increased according

to Andrews et al. (2016). Furthermore, potential catch-up after a financial crisis is of particular importance because Cerra and Saxena (2008) showed that the per capita income ranking has fell for several countries after a financial crisis, e.g. for Sweden after the banking crisis in the early 1990s. Even though TFP is a driving force for economic growth that is likely to be affected during economic downturns—it has hardly been investigated during the financial crisis 2008–2009 and the following period.

The manufacturing sector is of specific importance, due to its export dependence and potential for spill-over into other sectors (Kaldor 1966). In addition, several studies show that negative TFP shocks within manufacturing are the primary cause of economic stagnations (see e.g., Fukao and Kwon 2006). Sweden went from one of the weakest countries, (in terms of labor productivity) within the OECD area to being one of the strongest during the period 1992–2002, which Oh et al. (2012) analyzed. In the early 1990s, Sweden abandoned the fixed exchange rate, which is, at least partly, the explanation for the increase in competitive power during this period (Bergvall 2002).

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The aim of this paper are: (a) to examine TFP and its decomposed factors before, during and after the financial crisis in 2008–2009; (b) to analyse the level of technical efficiency. A four-component stochastic frontier model (SFM) for the Swedish manufacturing industry is applied for the period 1997–2013, which permits analysis of a potential catching-up following the crisis. For comparison purpose, the domestic service sector is incorporated in the analysis since it, potentially, is less affected by changes in world demand. Additional to the empirical analysis, a question is raised regarding interpretation of TC in stochastic frontier analysis (SFA).

To investigate and compute TFP and its components, we use the SFM that was simultaneously proposed by Colombi et al. (2014), Kumbhakar et al. (2014) and Tsionas and Kumbhakar (2014). In this model, inefficiency is decomposed into a persistent and a transient component separated from firm-heterogeneity and random noise, respectively. This separation is interesting of several reasons. First, productivity differences are shown to be increased by Andrews et al. (2016), which is closely related to the topic of efficiency in SFA. Second, it gives insights whether firms with a low level of persistent efficiency drop out from the market after the financial crisis. Third, the transient part of efficiency would become lower if existing firms perform worse during and after the financial crisis. Additionally, technical change (TC), returns to scale (RTS) and a scale change (SC) component are also identified. The TFP change is obtained as the sum of TC and SC, where TC represent a shift of the production function and SC indicates movements towards or away from optimal scale. To be noted is that this type of identification procedure does not separate the change of technical efficiency from TC as performed in, for example, Bauer (1990).

Our findings show improvement potentials in efficiency. The persistent part for manufacturing (service) is 0.796 (0.754) and the transient part 0.787 (0.762). Both the manufacturing and the private-service sector had a decline in efficiency during the financial crisis, but it was smaller for the service sector. During the post-crisis period, firms within both sectors caught up to the level of efficiency they had before. Furthermore, the manufacturing (service) had an annual average TFP growth of 1.17% (1.24%) measured over the whole period. However, substantial differences are observed in TFP change over time when separating the time-periods; i.e., 1997–2007 and 2007–2013, respectively. The manufacturing sector has a TFP growth of 1.98%, and the service sector, 1.80%, during the former period, i.e. before the crisis. This can be compared with 0.44 and 0.54% in the latter. This difference between the pre- and post-periods is statistically significant on the 1% level. However, it should be stated that a causal interpretation between the financial crisis and a lower TFP growth cannot

Fig. 1 Development of value added in the manufacturing and service sectors

be made. Additionally, a pure separation, whether this is driven by inefficient firms or frontier firms, cannot be performed, i.e. the production function can be pushed towards the origin by inefficient firms. Nevertheless, for manufacturing, the lower transient efficiency during the financial crisis can still be observed when time is indicated by year fixed effects, meaning that firms with low efficiency affect TC, at least, to some extent. However, due to the lower TC during 2007–2013, policy makers should target interventions that enhance technology, e.g., increasing the attractiveness of innovating. In addition, care should be taken when designing these policies so they do not sustain low-productive firms that would otherwise close down.

The remainder of the paper is organized as follows. The background of this study is presented in Section 2. In Section 3, different ways of measuring efficiency and TFP, with a focus on stochastic frontier models and interpretation, are described. The methodology used in this paper is presented in Section 4. Section 5 considers the data, and the results are presented in section 6. Finally, section 7 concludes and provides policy recommendations.¹

2 Background

Data from OECD on labor productivity suggests that Sweden was lower in comparison to other countries during the period 2007–2013 (OECD 2015). A description of the development of the aggregated value added in the included sectors, standardized in 1997, during the studied period, is shown in Fig. 1.

Figure 1 indicates a steady growth of aggregated value added with the exception of the period 2000–2002 for manufacturing. Corresponding to the period during the financial crisis, both sectors indicate a decline that is steeper for manufacturing. However, the service sector continues to increase after the small decline while the aggregated value

¹ This figure is based on own calculations from the data.

added in manufacturing shrinks. TFP growth in manufacturing will not, however, be affected if this reduction occurred due to reallocation of inputs to other sectors.

There are studies considering the TFP growth within manufacturing in other countries using stochastic frontier models. Generally, these studies use a time trend approach (see e.g., Kim and Han 2001; Gounder and Xayavong 2004; Kim and Shafi'i 2009). One exception is Zheng et al. (2008), who use both a time trend and additional time dummies for some years in order to capture external shocks.

A few, but not many, studies investigate impacts on productivity and efficiency during and after the financial crisis of 2008–2009. For instance, Kapelko et al. (2014) examine dynamic inefficiency of the Spanish constructing sector pre- and post-financial crisis. They found that the dynamic cost inefficiency is larger before the crisis. In addition, Kapelko and Oude Lansink (2015) study technical efficiency, and its determinants, for the construction sector in Spain using data envelopment analysis (DEA). Technical efficiency is shown to be significantly lower during the beginning of the crisis. TFP and labor productivity have been studied by Harris and Moffat (2016) in the UK. The significant decline post-2008 did not recover before 2012. Therefore, they concluded that the loss in productivity is likely to be permanent rather than cyclical. Recently, Kapelko et al. (2017) investigated the impact on dynamic productivity growth in the Spanish food manufacturing industry using the Luenberger productivity indicator. Negative impacts on productivity were found. However, diverse effects are observed between different sub-industries and firm-sizes.²

To the best of our knowledge, no study targets TFP change or the level of technical efficiency for manufacturing firms in Sweden during and after the financial crisis during 2008–2009. However, there are studies of the Swedish manufacturing sector. The earliest study is Carlsson (1972) who studies technical efficiency in Swedish production. Carlsson (1972) concludes the adjusted average efficiency index to be between 0.577–0.905, depending on the industry, using cross-sectional data from 1968.³ Additionally, Kumbhakar and Heshmati (1996) as well as Oh et al.

