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What Do We Know About Productivity in Swedish Firms?

Tillväxtanalys
Myndigheten för tillväxtpolitiska utvärderingar och analyser

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Myndigheten för tillväxtpolitiska utvärderingar och analyser
Studentplan 3, 831 40 Östersund
Telefon: 010 447 44 00
E-post: info@tillvaxtanalys.se
www.tillvaxtanalys.se
För ytterligare information kontakta: Marie Gartell
Telefon: 010-447 44 87
E-post: marie.gartell@tillvaxtanalys.se
Omslagsbild: Johnér Bildbyrå

Förord

Tillväxtanalys uppdrag är att utvärdera och analysera effekterna av statens insatser för en hållbar nationell och regional tillväxt. Vi ska också ge underlag och rekommendationer för utveckling, omprövning och effektivisering av politiken.

Syftet med den här rapporten är att anpassa ett totalfaktorproduktivitetsmått (TFP) som kan användas för att studera produktivitet baserat på svenska registerdata. Rapporten är skriven av Jonas Månsson, Blekinge Tekniska Högskola, Christopher O'Donnell, University of Queensland samt Anupama Unnikrishnan, Blekinge Tekniska Högskola.

Peter Svensson, analytiker och ämnessakkunnig vid Tillväxtanalys, har varit projektledare. I projektet har också Magnus Gustavsson, Tillväxtanalys, medverkat. Projektets referensgrupp har bestått av Lars Persson, Institutet för Näringslivsforskning samt Pär Hansson, Tillväxtanalys. Vi har även fått synpunkter från deltagare vid det seminarium som hölls på Blekingen Tekniska Högskola samt Tillväxtanalys.

Ett varmt tack till er som har bidragit med värdefulla inspel.

Östersund juni 2025

Sverker Härd,
Generaldirektör, Tillväxtanalys

Innehållsförteckning

Sammanfattning

Studiens syfte och betydelse

Ekonomisk tillväxt är ett centralt mål i ekonomisk politik. En viktig källa till tillväxt är ökad produktivitet. Eftersom uppföljning av produktivitet i Sverige bygger på föråldrade eller partiella metoder, har denna studie haft som syfte att använda moderna metoder för att mäta totalfaktorproduktivitet (TFP). TFP ger en mer heltäckande bild av produktivitet än enklare mått som arbetsproduktivitet (AP). En fördel med den mer moderna metoden för att mäta produktivitet är att de kan delas upp i drivkrafterna för densamma. Detta gör det möjligt att på ett mer precist sätt inrikta policyrekommendationer och åtgärder.

Metod och utmaningar

Produktivitetsmätning är särskilt utmanande när det finns flera inputs och outputs. Moderna metoder, som bygger på distansfunktioner och axiombaserade index (t.ex. Malmquist och Hicks-Moorsteen), klarar detta bättre än äldre index som kräver prisinformation, men även dessa flitigt använda produktivitetsindex har brister. Den valda metoden i rapporten uppfyller samtliga axiomatiska krav för ett produktivitets-index och kan identifiera bakomliggande drivkrafter till TFP-utvecklingen, såsom tekniska framsteg, effektivitetsförändringar och förändringar i skala och inputmix. I modellen har vi även byggt in andra förklaringar till den observerade TFP-utvecklingen. Bland annat illustreras hur exogena faktorer, dvs. faktorer utanför företagets kontroll, kan hanteras. Likaså illustreras hur faktorer som enbart påverkar effektiviteten, i vårt fall egenskaper hos företagsledningen, kan hanteras.

Resultat

Riskabelt att använda arbetsproduktivitet som en proxy för TFP

Ett första resultat av studien är att vi visar att arbetsproduktivitet ibland är en dålig approximation av TFP, vilket kan leda till felaktiga policybeslut.

Produktiviteten och dess drivkrafter

För att illustrera resultaten har vi valt ut tre sektorer för en mer omfattande analys. Dessa är *Högteknologisk tillverkning*, *Transport*- och *Jordbrukssektorn*. Resultaten för dessa sektorer visar:

- **Högteknologisk tillverkning:** Hög TFP-tillväxt, drivet av teknologiska framsteg och bättre produktionsförutsättningar.
- **Transportsektorn:** Negativ TFP-utveckling, troligen till följd av försämrad produktionskapacitet på grund av bristande reinvesteringar.
- **Jordbrukssektorn:** Minskad TFP på grund av ökande ineffektivitet, eventuellt till följd av grön omställning och bristande teknikadoption.

Betydelsen av lokalisering och företagsledaregenskaper

Effektivitet påverkas även av exogena faktorer exempelvis företagets geografiska placering. Resultaten visar att företag i norra Sverige tenderar att vara mindre effektiva, medan storstadslokalisering gynnar produktivitet. När det gäller företagsledningens egenskaper (ålder, erfarenhet, antal barn) är huvudresultatet att det finns en korrelation mellan egenskaper och effektivitetsförändringar, men att den är olika för olika sektorer.

Förslag till vidare forskning

1. Våra analyser bygger alla på en och samma modell och samma uppsättning output och input. Ett första förslag är att på basis av de resultat vi presenterat göra en djupare analys av enskilda sektorer genom att anpassa modeller ytterligare efter sektorernas unika förutsättningar.
2. Ofta är det mer intressant att tala om sektorers/länder utveckling än enskilda sektorer. Vi är dock inte helt klara över hur denna aggregering ska gå till utan att det introduceras felaktigheter. Ett andra förslag är därför att titta närmare på hur denna aggregering mellan sektorer och länder kan göras.
3. I de delar där vi studerar företagsledningens roll för effektiviteten har våra variabelval utgått från tidigare publicerad forskning snarare än en djupare förståelse för detta samband. Ett tredje förslag är därför att mer djupgående utforska hur företagsledning påverkar produktivitet, gärna med hjälp av forskare inom management.
4. Slutligen, det program som vi använt för att ta fram resultaten finns att ladda ner och använda på Tillväxtanalys webb; www.tillvaxtanalys.se. Det är således fritt att använda och vidareutveckla de tillgängliga verktygen som vi tagit fram.

Summary

Purpose and significance of the study
Economic growth is a central goal of economic policy. An important source of growth is increased productivity. Since monitoring of productivity in Sweden is based on outdated or partial methods, this study has aimed to use modern methods to measure total factor productivity (TFP). TFP provides a more comprehensive picture of productivity than simpler measures such as labor productivity (LP). An advantage of the more modern method of measuring productivity is that they can be broken down into the drivers of the same. This makes it possible to target policy recommendations and measures in a more precise way.

Method and challenges
Productivity measurement is particularly challenging when there are multiple inputs and outputs. Modern methods, which are based on distance functions and axiom-based indices (e.g. Malmquist and Hicks-Moorsteen), handle this better than older indices that require price information, but even these widely used productivity indices have shortcomings. The method chosen in the report meets all axiomatic requirements for a productivity index and can identify underlying drivers of TFP development, such as technological progress, efficiency changes and changes in scale and input mix. We have also built other explanations for the observed TFP development into the model. Among other things, it illustrates how exogenous factors, i.e. factors outside the company's control, can be handled. It also illustrates how factors that only affect efficiency, in our case characteristics of the company's management, can be handled.

Results

Risky to use labor productivity as a proxy for TFP
A first result of the study is that we show that labor productivity is sometimes a poor approximation of TFP, which can lead to incorrect policy decisions.

Productivity and its drivers
To illustrate the results, we have selected three sectors for a more comprehensive analysis. These are High-tech Manufacturing, Transport and Agriculture. The results for these sectors show:

- High-tech Manufacturing: High TFP growth, driven by technological progress and improved production conditions.
- Transport: Negative TFP development, probably due to deteriorating production capacity due to lack of reinvestment.
- Agriculture: Reduced TFP due to increasing inefficiency, possibly due to green transition and lack of technology adoption.

The importance of localisation and management characteristics
Efficiency is also affected by exogenous factors, such as the geographical localisation of the company. The results show that companies in northern Sweden tend to be less efficient, while metropolitan location benefits productivity. Regarding management

characteristics (age, experience, number of children), the main result is that there is a correlation between characteristics and efficiency changes, but that it is different for different sectors.

Suggestions for further research

1. Our analyses are all based on one and the same model and the same set of outputs and inputs. A first suggestion is to use the results we have presented to conduct a deeper analysis of individual sectors by further adapting models to the sectors' unique conditions.
2. It is often more interesting to talk about the development of sectors/countries than individual sectors. However, we are not entirely sure about how this aggregation should be done without introducing errors. A second suggestion is therefore to look more closely at how aggregation between sectors and countries can be done.
3. In the parts where we study the role of corporate management in efficiency, our variable choices have been based on previously published research rather than a deeper understanding of this relationship. A third suggestion is therefore to explore in more depth how corporate management affects productivity, preferably with the help of management researchers.
4. Finally, the program we used to produce the results can be downloaded and used on the Tillväxtanalys website; www.tillvaxtanalys.se. You are therefore free to use and further develop the available tools that we have developed.

1. Introduction

According to the OECD (2001), productivity "is commonly defined as a ratio of a volume measure of output to a volume measure of input use ...there is no disagreement on this general notion" (OECD, 2001, p. 11). Common measures of productivity include labour productivity (i.e., output volume divided by the volume of labour), land productivity (i.e., output volume divided by land area), multi-factor-productivity (MFP) (i.e., output volume divided by the volume of a subset of inputs, usually just capital and labour) and total factor productivity (TFP) (i.e., output volume divided by the volume of all inputs).[1] Except in restrictive special cases, for example, when inputs are used in fixed proportions (i.e., they are perfectly correlated), these different measures will tell different stories about productivity change.

Several studies aim to measure the productivity of Swedish firms. Some studies focus on measures of labour productivity (see, e.g., Persson, Edmark, Norbäck, & Prawitz, 2024; Jagrén, 2024; Boumediene & Grahn, 2015) while others use a growth accounting approach to measure TFP (see e.g. Tillväxtanalys, 2021; Eklund & Thulin, 2020; Lappi, 2024; Lappi, Norbäck, & Persson, 2024; Hermasson & Han-Suck, 2024). However, some studies compute TFP using more modern index methods, for example, Färe, Grosskopf, Lindgren, & Roos, 1992; Hjalmarsson & Veiderpass, 1992; Färe, Grosskopf, Lindgren, & Roos, 1994; Mattsson, Månsson, & Greene, 2020; Unnikrishnan, Månsson, & Deiaco, 2025, to mention a few.[2] Most of these studies target a specific industry and use primary data.

1.1 Labour productivity

Economic interest in labour productivity stems from the fact that it is often associated with improved living standards: if markets are competitive, then increases in the marginal product of labour will lead to higher wages. That said, the easiest way to improve labour productivity is generally not by increasing the marginal product of labour; rather, if the marginal product of any non-labour input is positive, then the easiest way to increase labour productivity is to use more of that non-labour input in the production process. A preoccupation with labour productivity can be problematic: as Farrell (1957, p. 263) points out, it can lead to a reduction in living standards through over-capitalisation. With this in mind, many economists have turned their attention to measures of TFP.

1.2 Total Factor Productivity

The growth accounting approach to TFP measurement is underpinned by several important assumptions. These assumptions can be traced back to the seminal work of Solow (1957). Under the Solow assumptions, the technical change component in a simple production function model can be viewed as a proper measure of TFP (proper in the sense that it satisfies important axioms from index theory). Moreover, with some additional assumptions about markets and firm behaviour, it can be computed as a

[1] The use of the term multifactor productivity instead of total factor productivity can be traced back to the OECD. OECD researchers who wanted to construct a measure of total factor productivity found that it was impossible in practice to measure every single input, so they could only compute what is technically a measure of multifactor productivity.