(2012) investigated TFP in Sweden.⁴ Both these studies uses panel data for the estimation. The years covered are 1964–1989 and 1992–2000. Using panel data and average translog production functions, Kumbhakar and Heshmati (1996) and Oh et al. (2012) determine the time effect by a trend and dummies, i.e., the general index (GI) model (Baltagi and Griffin 1988). Both Kumbhakar and Heshmati (1996) and Oh et al. (2012) estimate RTS and decompose TFP growth into TC and SC.⁵ TC is further separated into neutral, non-neutral and scale augmenting TC.⁶ Kumbhakar and Heshmati (1996) conclude a TFP growth of approximately 1.91%, on average, for their preferred model. Further, a negative TFP change was shown for several years driven by negative TC. Similar results are found in Oh et al. (2012), i.e., TFP change is 1.9–2.0% in the preferred, most flexible, models. Both studies argue that the GI is advantageous when the pattern of TC is erratic, to capture the years with negative TC. However, we argue that it does not give an estimate of the technical change in its original interpretation, i.e., a development of the technology. The reason is that cyclical factors, to a large extent, are captured because inputs are not fully flexible. For example, employees can, generally, not be terminated directly, and capital in standard models is assumed to be fixed in the short run. More discussion on interpretation of TC is provided in the next section.

In summary, only two studies in Sweden investigate TFP in the manufacturing sector and one considers efficiency. Each of these analyzes data that are at least 16 years old. Furthermore, neither of them focuses on the financial crisis of 2008–2009 nor estimate a stochastic frontier model.

3 Measuring productivity and efficiency

There are a number of different ways to measure TFP used in the literature. These can be divided into non-parametric measures such as the Divisia index or the Malmquist index (Caves et al. 1982; Diewert 1976; Färe et al. 1994), parametric measures like average production functions (Solow 1957) and SFA (Aigner et al. 1977; Meeusen and van Den Broeck 1977). Non-parametric measures based on DEA (Charnes et al. 1978) have the limitation of interpreting all deviation from the frontier as inefficiency and being sensitive to outliers. Thus, a parametric approach is applied

² A few studies can also be found that relate to the banking sector, e.g., Papagiannis (2014) and Das and Patra (2016). Furthermore, Aguiar et al. (2017) estimate a stochastic frontier for OECD countries, among other countries, concluding an annual TFP growth of 0.29% from 2001–2011. Efficiency and productivity during the Asian crisis is also investigated by Park and Weber (2006), who also elaborate on the issues with concluding technical regress.

³ Carlsson (1972) provides a comprehensive theoretical part on competition which will not be described further here.

⁴ Productivity is also considered in a few other studies centering on bad outputs, energy efficiency and climate, e.g. Lundgren et al. (2015), Bostian et al. (2016), Färe et al. (2016), and Lundgren and Zhou (2017).

⁵ Oh et al. (2012) reported an RTS of between 1.022–1.030 for manufacturing and 1.020–1.026 for service.

⁶ As Oh et al. (2012) use a production function, there is no scale augmenting TC.

where SFA is the standard point of departure when modeling technical efficiency (see e.g., Greene 2008; Kumbhakar et al. 2017, for overviews). This section briefly describes the development of measuring efficiency with focus on SFA. Thereafter, a comparative description of measuring TFP using SFA and average production functions, including a discussion of interpretations, is provided.

3.1 Efficiency

Usage of panel data in the scope of SFA started in the early 1980s by Pitt and Lee (1981) and Schmidt and Sickles (1984), among others. The standard model can be formulated as:

$$y_{it} = f(\mathbf{x}_{it}, t; \boldsymbol{\beta}) \exp(-u_{it}), \quad (1)$$

where y_{it} is the output for each firm i ($i = 1, \dots, N$) at time t ($t = 1, \dots, T$), $\mathbf{x}_{it}$ is the vector of inputs quantities, t is the time trend and $\boldsymbol{\beta}$ is the corresponding coefficient to be estimated. Finally, technical inefficiency, referred to as u_{it} , is non-negative. The SFA assumes that an idealized production frontier can be found where the one-sided deviation from the frontier is referred to as inefficiency. Throughout the development of new models in the SFA literature, a debate regarding identification and/or interpretation of the efficiency term has been present. In the early cases, inefficiency may change between producers, but not over time (see e.g., Pitt and Lee 1981; Kumbhakar 1987; Battese and Coelli 1988). The assumption of constant inefficiency is argued to be unrealistic when the number of time periods is large and the competition is high. Therefore, inefficiency can also be considered as time-varying (see e.g., Kumbhakar 1990, Lee and Schmidt 1993).

During the 1990s, the error term was separated into three parts. Kumbhakar and Heshmati (1995) developed a model that views the time-invariant effect as persistent inefficiency. However, the persistent part in these models does not account for the fact that the time-invariant effect is likely to be, partly, a result of firm-heterogeneity. Therefore, Greene (2005a, 2005b) decomposes the error into firm-specific time-varying inefficiency, firm-specific random- or fixed effects, to capture latent heterogeneity and random noise. The issue here is that any producer-specific and time-invariant component is considered as unobserved heterogeneity. Thus, the differences between the different three-component models are related to interpretation. Consequently, both models have the drawback that firm-heterogeneity and persistent inefficiency is not disentangled.

There has been renewed interest in efficiency modeling due to the methodological development, starting with Colombi et al. (2014), Tsionas and Kumbhakar (2014) and Kumbhakar et al. (2014) that simultaneously proposed

separation of the disturbance into four components. Furthermore, Filippini and Greene (2016) proposed implementation of the model by a simulated maximum likelihood approach. These models separate persistent inefficiency from firm-heterogeneity and transient inefficiency from random noise. Persistent inefficiency is important, from a policy perspective, because it includes time-invariant effects of inputs such as management and other unobserved factors (Mundlak 1961). For further description of the development and comparisons of models, see e.g., Filippini and Greene (2016), Heshmati et al. (2018) or Kumbhakar et al. (2017).⁷

In the analysis, we have made the standard assumption regarding exogeneity of inputs. If the assumption does not hold, it might cause underestimation of the output elasticity of capital and firm-level technical efficiency according to e.g. Shee and Stefanou (2015). Methods to handle endogeneity when estimating an average production function are e.g. Olley and Pakes (1996) and Levinsohn and Petrin (2003) that attempts to identify unobserved productivity shocks by investments and intermediate inputs, respectively. These approaches were extended in Akerberg et al. (2015) to handle the functional dependence. A few problems with the above mentioned methods are discussed by, for example, De Loecker (2011) and Van Beveren (2012). Above mentioned studies estimate average production functions and, for example, Shee and Stefanou (2015) note that it has to a large extent been ignored in SFA. Shee and Stefanou (2015) proposed an extension of the semi-parametric approach suggested in Levinsohn and Petrin (2003) to the SFA case. Another example that attempt to handle endogeneity in SFA is Lai and Kumbhakar (2018).

3.2 Total Factor Productivity

TFP is often empirically measured by a production function which is identical to the stochastic frontier model without an inefficiency component, i.e., inefficiency is zero, written as equation 2.

$$y_{it} = f(\mathbf{x}_{it}, t; \boldsymbol{\beta}). \quad (2)$$

Before elaborating on the potential interpretation issues, the time derivative of the translog production function is presented in equation 3.

$$\frac{\partial y_{it}}{\partial t} = \beta_t + \beta_{tt}t + \sum_i \beta_{it}\mathbf{x}_i, \quad (3)$$

where both β_t and β_{tt} are equivalent for all firms. The expression in equation 3 is often claimed to be firm-specific. However the firm-specific part can be questioned because it

⁷ Other studies also incorporate determinants of the different components of efficiency, e.g., Badunenko and Kumbhakar (2017) and Lai and Kumbhakar (2018).

only differs depending on the level of inputs, as can be seen in equation 3 (Baltagi et al. 1995).⁸ Studies that investigate TFP using an average function generally interpret equation 3 as TC_{it} , i.e., shift of the production function.⁹ In SFA, most attention targets identification and/or interpretation of efficiency (see e.g., Kumbhakar et al. 2017 for an overview) meaning that less effort is given TC_{it} . However, for example, Kumbhakar (2000) show that TC_{it} from the average production function can be separated into frontier shift (TC_{it}) and technical efficiency change (TEC_{it}) by usage of SFA.¹⁰ If TC_{it} and TEC_{it} are considered separately, the straightforward economic interpretation is often argued to be the main advantage, i.e., shift of the frontier and catching-up to best practice (see e.g., Pires and Garcia 2012). Regardless of the straightforward interpretation, identification of the separate components is crucial for usefulness.

Identification should require different estimates of TC_{it} depending on whether a stochastic frontier model or an average model has been estimated (given that TEC_{it} is different from zero). However, these models only differ in their distribution assumption of the disturbance, which is not likely to affect the estimated coefficients in the production function but only the intercept (Aigner et al. 1977). In SFA, each firm obtains an estimate of TC_{it} regardless of whether they operate on the frontier. The average of these estimates is then considered as the TC_{it} and, commonly, interpreted as a frontier shift.¹¹ Conclusively, the TC_{it} in SFA will equalize the TC_{it} in the average function if the coefficients do not differ. In this aspect, Kumbhakar and Lien (2017) state that no differences in TC_{it} between their model 1 (Kumbhakar and Heshmati 1995) and model 2 (Greene 2005a, 2005b) is expected because their deterministic parts are equivalent.¹² However, despite the equivalence of the deterministic parts—the implications of the different time derivatives are different given the previous argument that SFA interprets it as frontier shift. Little attention to these interpretation issues can be found in the

literature. Based on these arguments, a reliable estimate of frontier shift can be difficult to find using these models, given that the interpretation is development of the frontier firms. An additional issue relates to disentangle TC_{it} and TEC_{it} . Problems occur both based on previous arguments on potential issues of identifying the frontier shift as well as the fact that the components have simultaneous time variation (see e.g., Greene 2005b).¹³ The contradictory interpretation is addressed by, for example, Lovell (1996).

This section can, apart from the brief overview, be summarized in three points. First, it provides motives to raise the question of how TC_{it} should be interpreted in SFA, i.e., should it be understood as a frontier shift? Second, a clear-cut separation between TEC_{it} and TC_{it} should be performed with care in SFA. The reason is that identification issues occur, from an econometric point of view, in reliably assigning the simultaneously changing time components to either TC_{it} or TEC_{it} . Third, applied researchers should, if no separation is performed, be clear in how TC_{it} is interpreted, i.e., the estimate of TC may include what, for example, Kumbhakar (2000) address as both TC_{it} and TEC_{it} .

4 Methodology

This paper adopts the four-component SFM because it improves previous models in several ways. First, previous models in the manufacturing sector are likely to fail in identifying factors with persistent effects on efficiency (see e.g., Heshmati et al. 2018). Second, a common assumption is that inefficiency is independent over time. More reasonable is to assume that one component of efficiency can be removed and another is fixed. Third, identification of these components is important from a policy perspective, since different interventions are necessary depending on what is to be targeted (see e.g., Kumbhakar and Lien 2017).

Each of the four proposed four-component models identifies the transient and persistent efficiency consistently, but in different ways, i.e. in one or several steps. This paper applies the Kumbhakar et al. (2014) multistep procedure because it is straightforward to implement and verification is possible in each step.¹⁴ A translog specification is used to

⁸ There are other extensions regarding firm-specific components that provide more reliable estimates, e.g., Sun, Kumbhakar and Tveterås (2015). Unreliable estimates on the firm-level are particularly problematic when a second-stage regression on determinants is performed, which, for example, Baltagi et al. (1995) and Wang and Schmidt (2002) previously addressed.

⁹ To obtain the estimate of TFP change, a component of SC is also calculated and added together with TC_{it} , as shown in the methodology.

¹⁰ A similar decomposition is also performed by Bauer (1990).

¹¹ This is different from Nishimizu and Page (1982), who estimate TC based on a subset of frontier firms. Further, it should be noted that Aigner et al. (1977) did not have the concern of this separation because they use a cross-section.