[2] International reviews are e.g. Van Biesebroeck, 2007; Van Beveren, 2012.

residual. Unfortunately, there is now a tendency among economists to view the residuals in many types of production function models as measures of TFP, even when the Solow assumptions do not hold. Notable examples include the residuals defined by Olley and Pakes (1996) and Levinsohn and Petrin (2003). The implications are profound. Consider, for example, the measure of productivity defined by Olley and Pakes (1996, p. 187). If firms A and B are the same age and produce exactly the same outputs, but firm A uses exactly half as much of each input as firm B, then all sensible measures of productivity will correctly indicate that firm A is twice as productive as firm B. However, given the estimates reported in their Table VI, the Olley and Pakes (1996) measure of productivity will indicate that firm A is only $2^{0.963} = 1.95$ times more productive than firm B. This is nonsense. In this paper, we avoid this type of error by computing proper measures of TFP.

As we shall see, constructing a proper measure of TFP is reasonably straightforward. Explaining changes in TFP is a little more difficult. If productivity is a measure of output volume divided by input volume, then explaining changes in TFP involves explaining changes in output and input volumes. Economists have many models that can be used for this purpose. The most naive models are production function models of the type used by Solow (1957). The Solow model allows for technical progress (i.e., the discovery of new techniques for transforming inputs into outputs) but does not explicitly allow for other sources of productivity change. In this paper, we use a more sophisticated model that besides technical progress also allows for efficiency change and economies of scale (i.e., the productivity benefits associated with changing the scale of operations), environmental variables (i.e., variables that are physically involved in the production process but never within the control of firm managers, such as temperature in farming) and technical inefficiency (i.e., the failure of managers to properly implement the best production techniques). Given the rich information obtained from the model, policy implications of the results could in a more direct way be transferred to policy recommendations targeting the drivers of TFP. Our model also allows for measurement errors and other sources of statistical noise.

1.3 A model that fulfils production economic axioms

Our model is a type of stochastic production frontier model.[3] These types of models were first developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977). They can be viewed as a single equation regression models with two error terms, one representing technical inefficiency and the other representing statistical noise. O'Donnell (2018, Section 8.5) shows how stochastic production frontier models can be used to decompose proper measures of TFP change into measures of technical progress, environmental change, changes in economies of scale and substitution, technical efficiency change, and changes in statistical noise. In this paper, we are particularly interested in the technical efficiency component. O'Donnell (2018, p. 365) suggests that managers may fail to properly implement the best production techniques (i.e., they may be technically inefficient) due to a lack of knowledge, training and experience. As shown in Table 7, the literature suggests that technical inefficiency may also be due to gender,

[3] In absences of prices or value shares we could also have used Additive indexes that use averages of DEA estimates of shadow prices as weights (see e.g. Førsund, 2018); Principal Component Analysis (PCA) indexes (see e.g., Feroze & Chauhan, 2010) or Benefit-of-the-doubt (BOD) indexes (see e.g., Bogetoft & Wittrup, 2021).

age and education. To account for these possibilities, this paper combines our single equation stochastic frontier model with an equation that explains technical inefficiency as a function of management characteristics (e.g., age, education, gender). The resulting two-equation system has the same structure as the inefficiency effects model of Battese and Coelli (1995).

1.4 The structure of the report

The structure of the report is as follows. Sections 2 and 3 discuss how TFP change is measured and estimated, including the growth accounting approach, the alternative approach that we have chosen to measure TFP change and the estimation of managerial and environmental factors explaining TFP change. Section 4 reviews the studies on technical efficiency and managerial characteristics. Section 5 defines key concepts and describes the data, covering output and input definitions, managerial characteristics, data reduction, and descriptive statistics. Section 6 presents the results. In the results section, firstly, we address the question of how well labour productivity (LP) matches with TFP. We show that the correlation between LP and TFP is high for some sectors, but low for other sectors. Thus, making a general claim that LP and TFP are highly correlated is questionable and potentially hazardous for policymakers. Secondly, we present the detailed TFP results and its decomposition for three sectors: the High-Tech Manufacturing, Agricultural, and Transport sectors. This is done along with the role of managerial characteristics and environmental factors. Finally, Section 7 concludes the study with a summary of findings and key takeaways.

2. Measuring TFP Change[4]

Measures of TFP change are measures of output volume change divided by measures of input volume change (i.e., output volume indexes divided by input volume indexes).[5] Our empirical work involves firms that produce a single (aggregate) output using multiple inputs. The fact that there is only one output means it is trivially simple to construct the output index: let Q_{it} denote the (aggregate) output of firm *i* in period *t*; the index that compares the output of firm *i* in period *t* with the output of firm *k* in period *s* is simply $QI(Q_{ks},Q_{it}) = Q_{it}/Q_{ks}$. Constructing the input index is a little more complicated.

An input volume index is a formula that tells us how to assign numbers to bundles of inputs. Proper input volume indexes assign numbers in such a way that the patterns in the numbers reflect the patterns in the bundles. For example, if bundle A contains twice as much of every input as bundle B, then a proper input volume index will assign a number to bundle A that is twice as big as the number assigned to bundle B. Countless proper input volume indexes are available.

$$XI(x_{ks}, x_{it}) = \frac{X(x_{it})}{X(x_{ks})} \tag{1}$$

Let $x_{it} = (x_{1it},...,x_{Mit})'$ where x_{mit} is the volume of input *m* used by firm *i* in period *t*. A proper index that compares the inputs of firm *i* in period *t* with the inputs of firm *k* in period *s* is any variable of the form where $X(\cdot)$ is a non-negative, non-decreasing, linearly-homogeneous, scalar-valued aggregator function. Such an index is proper in the sense that it satisfies the input index axioms listed in O'Donnell (2016, p. 332). Possibly the two most important axioms are the transitivity axiom and the proportionality axiom. In a cross-sectional context, for example, the transitivity axiom says that a direct comparison of the inputs of two firms should yield the same index number as an indirect comparison through a third firm. For example, if firm A used twice as many inputs as firm B, and firm B used three times as many inputs as firm C, then all direct and indirect compare-sons should say that firm A used six times as many inputs as firm C. The proportionality axiom says that if firm A used λ times as much of every input as firm B, then the index that compares the inputs of firm A with the inputs of firm B (using the latter as the reference firm) should take the value λ.