¹² The Kumbhakar and Heshmati (1995) model is a multistep procedure with an average function in the first stage, and Greene (2005a, 2005b) is a frontier model, i.e., true random effect and true fixed effect.

¹³ This is in contrast to the long debate in the literature regarding different components of efficiency previously briefly described.

¹⁴ The usual argument against the Kumbhakar et al. (2014) alternative is that it is not as efficient as the single-stage procedures. However, this is not crucial when the number of observations is large. Furthermore, the maximum likelihood model suggested by Colombi et al. (2014) is “computationally prohibitive when T is large” (Tsionas and Kumbhakar, 2014, p. 115). The Filippini and Greene (2016) version has also been estimated; however, numerical issues occurred in parts of the data set. More detailed discussions regarding the different estimation procedures are performed in, for example, Filippini and Greene (2016), Heshmati et al. (2018) and Filippini et al. (2018).

Table 1 Descriptive statistics of the used variables

	Manufacturing			Service		
	<i>L</i>	<i>K</i>	<i>Y</i>	<i>L</i>	<i>K</i>	<i>Y</i>
Mean	33.62	39,618.2	22,045.7	15.84	18,295.8	8818.5
SD	258.6	1,372,265.1	289,780.4	203.8	738,935.1	12,7398.7
Observations	248,991	248,991	248,991	920,043	920,043	920,043

allow for different RTS (Christensen et al. 1973). The model is specified in equation 4.

$$y_{it} = a_0 + f(\mathbf{x}_{it}, t; \boldsymbol{\beta}) + \mu_i - \eta_i + v_{it} - u_{it}. \quad (4)$$

The first disturbance component (μ_i) captures firms' latent heterogeneity (Greene 2005a, 2005b) which is disentangled to identify the second component, persistent inefficiency (Kumbhakar and Heshmati 1995). Random shocks are represented by the third component (v_{it}) and, finally, the last term is the transient (u_{it}) inefficiency. The product of the persistent and transient efficiency is referred to as overall efficiency as suggested by Kumbhakar et al. (2014). A short description of how the different components are identified will now be provided.

To apply the Kumbhakar et al. (2014) multistep procedure, equation 4 is rewritten to panel data type as equation 5:

$$y_{it} = \alpha_0^* + f(\mathbf{x}_{it}; \boldsymbol{\beta}; t) + \alpha_i + \varepsilon_{it} \quad (5)$$

where one can define $\alpha_0^* = a_0 - E(\eta_i) - E(u_{it})$; $\alpha_i = \mu_i - \eta_i + E(\eta_i)$; and $\varepsilon_{it} = v_{it} - u_{it} + E_{it}(u_{it})$ for estimation purposes. Using this specification, α_i and ε_{it} have zero mean and constant variance. The multistep procedure is applied in three steps. First, equation 5 is a standard panel data model and is estimated by random effects to obtain $\hat{\boldsymbol{\beta}}$.¹⁵ Additionally, predicted values of the time-invariant component, α_i , and the time-varying component, ε_{it} , are acquired. Second, identification of the transient efficiency requires the assumptions that v_{it} is i.i.d. $N(0, \sigma_v^2)$ and u_{it} is i.i.d. $N^+(0, \sigma_u^2)$. Using these assumptions, the transient inefficiency is identified by standard SFA through the Jondrow et al. (1982) procedure. Transient efficiency is then calculated as $\exp(-u_{it})$. The third step is a repetition of the second using the time-invariant components and assuming that μ_i is i.i.d. $N(0, \sigma_\mu^2)$ and η_i is i.i.d. $N^+(0, \sigma_\eta^2)$.

Furthermore, TC is estimated as equation 3. Therefore, TC is interpreted as a movement of the average production function, i.e., this is not equivalent to a shift of the frontier

meaning that a separation between TC and TEC cannot be made. RTS is calculated as the sum of the input elasticities, i.e., $\sum_i \epsilon_i$, where $\epsilon_i = \partial f / \partial \ln x_i$. Based on RTS, the SC is calculated as $(RTS - 1) \sum_i \lambda_i \dot{x}_i$, where $\lambda_i = \epsilon_i / RTS$ and $\dot{x}_i$ represents the change in inputs.

5 Data

An unbalanced firm-level panel data set that covers all Swedish firms within the manufacturing and service industries during the period 1997–2013 is obtained from Statistics Sweden (SCB).¹⁶ This period is of particular interest due to the global financial crisis. The reason is the investigation possibilities of how an export-dependent sector (in comparison to a sector likely to export less) in Sweden, such as manufacturing (service), performed before, during and after the crisis. Included firm characteristics are: capital assets (*K*), number of full-time employees (*L*), and value added (*Y*). *K* and *Y* are in 1997 prices measured in thousands of SEK. Descriptive statistics is reported in Table 1.

The descriptive statistics in Table 1 is reported after elimination of outliers. No universally accepted method for outlier detection is present in the literature. However, we follow the most recent study on TFP for Swedish manufacturing firms and identify an observation as an outlier if the value added the present year changes more than 80% in comparison to the previous year (Oh et al. 2012).¹⁷ Furthermore, the included variables are incorporated in the production function as logarithms. Observations where the logarithm becomes missing or zero are eliminated because their marginal products do not make economic sense. After this exclusion, the data consists of 30,144 unique firms over time that becomes 248,991 observations within different sub-sectors of manufacturing. The sector classification of Statistics Sweden is used to categorize the manufacturing sector into 11 sub-sectors. For the service sector, there is not a specific main category provided by Statistics Sweden.

¹⁵ A fixed effect model is also possible to use. However, the estimates of RTS becomes unreliable, e.g., 0.845 for manufacturing using that so the random effect is chosen, therefore it is more relevant to rely on economic intuition, i.e. the RTS should be close to CRS. Additionally, a random effect is motivated by the fact that we have heterogeneity within the sectors, manufacturing and service, used for the analysis. For further discussion, see e.g. Bell and Jones (2015).

¹⁶ The manufacturing sector consists of the two-digit SNI2002 from 15 to 37, and the service sector is defined SNI2002 50–52, 60–64 and 71–74. All sector codes are transformed to the SNI2002 using the key provided by Statistics Sweden.

¹⁷ We have also used other thresholds, for example 60%, with consistent results.

However, three sub-sectors are included as service: (1) wholesale and retail trade, (2) transport and storage, and (3) renting and business activities. These are aggregated to 920,043 observations, and the descriptive statistics, after the same elimination as for manufacturing, is presented in Table 1.¹⁸

6 Results

The first part of the results considers efficiency and its different components, which provide an estimate of performance in relative terms. Second, RTS, TC and SC are presented, where the two latter components sum to TFP change.¹⁹

6.1 Technical efficiency

In this section, overall, persistent and transient efficiency will be analyzed. At first, these components are reported as averages over time in Fig. 2.

In Fig. 2, the blue lines show the different components of efficiency for the manufacturing and the red lines show the service sector. The persistent part for manufacturing (service) is 0.796 (0.754) and the transient part is 0.787 (0.762), which indicates improvement potentials.²⁰ An interpretation of this is that manufacturing has its largest share of inefficiency in the transient component, while the service sector has the largest inefficiency in the persistent part. However, the differences are fairly small. A potential outcome on persistent efficiency during and after a financial crisis would be an improvement, since firms with a low persistent efficiency are likely to be driven out of the market. In our case, this does not occur, meaning that the firms with low persistent efficiency remain in the market.

The transient part of efficiency drops during 2000–2003 and 2007–2009, with larger changes for manufacturing in comparison to the service sector.²¹ Corresponding to the period after the financial crisis, i.e., after 2009, both sectors increase their transient efficiency to levels equivalent to that

Fig. 2 The different components of efficiency over time for manufacturing and service

as before the decline—however, the changes are small for the service sector. Subsequently, transient efficiency does not show any considerable changes over time with the exception of the erratic change during the crisis. Diverse effects of the financial crisis could be observed on efficiency in the previous literature for other sectors and countries. Consistent with our results, for example, is a lower efficiency in the beginning of the crisis found by Kapelko and Oude Lansink (2015) for the Spanish construction sector. However, our study does not indicate any significant difference in efficiency for the whole post-crisis period, 2007–2013, compared to the previous period. Comparing the level of efficiency by sector, it can be observed that the manufacturing sector has higher efficiency, which is expected in order to the higher competition, internationally. Focusing on manufacturing (service) in relation to firm size, it can be observed that the transient efficiency is approximately the same, regardless of size. However, the persistent efficiency is 0.784 (0.745) for the smallest firms, i.e., fewer than 10 employees, and 0.848 (0.828) for firms with more than 300 employees. This is intuitive because large firms are more likely to compete in an international market.²² Heterogeneity can, therefore, be observed in size, which is consistent with Kapelko and Oude Lansink (2015). Differences may also be present between sub-sectors; Table 2 reports the efficiency scores separated on these.

Table 2 reports the components of efficiency separated on the different sub-sectors for the whole time period.²³ Persistent efficiency differs from 0.703 for RENT to 0.842 within BASI. A low level of persistent efficiency should not be present in a competitive sector. The RENT sector is likely to consist of many local firms and the competition may be low on the local level. However, BASI, COKE and MACH, with the highest persistent efficiency, are more

¹⁸ Descriptive statistics for the different sub-sectors is provided in the appendix.

¹⁹ As pointed out in Section 3, endogeneity of inputs could bias the results. However, our results, before the financial crisis, are in line with previous studies on Swedish data and a larger elasticity of capital would generate a larger RTS, which is economically non-intuitive on a competitive market. Therefore, it seemed reasonable to maintain the assumption.

²⁰ Kernel distributions of the different components of efficiency are shown for manufacturing (service) in Fig. 3 (A2) in the appendix. Further, a table showing the exact efficiency scores to construct Fig. 2 is provided in the appendix.

²¹ The same pattern is shown if time is represented by dummy variables for manufacturing, but no differences in efficiency can be observed for the service sector.

²² The other size groups are 10–50, 50–100 and 100–300 employees and the persistent efficiency for manufacturing (service) are 0.824 (0.787), 0.821 (0.803) and 0.828 (0.811), respectively.

²³ Only small changes occur if this is performed by the time periods 1997–2007 and 2007–2013. A table of this separation is provided in the appendix.

Table 2 Persistent, transient and overall efficiency by sub-sector

By industry for 1997–2013	Persistent	Transient	Overall
All manufacturing	0.796	0.787	0.627
Food products, beverages and tobacco	0.775	0.798	0.619
Textile and leather products	0.747	0.768	0.575
Wood and products of wood	0.768	0.800	0.616
Pulp, paper, paper products, publishing and printing	0.771	0.777	0.600
Coke, refined petroleum products, nuclear fuel, chemicals, rubber and plastic products (COKE)	0.838	0.777	0.651
Other non-metallic mineral products	0.746	0.805	0.602
Basic metals and fabricated metal products (BASI)	0.842	0.804	0.678
Machinery and equipment n.e.c. (MACH)	0.835	0.788	0.659
Electrical and optical equipment	0.777	0.767	0.597
Transport equipment	0.760	0.787	0.599
Manufacturing n.e.c.	0.792	0.800	0.635
All service firms	0.754	0.762	0.576
Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	0.775	0.767	0.596
Transport, storage and communication	0.828	0.801	0.664
Renting and business activities (RENT)	0.703	0.747	0.527

n.e.c. not elsewhere classified

likely to have a large share of firms that operate in an international market. Differences, however, can be observed between these sub-sectors regarding the transient component. A potential mechanism behind this is differences in handling volatility in demand, i.e., flexible inputs. Studying the capital labor ratio between these sub-sectors, it can be observed that BASI has the lowest amount of capital given the labor, which is a sign of higher flexibility given that capital is a fixed input. Overall, BASI is the sector with highest efficiency and RENT has the lowest overall efficiency. To summarize, heterogeneity could be observed between sub-sectors and size groups. Only small changes in the efficiency components could be observed over time, with the exception of the period of 2009, i.e., the global financial crisis.

6.2 Technical change, scale change and total factor productivity

TC, SC and TFP are reported over time for the manufacturing and service sector in Table 3.