In practice, the choice of aggregator function $X(\cdot)$ is a matter of taste. Additive indexes are constructed using linear aggregator functions, while multiplicative indexes are con-structed using double-log aggregator functions. The parameters in these aggregator functions are weights that reflect the relative importance of different inputs. It is common to use market prices and value shares as weights: the Lowe index, for example, is an

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[4] See e.g. O'Donnell (2018) for a more comprehensive and textbook style presentation of the content in sections 2-4.

[5] Some authors have a different view. In e.g. Jagrén (2024) it is stated that "Normal measures of productivity use the monetary value of what is produced in one year" (own translation). If monetary values are used instead of volumes, then resulting measures of "productivity" are normally referred to as measures of profitability, or return-to-the-dollar.

additive index that uses average market prices as weights, while the geometric Young (GY) index is a multiplicative index that uses average value shares as weights.

The Lowe and GY indexes are proper indexes. Unfortunately, the input volume indexes most widely used by economists and statistical agencies are not proper: the binary Fisher (BT) and binary Törnqvist (BT) indexes violate the transitivity axiom, while the chained Fisher (CF), chained Törnqvist (CT), Elteto-Koves-Szulc (EKS) and Caves, Christensen & Diewert (CCD) indexes violate the proportionality axiom. Except in restrictive special cases, the well-known Malmquist productivity index (see e.g. Färe et al. (1992) and the (Bjurek)Hicks-Moorsteen productivity index (see e.g. (Bjurek, 1996; Hicks, 1961; Moorsteen, 1961) also violate the transitivity axiom. For more details, see O'Donnell (2016, Chapter 3).

2.1 The Growth Accounting Approach

The growth accounting approach to TFP measurement has its antecedents in the work of Solow (1957). Solow assumed that there is only one (aggregate) output, and that output growth could be attributed to a combination of input growth and technical change. Working with time-series data, he assumed a production relationship of the form

$$Q_t = A(t)f(x_t) \tag{2}$$

where Q_t denotes the volume of output in period t, $x_t = (x_{1t},\ldots,x_{Mt})'$ is a vector of inputs, $A(t)$ is a measure of technical change, and $f(\cdot)$ is a non-negative function that is non-decreasing and linearly-homogeneous in inputs. These properties of $f(\cdot)$ mean it can be viewed as an input aggregator function. It follows that $f(x_t)/f(x_s)$ can be viewed as an input volume index. The associated index that compares TFP in period t with TFP in period s is

$$TFPI\ (x_s, Q_s, x_t, Q_t) = \frac{Q_t/Q_s}{f(x_t)/f(x_s)} = \frac{A(t)}{A(s)}. \tag{3}$$

With some additional assumptions concerning market structure (e.g., that firms are price-takers in input markets), managerial behaviour (e.g., managers successfully minimise cost), and the functional form of $f(\cdot)$ (e.g., Cobb-Douglas), it is possible to compute $f(x_t)$ without estimating an econometric model. The technical change component in (2) can then be computed as a residual. Today, residuals that are computed in this way are commonly known as Solow residuals.

2.1.1 Two main problems with the growth account approach

There are two main problems with the growth accounting approach. First, because it was developed in a time-series context, it does not lend itself to multilateral comparisons (i.e., comparisons across firms). Second, it is underpinned by a production relationship that does not allow for technical inefficiency, environmental change, variable returns to scale, or various sources of statistical noise.

2.2 Our Alternative Approach

To avoid the problems with the growth accounting approach, we consider a more general production relationship of the following form:

$$Q_{it} = A(z_{it}, t) f(x_{it}) exp(v_{it} - u_{it}) \tag{4}$$

where $z_{it} = \{z1_{it},...,zJ_{it})'$ is a vector of environmental variables, $A(z_{it},t)$ is a measure of technical and environmental change, f(·) is a non-negative function that is non-decreasing and homogeneous of degree r in inputs, u_{it} is a non-negative technical inefficiency effect, and vit is an unobserved random variable that accounts for measurement errors (e.g., the possibility that the aggregate output does not accurately measure changes in output volumes), functional form errors (e.g., the possibility that $A(\cdot)$ and $f(\cdot)$ do not represent the true production function) and other sources of statistical noise (e.g., omitted variables). In this case, the properties of $f(\cdot)$ mean that $f(\cdot)1/r$ can be viewed as an input aggregator function, and that $[f(x_{it})/f(x_{ks})]1/r$ can be viewed as an input volume index. The associated index that compares TFP of firm *i* in period *t* with the TFP of firm *k* in period *s* is

$$TFPI\left(x_{ks,} Q_{ks}, x_{it}, Q_{it}\right) = \frac{Q_{it}/Q_{ks}}{[f(x_{it})/f(x_{ks})]^{1/r}}. \tag{5}$$

If $f(\cdot)$ is *linearly* homogeneous (i.e., if $r = 1$), then this index becomes a panel data version of the TFP index defined by (3).

3. Explaining TFP Change

Arguably, the simplest way for an economist to explain changes in TFP is to divide both sides of (4) by $f(x_{it})^{1/r}$ to obtain:

$$\frac{Q_{it}}{f(x_{it})^{1/r}} = A(z_{it}, t) f(x_{it})^{1-1/r} \exp(v_{it} - u_{it}) \tag{6}$$

A similar equation holds for firm k in period s. Dividing one equation by the other yields the following decomposition of the TFP index defined by (5):

$$TFPI\left(x_{ks}, Q_{ks}, x_{it}, Q_{it}\right) = \frac{A(z_{it}, t)}{A(z_{ks}, s)} \times \left[\frac{f(x_{it})}{f(x_{ks})}\right]^{1-1/r} \times \frac{\exp(-u_{it})}{\exp(-u_{ks})} \times \frac{\exp(v_{it})}{\exp(v_{ks})} \tag{7}$$

The first term on the right-hand side is a technical progress and environment index (TPEI) (i.e., a measure of technical progress and changes in the production environment), the second term is an output-oriented scale and mix efficiency index (OSMEI) (i.e., a measure of changes in economies of scale and substitution), the third term is an output-oriented technical efficiency index (OTEI) (i.e., a measure of changes in technical efficiency), and the last term is a statistical noise index (SNI) (i.e., a measure of changes in functional form errors etc.).