In Table 3, the TC, SC and TFP are reported for the manufacturing (on the left) and service sector on the right. On average, the RTS is 1.025 and 0.989 for manufacturing and service, respectively.²⁴ It can be observed that the effect of changes in SC is approximately zero for manufacturing and slightly negative for the service sector. The contributor

Table 3 TFP and its components using a single time trend

By year	Manufacturing			Service		
	TC	SC	TFP	TC	SC	TFP
1997	–	–	–	–	–	–
1998	1.74%	0.05%	1.79%	2.06%	–0.33%	1.74%
1999	1.64%	0.01%	1.65%	1.95%	–0.21%	1.74%
2000	1.55%	0.03%	1.58%	1.85%	–0.34%	1.51%
2001	1.47%	0.03%	1.50%	1.77%	–0.24%	1.53%
2002	1.40%	0.01%	1.41%	1.70%	–0.18%	1.52%
2003	1.33%	0.00%	1.33%	1.62%	–0.12%	1.50%
2004	1.26%	0.01%	1.27%	1.52%	–0.12%	1.40%
2005	1.19%	0.04%	1.23%	1.45%	–0.13%	1.32%
2006	1.12%	0.06%	1.18%	1.37%	–0.14%	1.23%
2007	1.06%	0.09%	1.15%	1.31%	–0.13%	1.18%
2008	1.00%	0.10%	1.10%	1.24%	–0.12%	1.12%
2009	0.90%	–0.09%	0.82%	1.15%	–0.06%	1.08%
2010	0.83%	–0.03%	0.80%	1.07%	–0.07%	1.00%
2011	0.77%	0.10%	0.87%	1.00%	–0.05%	0.94%
2012	0.70%	0.07%	0.77%	0.91%	–0.03%	0.88%
2013	0.61%	0.00%	0.61%	0.82%	–0.03%	0.79%
Mean	1.14%	0.03%	1.17%	1.36%	–0.13%	1.24%

to TFP growth is, instead, TC, which indicates an annual progress of between 0.61 and 1.74% for manufacturing and between 2.06 and 0.82% for service. These changes are smooth over time by construction and the technical progress is interpreted as a shift upwards of the average production

²⁴ The input elasticities and RTS for the manufacturing and service sectors are reported in Table 5 in the appendix.

Table 4 TFP separated on time periods and sub-sectors

	1997–2007	2007–2013	1997–2013
Manufacturing			
All manufacturing	1.98%	0.44%	1.17%
Food products, beverages and tobacco	1.47%	2.21%	1.35%
Textile and leather products	1.22%	−0.21%	0.65%
Wood and products of wood	2.67%	−0.74%	1.25%
Pulp, paper, paper products, publishing and printing	1.29%	−0.14%	0.84%
Coke, refined petroleum products, nuclear fuel, chemicals, rubber and plastic products	2.02%	1.64%	1.40%
Other non-metallic mineral products	2.48%	0.44%	1.45%
Basic metals and fabricated metal products	2.07%	0.41%	1.14%
Machinery and equipment n.e.c.	1.99%	0.48%	1.26%
Electrical and optical equipment	2.49%	0.24%	1.64%
Transport equipment	1.99%	1.28%	1.07%
Manufacturing n.e.c.	1.74%	0.36%	1.00%
Service			
All service firms	1.80%	0.54%	1.24%
Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	1.99%	0.67%	1.34%
Transport, storage and communication	1.41%	0.28%	0.69%
Renting and business activities	1.62%	0.48%	1.29%

n.e.c. not elsewhere classified

function. This occurs if: (1) inefficient firms catch-up or (2) the frontier firms perform better. These effects are not directly disentangled in this paper, i.e., TC is not interpreted separated from TEC based on the arguments elaborated in Section 3. Since the prior results are smooth over time, we would like to pinpoint the periods before and after the financial crisis by estimating TFP on the sub-sector level separated into these periods, i.e., 1997–2007 and 2007–2013.²⁵ These results are reported in Table 4.

In Table 4, TFP is reported over the whole studied periods, 1997–2013, and separated before and after the crisis, i.e. 1997–2007 and 2007–2013, respectively. From the right column in Table 4, it can be observed that the average TFP growth was 1.17 and 1.24% for manufacturing and service, respectively. This is mainly driven by TC, which is reported separately in the appendix. By separating the pre- and post-financial crisis periods it can be observed that manufacturing showed a TFP growth of 1.98%, and service 1.80%, during the pre-crisis period. In comparison, both industries indicate a substantially lower annual TFP growth from 2007–2013, i.e., 0.39 and 0.54% for manufacturing and service, respectively. In comparison to the previous literature on Swedish data, TFP change during the pre-crisis

period is in the same range, but the post-period is lower. Furthermore, our findings points in the same direction as the result in Harris and Moffat (2016), i.e. TFP has not recovered after the financial crisis. By performing the same separation on the sub-sectors, this pattern is observed in all sub-sectors with a few exceptions, which are consistent with Kapelko et al. (2017).²⁶ It should, however, be noted that we cannot identify whether this is a causal effect of the financial crisis.

The majority of the sectors indicate a pattern of lower TFP change after 2007. The exception is food, beverages and tobacco and a potential mechanism behind that is that these goods are less likely to be affected by cyclical changes than other products. Furthermore, a few sub-sectors indicate a negative TFP change driven by negative TC, which has an economically counterintuitive interpretation.²⁷ At least two potential scenarios can explain the mechanism that will emerge as a technical regress in the model: (1) absence of reinvestment in capital, which made the capital stock less productive and (2) a decline in demand that made the firms unwilling to produce more outputs, while the inputs were not adjusted accordingly. The latter should, however, only affect firms in the short-run, and as we use a time trend over

²⁵ The single time trend does not incorporate technology shifters analyzed by e.g., Heshmati and Kumbhakar (2014).

²⁶ The reason that the TFP for the whole period is not between the single periods for all sub-sectors is that the first year in each sub-period is not accounted for in the measure of TC and SC (see Kumbhakar et al. 2015, p. 291–292).

²⁷ A similar table of TC is provided in Table 8 the appendix.

several years to represent TC, the cyclical changes should be smoothed. Recapping from the previous discussion, the interpretation is, in our case, not necessarily a movement inward of the production frontier, since TEC and TC are, partly, collapsed. Erratic changes will be captured in the transient efficiency component previously analyzed and continuous efficiency changes, i.e., poor performing firms that do worse over time are captured in TC. Consequently, whether or not the lower TFP growth in the latter period is driven by weaker progress of frontier firms, or less improvement of inefficient firms in relation to the frontier, cannot be directly disentangled. However, the decline in transient efficiency during 2009 also holds if time is indicated by dummies for the manufacturing sector. Therefore, it is possible to state that the lower TC during the post-period is, at least, partly driven by inefficient firms within the manufacturing sector.²⁸

This study adopted a time trend to smooth the changes and separated the time period into 1997–2007 and 2007–2013 due to the suspicion of different patterns with the source in the financial crisis. However, previous research on TFP within manufacturing on Swedish data, among others, argues that the time trend performs poorly when changes are erratic. Thus, a short year-by-year analysis, i.e., time dummies, is also performed, represented by Fig. 5 in the appendix. These results indicate that the manufacturing caught up to its previous level in 2011—but not to its previous trend.²⁹ In contrast, the service sector is, visually, at the same trend as previously, which is in line with what was shown for aggregated value added in Fig. 1.