In practice, identifying the TPEI and OSMEI components in (7) involves choosing the functions $A(\cdot)$ and $f(\cdot)$. In this paper, we choose the following theoretically plausible functions:

$$A(z_{it}, t) = exp(\alpha + \lambda t) \prod_{j=1}^{J} z_{jit}^{\delta_j} \tag{8}$$

and

$$f(x_{mit}) = \prod_{m=1}^{M} x_{mit}^{\beta_m} . \tag{9}$$

If there is no statistical noise, then β_m is equal to the m-th output elasticity and $\eta \equiv \sum_m \beta_m$ is equal to the elasticity of scale. With equations (8) and (9), the TPEI and OSMEI components of TFP change are given by:

$$\frac{A(z_{it},t)}{A(z_{ks},s)} = \frac{exp(\lambda t)}{exp(\lambda s)} \times \prod_{j=1}^{J} \left(\frac{z_{jit}}{z_{jks}}\right)^{\delta_j} \tag{10}$$

and

$$\left[\frac{f(x_{it})}{f(x_{ks})}\right]^{1-1/r} = \prod_{m=1}^{M} \left(\frac{x_{mit}}{x_{mks}}\right)^{\beta_m - \lambda_m} \tag{11}$$

where, if there is no statistical noise, $\lambda_m \equiv \beta_m/\eta$ is equal to the m-th cost-minimising cost share. If η is equal to one, then the OSMEI component is also equal to one.

We are particularly interested in the drivers of technical inefficiency. This leads us to specify an inefficiency effects model of the type proposed by Battese and Coelli (1995):

$$u_{it} = \xi + \sum_{g=1}^{G} \phi_g a_{git} + w_{it} \tag{12}$$

where a_{git} is the g–th attribute of manager i in period t (e.g., age, gender), and w_{it} is an unobserved random variable representing functional form errors (i.e., the possibility that technical inefficiency is not a linear function of manager attributes) and other sources of statistical noise (e.g., an omitted attribute). With this function, the OTEI component of TFP change is given by:

$$\frac{\exp(-u_{it})}{\exp(-u_{ks})} = \prod_{g=1}^{G} \frac{\exp(-\phi_g a_{git})}{\exp(-\phi_g a_{gks})} \times \frac{\exp(-w_{it})}{\exp(-w_{ks})} \tag{13}$$

The first G terms are indexes that measure the relation between different managerial attributes on technical efficiency. The last term is a statistical noise index. If predictions of the u_{it} and estimates of the ϕ_g are available, then the statistical noise index can be computed as a residual.

4. Estimation

Measuring and explaining TFP change involves estimating the unknown parameters in equations (8), (9) and (12). Substituting equations (8) and (9) into equation (4) yields the following stochastic production frontier model:

$$Q_{it} = exp(\alpha + \lambda t) \prod_{j=1}^{J} z_{jit}^{\delta_j} \prod_{m=1}^{M} x_{mit}^{\beta_m} \exp(v_{it} - u_{it}) \cdot \tag{14}$$

The system of equations defined by (12) and (14) is a model of the type considered by Battese and Coelli (1995). We follow those authors and assume that v_{it} is an independent normal random variable with a mean of zero and a variance of σ_v^2, and that w_{it} is a normal random variable with a mean of zero and a variance of σ_u^2 that has been truncated from below such that $u_{it} \geq 0$. We then estimate the parameters in (12) and (14) using the method of maximum likelihood.

5. Technical Efficiency and Managerial Characteristics: A Literature Review

Our focus is on technical efficiency, and we have selected specific managerial characteristics for analysis. Within the literature on technical efficiency and managerial characteristics, age, education, experience, and gender are the most prominently studied factors across various sectors. However, variables such as immigration status, having children, marital status, and second-generation immigrant status are largely absent from these discussions. While these factors have been considered in broader assessments of productivity and performance, they have not been extensively examined in the context of technical efficiency. In our study, we incorporate these under-explored variables to provide a more comprehensive analysis.[6]

5.1 Age, education, experience and gender

The surveyed studies have found varying relationships between age, education, experience, and gender in different sectors. Studies within the agriculture sector that incorporate a quadratic function for age often find an inverse U-shaped relationship with efficiency, where productivity increases with age up to a certain point, typically peaking in middle age, before declining. (Addo & Salhofer, 2022; Karagiannis & Sarris, 2005; Qian, Zhu, Antonides, & Heerink, 2024). Some studies suggest that experience enhances efficiency, as older farmers accumulate skills over time (Madau, 2007; Villano & Fleming, 2006; Chen, Huffman, & Rozelle, 2009). However, others caution that older farmers may struggle to adopt new technologies, leading to reduced efficiency (Featherstone, Langemeier, & Ismet, 1997; Rasmussen, 2010; Koirala, Mishra, & Mohanty, 2016; Bozoˇglu & Ceyhan, 2007; Battese & Coelli, 1995).

The relation between formal education and efficiency remains inconclusive, with some studies indicating that practical skills and experience are more crucial than formal schooling (Hong, Heerink, Zhao, & van der Werf, 2019; D. A. Ali, Bowen, & Deininger, 2020). In the manufacturing sector, experience is generally linked to higher efficiency, while the role of education is less clear (Alvarez & Crespi, 2003; Noor & Siang, 2014; Bhasin & Akpalu, 2002). Training and access to credit improve efficiency, but older business owners tend to have lower efficiency levels (Leza, Rajaan, Kuma, & Sodo, 2016; Bhasin & Akpalu, 2002). In service industries, higher education and experience are widely associated with increased efficiency (Amare, Yitayal, & Amare, 2020; Assaf & Matawie, 2009; Kisaka, Kising, & Wafubwa, 2014). Specialized education has been shown to enhance financial sector efficiency, particularly in banking (Kauko, 2009; Ben Mohamed, Meshabet, & Jarraya, 2021). Similarly, managerial experience plays a key role in improving efficiency in healthcare settings (Amare et al., 2020; Ahmed et al., 2019).

The impact of gender on efficiency varies across sectors. In agriculture, some studies suggest that female-managed farms are more efficient despite producing lower output volumes, often due to resource constraints rather than managerial ability (Dadzie & Dasmani, 2010; Moock, 1976; Saito, Mekonnen, & Spurling, 1994; Bozoˇglu & Ceyhan, 2007). Other studies argue that male-managed farms tend to be more efficient, largely

[6] The surveyed studies are summarised in Appendix B

because men have greater access to resources (Danso-Abbeam, Baiyegunhi, & Ojo, 2020; FAO, 2011; Kilic, PalaciosL´opez, & Goldstein, 2015). However, when access to inputs is equalized, gender differences in efficiency often disappear (Ma, Heerink, Feng, & Shi, 2017; Tan, Heerink, Kuyvenhoven, & Qu, 2010). In service industries, findings are mixed, with some studies indicating that male CEOs achieve higher efficiency (Gutierrez-Romero, Blanco-Oliver, Montero-Romero, & Carbonero-Ruz, 2021; Makheti, 2017), while others find that female managers perform better in certain contexts (Sengupta, Datta, & Mondal, 2015). The relationship between remuneration and efficiency is also debated. Some studies suggest that higher CEO remuneration is linked to improved efficiency, as it serves as an incentive for better performance (Matolcsy & Wright, 2011; Amornkitvikai & Harvie, 2011). However, others find a negative relationship, arguing that excessive pay can lead to inefficiencies due to misaligned incentives and reduced employee motivation (Zaabouti & Ben Mohamed, 2025).

5.2 Conclusions

To conclude, the literature suggests varying relationships between manager characteristics and technical efficiency, with results often depending on specific contexts. Although education and experience showed relatively consistent positive associations, other characteristics such as gender and age appeared more context-dependent, suggesting that the relationship between manager characteristics and technical efficiency varies across industries and regional contexts.

6. Definitions and Data

6.1 Definition of Output and Inputs

The output variable used is real production value (an implicit volume index). The three input variables are volumes of labour (numbers), capital (an implicit volume index consisting of building, land, machinery and inventories) and intermediate inputs (also an implicit volume index).[7] Output and inputs that are expressed as values in the data are transformed into volume approximations by deflating by a sector-wise production price index (PPI).[8]

6.2 Identification of Operational Manager, Managerial Characteristics and Environmental Variables.

Key variables in our analysis are the managerial characteristics. Statistics Sweden uses an algorithm to define the operative leader/manager of a firm. The algorithm presented by F. Andersson and Andersson (2012) identifies the manager using different data sources, information types, and a point system. The system, in short, dedicates different points to different types of information, where higher points are seen as a more reliable source than lower points. The person with the highest score is then seen as the operative manager of the company. The point system is presented in Table 1.

Table 1: Point System to Determine Manager

Manager indicator	Points
CEO according to the Swedish Companies Registration Office	1000000
CEO in Employment register, more than 10 employed, Statistics Sweden	100000
CEO in Employment register, less than 10 employed, Statistics Sweden	10000
Co-Owner, Statistics Sweden	1000
Deputy CEO	800
Chairman of board	700
Deputy Chairman of board	600
Serving board member	500
Board member	400

[7] The aggregated measures of labour and capital can, if data is accessible, be divided into finer groups. For example, labour can be divided into highly educated and low educated, and intangible capital can be included. The latter is a factor that has been pointed out as a main productivity driver in some sectors in Sweden (see e.g. Andersson, Larsson, & Wernberg, 2019; Tillväxtanalys, 2021)

[8] Using PPI as a deflator is not without its problems. For example, Lind and Song (2012) claim that there could exist systematic errors in PPI that result in an underestimation of productivity

For example, for limited companies (aktiebolag), the yearly accounting report states the CEO, and if this is the case, the "likely manager" algorithm allocates 1,000,000 points. If the person is registered as CEO in the employment register of Statistics Sweden and the company has more than 10 employees, 100,000 points are allocated. By adding all points, the person with the highest total score is appointed as the operational manager.

We consider seven managerial attributes: age (in years), the number of children, and income (SEK 100) are continuous variables, while gender, immigrant, second-generation immigrant, upper secondary education degree, post-upper-secondary education degree and marital status are binary coded variables.

6.3 Environmental variables

As environmental variables, we are using dummy variables for Norrland and Storstad. Norrland, the northernmost region of Sweden, is included because firms in this area generally require more inputs (e.g., energy) to produce the same outputs due to the harsher northern climate. Storstad is a dummy that takes the value of one if the firm is located in Stockholm, Gothenburg or Malmö - the three biggest cities in Sweden. Again, we motivate this variable by the fact that different inputs (e.g., transport costs) are generally needed to produce the same outputs in locations with different population densities.

6.4 Data Reduction

We use data from Statistics Sweden (SCB) and data sources processed from other sources by SCB. There are two main sources: Företagsdata (FEK-data base) which provides information about production, and The Longitudinal Income Database (LISA), which provides information about, in our case, the manager.

The gross number of firms in the register for the years 2010-2021 is around 11 million registered firms, however, not all registered firms enter the analysis. The data reduction takes three steps. Firstly, we only include active firms, which we define as a firm that has reported a positive production value, which is our full sample of firms. Secondly, because the volume data were extracted from accounting records, the volumes of capital and intermediate inputs sometimes turned out to be negative. Negative input volumes are implausible. We therefore removed from the dataset any firms with recorded input volumes of less than zero. Thirdly, according to the algorithm for identifying operational managers presented in Andersson & Andersson (2012), management information only exists for employers with more than one person employed. Therefore, firms with zero employees have been eliminated. Finally, in step four, we match firm data with managerial data, and for some firms, we were unable to identify operational managers, so these employers were eliminated. Table 2 summarises the data reduction across these four steps.