7 Conclusion and policy recommendations

This study investigated TFP and its decomposed factors for the Swedish manufacturing and service industries between 1997 and 2013, targeting the financial crisis, using firm level panel data from Statistics Sweden. A four-component stochastic frontier is carried out, which permits decomposition of the disturbance into firm-heterogeneity, persistent efficiency, transient efficiency and random noise. Moreover, RTS, TC and SC are investigated, where the two latter sum to TFP change. Additionally, a discussion regarding interpretation in the scope of SFA is performed, where a question regarding how TC should be understood is raised.

The results show that there are potentials to improve efficiency where the persistent efficiency is 0.796 for manufacturing and 0.754 for the service sector. Further, the

transient efficiency is 0.787 and 0.762 for manufacturing and service, respectively. Over time, each of the components is fairly stable, with the exception of the transient component within the manufacturing sector during the financial crisis. Heterogeneity can be observed on size and sub-sectors, i.e., large firms and firms within sub-sectors that are more likely to compete in an international market have higher persistent efficiency. TFP growth is observed to differ substantially between the two periods, 1997–2007 and 2007–2013. During the pre-crisis period, TFP growth is 1.98 and 1.80% for manufacturing and service, respectively. This can be compared to the post-crisis period TFP growth of 0.44% for manufacturing and 0.54% for service, driven by a lower of TC. This pattern is fairly similar for all sub-sectors, with a few exceptions. Lower TC can have its source in either slower shift of frontier firms, less catching-up of inefficient firms or a mix of these. This study does not make a distinction between TC and TEC. However, a decline in transient efficiency during 2009 could be observed for manufacturing also when time was represented by dummy variables. In comparison to the lower TC in our main model, this means that the slow-down, at least to some extent, is driven by inefficient firms in the manufacturing sector.

Our results indicate that TFP change is substantially lower during and after the financial crisis, driven by lower TC. This means that TC is not back on its original trend of around 2% annually, observed for our pre-crisis period as well as by Kumbhakar and Heshmati (1996) and Oh et al. (2012). Since TC is concluded to be the largest share of TFP change in this study, and previous studies in Sweden, it is an important source to drive TFP change and, thus, economic growth. Therefore, policy makers should target interventions that enhance technology, e.g., increase the attractiveness to invest and be innovative. However, TC can also be held back when firms that perform poorly stay in the market. Therefore, potential interventions should be targeted to firms with potential to drive the technology and not be given to low-productivity firms that would otherwise close down. Furthermore, the persistent efficiency can, for example, be related to regulations or differences in human capital that does not change over time. In contrast, the transient part of efficiency is handled by “carrots and sticks” (Kumbhakar and Lien 2017). Particularly, it is the persistent part that is necessary to identify, since firms with a low level of persistent efficiency are not sustainable in a highly competitive market. One common source of the persistent part is regulation meaning that all firms in the sector will suffer. However, further research is necessary to determine the particular sources that can drive persistent, transient efficiency and TFP growth in the right direction. Finally, since the aim of this paper is not to state an appropriate interpretation of TC in the scope of SFA, more emphasis

²⁸ This pattern is not observed for the service sector.

²⁹ This is, however, not TC in its original interpretation, since these changes are clearly a result of cyclical factors.

regarding this in relation to TEC should be taken in the future. In particular, a study can be made where a model attempt to separate between TC and TEC to be compared with another where no distinction is made as well as a more detailed analysis whether the components can be separated accurately.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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8 Appendix

Tables 5–9, Figs. 3–5

Table 5 Input elasticities and returns to scale

By year	Manufacturing			Service		
	Capital	Labor	RTS	Capital	Labor	RTS
1997	0.122	0.862	0.984	0.096	0.851	0.947
1998	0.120	0.866	0.986	0.093	0.858	0.951
1999	0.118	0.868	0.986	0.092	0.863	0.956
2000	0.117	0.872	0.989	0.091	0.869	0.960
2001	0.113	0.877	0.990	0.088	0.877	0.964
2002	0.110	0.882	0.992	0.085	0.885	0.969
2003	0.107	0.887	0.994	0.082	0.892	0.974
2004	0.103	0.893	0.996	0.080	0.900	0.979
2005	0.090	0.100	1.000	0.077	0.908	0.984
2006	0.096	0.906	1.002	0.074	0.916	0.989
2007	0.092	0.915	1.007	0.070	0.924	0.994
2008	0.087	0.924	1.011	0.067	0.932	0.999
2009	0.085	0.926	1.011	0.064	0.939	1.004
2010	0.082	0.933	1.015	0.062	0.947	1.008
2011	0.078	0.942	1.020	0.059	0.954	1.013
2012	0.075	0.948	1.023	0.057	0.961	1.018
2013	0.072	0.953	1.025	0.055	0.967	1.022

Table 6 Persistent, transient and overall efficiency separated on sub-sectors and time-periods

By industry	1997–2007			2007–2013		
	Persistent	Transient	Overall	Persistent	Transient	Overall
All manufacturing	0.795	0.788	0.627	0.796	0.788	0.628
Food products, beverages and tobacco	0.779	0.800	0.624	0.769	0.797	0.614
Textile and leather products	0.744	0.768	0.572	0.752	0.770	0.582
Wood and wood products	0.768	0.801	0.616	0.768	0.801	0.617
Pulp, paper, paper products, publishing and printing	0.770	0.777	0.599	0.772	0.780	0.604
Coke, refined petroleum products, chemicals, rubber and plastic products	0.837	0.779	0.652	0.839	0.777	0.653
Non-metallic mineral products	0.748	0.806	0.603	0.745	0.807	0.603
Basic metals and fabricated metal products	0.841	0.806	0.678	0.843	0.806	0.680
Machinery and equipment n.e.c.	0.835	0.789	0.659	0.836	0.791	0.662
Electrical and optical equipment	0.775	0.768	0.596	0.778	0.769	0.600
Transport equipment	0.760	0.789	0.601	0.759	0.786	0.598
Manufacturing n.e.c.	0.788	0.800	0.632	0.796	0.801	0.639
All service firms	0.754	0.763	0.576	0.754	0.764	0.578
Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	0.776	0.768	0.596	0.774	0.768	0.596
Transport, storage and communication	0.828	0.802	0.665	0.827	0.801	0.664
Renting and business activities	0.702	0.746	0.525	0.704	0.750	0.531

n.e.c. not elsewhere classified

Table 7 Persistent, transient and overall efficiency by year

Year	Manufacturing			Service		
	Persistent	Transient	Overall	Persistent	Transient	Overall
1997	0.794	0.783	0.622	0.752	0.754	0.567
1998	0.796	0.784	0.623	0.753	0.756	0.569
1999	0.795	0.791	0.629	0.754	0.77	0.58
2000	0.795	0.795	0.632	0.754	0.769	0.58
2001	0.795	0.789	0.628	0.755	0.766	0.578
2002	0.796	0.783	0.623	0.755	0.764	0.577
2003	0.797	0.775	0.618	0.756	0.759	0.574
2004	0.796	0.781	0.622	0.755	0.756	0.572
2005	0.795	0.786	0.626	0.754	0.758	0.572
2006	0.794	0.792	0.63	0.753	0.761	0.574
2007	0.796	0.805	0.642	0.754	0.774	0.585
2008	0.795	0.795	0.634	0.754	0.766	0.579
2009	0.795	0.769	0.613	0.754	0.756	0.572
2010	0.796	0.781	0.623	0.755	0.763	0.578
2011	0.796	0.79	0.631	0.754	0.766	0.579
2012	0.796	0.787	0.628	0.753	0.762	0.575
2013	0.797	0.785	0.626	0.753	0.762	0.575

Table 8 Technical change separated on time periods and sub-sectors

	1997–2007	2007–2013	1997–2013
By industry: manufacturing			
All manufacturing firms	1.93%	0.39%	1.14%
Food products, beverages and tobacco	1.45%	2.13%	1.37%
Textile and leather products	1.25%	−0.26%	0.68%
Wood and wood products	2.58%	−0.72%	1.19%
Pulp, paper, paper products, publishing and printing	1.22%	−0.27%	0.78%
Coke, refined petroleum products, chemicals, rubber and plastic products	2.00%	1.56%	1.40%
Non-metallic mineral products	2.37%	−0.36%	1.41%
Basic metals and fabricated metal products	2.06%	−0.72%	1.12%
Machinery and equipment n.e.c.	1.90%	0.46%	1.20%
Electrical and optical equipment	2.44%	0.21%	1.61%
Transport equipment	1.93%	1.22%	1.00%
Manufacturing n.e.c.	1.70%	0.36%	0.98%
By industry: service			
All service firms	1.92%	0.54%	1.36%
Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	2.05%	0.63%	1.43%
Transport, storage and communication	1.55%	0.26%	0.81%
Renting and business activities	1.75%	0.53%	1.44%

n.e.c. not elsewhere classified

Table 9 Mean (SD) of the included firm-characteristics on the sub-sector level

By industry for 1997–2013	<i>L</i>	<i>K</i>	<i>Y</i>	Obs.
Food products, beverages and tobacco	37.08 (182.0)	32,360.8 (318,626.1)	21,098.4 (117,714.1)	19,990
Textile and leather products	16.91 (65.24)	12,251.1 (223,642.8)	8270.2 (52,256.7)	8528
Wood and products of wood	19.82 (68.49)	12,506.0 (96,869.6)	9410.6 (36,509.4)	20,709
Pulp, paper, paper products, publishing and printing	32.25 (129.2)	43,464.4 (420,069.6)	22,500.1 (124,612.9)	29,272
Coke, refined petroleum products, nuclear fuel, chemicals, rubber and plastic products	52.19 (310.5)	206,579.1 (5,109,529.9)	59,944.8 (787,775.6)	15,172
Other non-metallic mineral products	38.71 (113.6)	28,140.5 (117,695.4)	22,460.9 (71,385.2)	6359
Basic metals and fabricated metal products	20.29 (97.31)	11,703.5 (164,087.7)	10,898.8 (78,673.7)	62,809
Machinery and equipment n.e.c.	39.61 (161.8)	33,683.6 (686,939.8)	24,061.0 (126,788.0)	31,026
Electrical and optical equipment	40.33 (448.3)	31,016.5 (650,910.4)	29,143.4 (485,419.4)	22,369
Transport equipment	108.9 (809.9)	138,829.1 (1,806,939.1)	69,128.2 (613,636.4)	11,767
Manufacturing n.e.c.	19.32 (72.18)	7680.1 (42,745.0)	9274.7 (34,293.4)	20,990
Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods	12.82 (105.6)	5794.8 (134,237.7)	6797.8 (62,456.6)	453,696
Transport, storage and communication	22.14 (360.9)	31,468.2 (1,270,571.5)	12,831.9 (251,486.8)	140,661
Renting and business activities	17.32 (213.3)	30,021.2 (905,392.7)	9899.9 (114,398.7)	325,686

n.e.c. not elsewhere classified

Fig. 3 Components of efficiency for the manufacturing sector

Fig. 4 Components of efficiency for the service sector

Fig. 5 Technical change measured with time dummies for manufacturing and services. Figure 5 shows TC over time measured with time dummies. This, however, is not TC in its original interpretation since these changes are clearly a result of cyclical factors. The solid line indicates that manufacturing caught-up to its previous level in³⁰ 2011. However, the average production function is on a similar level as before the crisis, indicating that it has not caught up to its original trend. In contrast, the service sector is, visually, at the same trend as previously. This was not shown for the TFP growth since (1) no scale effect is included here, and (2) the interaction of time is not included. An interpretation of this is that TC and TFP growth are largely affected by the financial crisis, especially the manufacturing sector. From Fig. 1, it could be observed that the aggregated value added has declined. Furthermore, Fig. 5 indicates a slowdown of growth that can have several explanations, e.g., absence of re-investment in capital or loss in competitive power in the international market. However, this is not in the scope of this study to investigate

³⁰ The differences in comparison to the previous results are due to: (1) interactions were previously included and (2) the calculation of TC of the separated period does not take the first year into account. However, the conclusion remains constant.

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