The pattern is the same for all years. Around 50 per cent of the firms have either zero or less capital or intermediate input, reducing the operational sample by the same share. After this reduction was done, the second step was to identify and remove employers with zero employees. Doing so reduced the sample by around 190,000 employers. Finally, the algorithm used to identify operational managers failed to do so for around 55.000 employers. Thus, the final sample to approximately 13 per cent of the original sample.[9]

6.5 External validity

The sample size reduction has potentially large implications for the external validity. In our case, it is obvious that we have a size bias since we exclude small firms without employees. However, we also made a separate analysis regarding the external validity regarding geography and industry. This analysis is presented in Appendix A. The results show that the final sample and the original sample, to a large extent, have similar shares in terms of industry and county representativeness.

[9] For the sector level estimates, sectors with less than 30 firms per year (11 industries) were, in most cases, aggregated to the closest corresponding sector. For example, performing arts (SNI90) was merged with

Table 2: Data reduction from total sample to used sample

Year	Total	Capital < 0	Intermediate input < 0	Left in sample	Labour = 0	Not identified manager	Identified operative manager	Share of original sample
2010	895023	221352	177176	571801	189164	53224	135940	**15%**
2011	925977	255649	183865	573816	191273	55276	135997	**15%**
2012	947314	285528	192137	567620	188587	54636	133951	**14%**
2013	933497	304668	195185	538615	186112	54293	131819	**14%**
2014	952177	324214	203616	536356	184350	54216	130134	**14%**
2015	963285	337514	198631	538700	184902	55539	129363	**13%**
2016	977951	350214	203642	541256	181108	53387	127719	**13%**
2017	982760	356303	205827	541441	191883	61311	130572	**13%**
2018	989212	363915	212059	238717	188136	57220	130916	**13%**
2019	1002177	371485	213537	545700	189780	62886	126894	**13%**
2020	1009964	370208	214169	556261	184616	56625	127991	**13%**
2021	1028491	382217	220272	561427	191104	59697	131407	**13%**

7. Descriptive Statistics

Given the data at hand, our model consists of three sets of variables: production variables, managerial characteristics and finally environmental factors. Descriptive statistics are presented in Table 3.

Table 3: Summary Statistics of Managerial Characteristics and Environmental Factors, N=1,572,703

Production	Mean	Std. dev.	Min	Max
Real production value (Output)	29366.9	565249.2	0.93	136000000
Labour (Input)	13.98	149.88	2.00	24271
Real capital (Input)	11200.8	309773.1	0.72	162000000
Real Intermediate input (Input)	23126.2	531775.3	0.65	146000000
Manager characteristics				
Age	48.72	10.74	16	99
Female	17%	0.37	0	1
Immigrant	16%	0.36	0	1
Upper secondary degree	54%	0.50	0	1
Post upper secondary degree	30%	0.46	0	1
Number of children	0.69	1.00	0	10
Net income (SEK100)	3966	5347	-872544	12222441
Second generation immigrant	11%	0.32	0	1
Married	58%	0.49	0	1
Environmental factors				
North of Sweden	12%	0.33	0	1
Big Swedish city	38%	0.49	0	1

The output variable and all the input variables except labour were computed from monetary values deflated by individual sector producer price indexes. As for the managerial characteristics, a few comments need to be made. As for Age, we have kept all observations, including the person who was 99 years of age. It could of course be argued that an upper threshold should be applied, limiting the operational managers' age to a maximum of 67 years of age, which is the normal retirement age in Sweden. In the model, we control for gender. As seen in the literature review, gender might play a role in the quality of managerial decisions; however, it is ambiguous in what direction gender influences the technical efficiency component. According to the data, around 17 per cent of the operational managers are female. We have variables that are related to immigrant background. The first variable indicates whether the manager was born outside of Sweden, while the second variable indicates whether the manager was born in Sweden and has at least one parent who was born outside of Sweden. In the final sample, 16 per cent had an immigrant background and around 11 per cent had a parent born outside of Sweden. Two variables indicate the highest degree. The first variable indicates whether a manager has an upper secondary school degree as the highest education (54 per cent), and the second indicates a post-upper secondary school degree (30 per cent). We expect that the correlation between higher education, post-upper secondary school degree, and efficiency is positive. We also have two variables that, to some extent, relate to family status. The first variable measures the number of children, and the second variable indicates whether the manager is married. The number of children ranges from 0 to 1, with a mean of 0.7. Around 58 per cent of the managers are married. Finally, we have included net income (income-deductible expenses) as a variable that captures unobserved ability.

8. Results

In the result section, we start by presenting our findings regarding the correlation between LP and TFP. Then, for illustrative purposes, we present sector-wise results for three sectors: the high-tech manufacturing sector (SNI26 and SNI21), the agricultural sector (SNI1) and the Transport sector (SNI49). The results for other sectors are presented in the online appendix, section A, of this report. [10]

8.1 Using LP as a Proxy for TFP

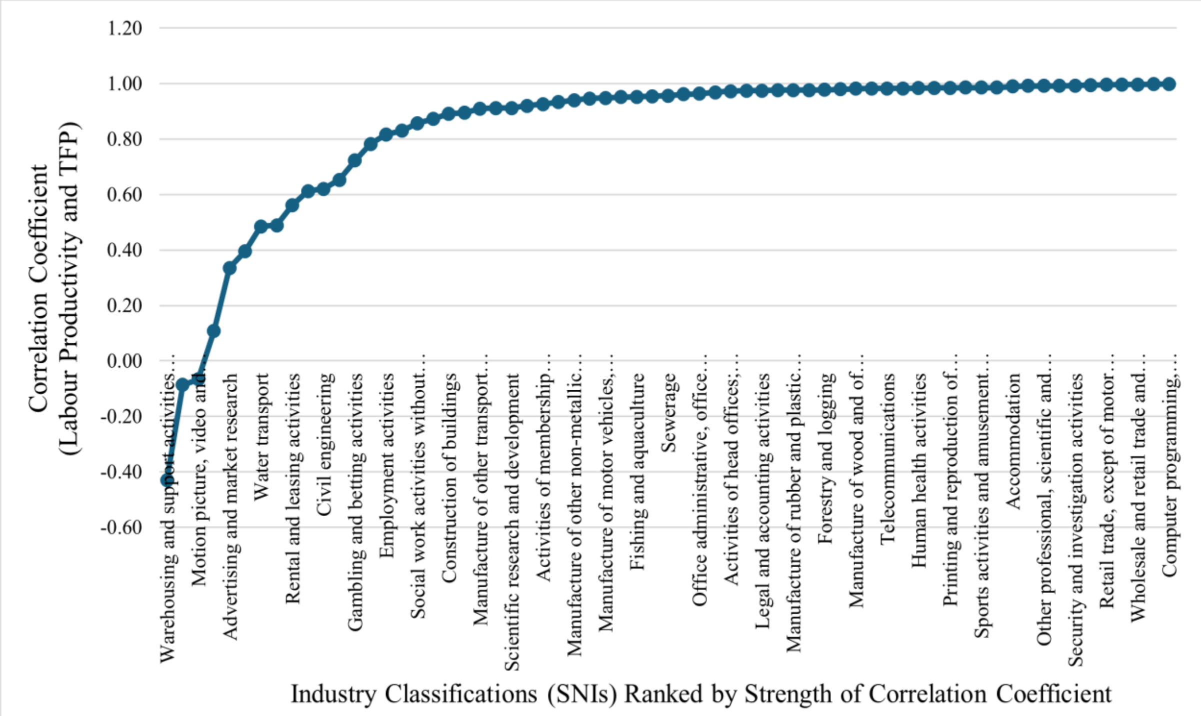
One of the reasons for conducting this study was to assess the argument that partial measures of productivity (usually LP) are often a good proxy for measures of TFP. In Figure 1, the correlation between LP and TFP is presented.

Poor correlation for some sectors has implications for policy recommendations

As seen from Figure 1, for most sectors, the correlation between the two measures is high. This indicates that labour and other inputs are used in reasonably fixed proportions. However, there are a few sectors where the correlation between LP and TFP is low, which indicates that labour productivity is a poor proxy for TFP. This does not mean that labour productivity as a measure is uninteresting; it only indicates that if the study has the ambition to say something about productivity in society, one has to be very careful. This is especially the case when the study aims to provide policy recommendations.

10 For a limited number of sectors, there were convergence issues, most likely due to the distributional assumption of the inefficiency term. For sectors 20 (manufacturing of chemical products), 28 (manufacturing of general purpose machines), 61 (telecommunication) and 72 (research and development), unrealistic estimates were obtained, and no information on the noise component could be identified. For 10 (food manufacturing), 15 (leather-based production, shoes, bags etc)), 68 (Outsourced property maintenance and rentals), 70 (Headquarter activities, PR etc), 81 (Property maintenance), 82 (business services), 87 (healthcare connected to residency) and 88 (Childcare) unrealistic estimates were obtained even though a noise component existed. We are using an SFA framework, and as shown in e.g. (Van Biesebroeck, 2007), SFA could be sensitive to data heterogeneity. In the same study it is shown that the DEA method is less sensitive to data heterogeneity.

Figure 1: Correlation Between LP and TFP



8.2 Sector results

In this section we present detailed results for three sectors that have been selected to show the diversity between sectors. The sectors are the high-tech manufacturing, agricultural and transport sectors, all defined at SNI 2 level. The TFP results for other sectors are presented in an online appendix.[11]

8.2.1 The High-Tech Manufacturing Sector

The high-tech manufacturing sector is, according to Eurostat[12] defined as the Manufacture of basic pharmaceutical products and pharmaceutical preparations (21) and the Manufacture of computer, electronic and optical products (26). Due to limited observation in the pharmaceutical sector, the sectors are merged before the analysis.

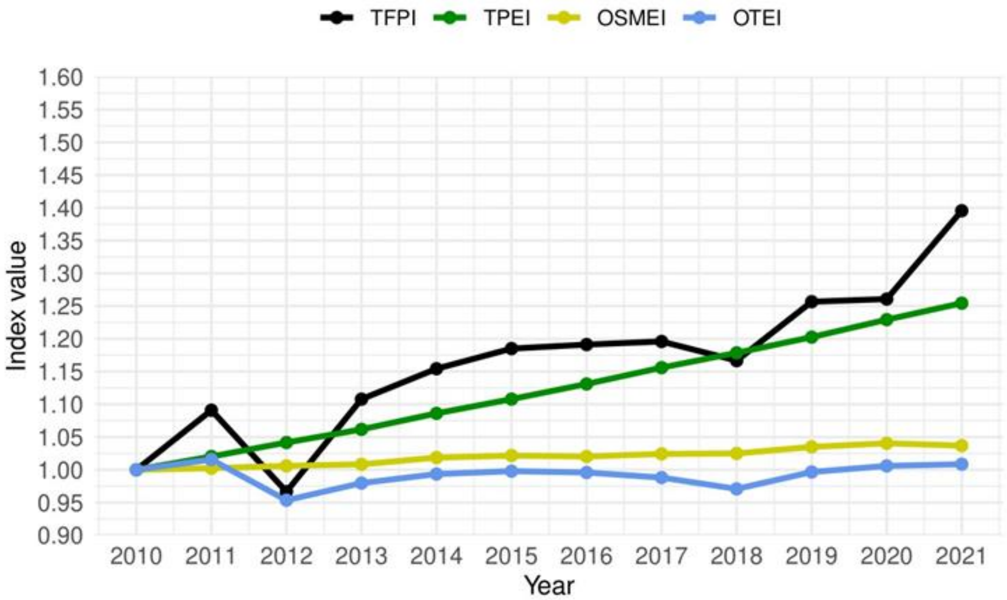
8.2.1.1 TFP Change and the Drivers of TFP Change

In Figure 2, the productivity development between 2010-2021 and its components are presented. This figure shows that the cumulative TFP growth during the period was almost 40 per cent, and had been positive in all years except for 2012 and 2018.

[11] For the regressions of managerial characteristics and technical efficiency, we do not, in this study, make any causal claims.

[12] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries

Figure 2: TFP and its Components, 2010-2021, High Tech Manufacturing Sector (SNI21 and SNI26)



8.2.1.2 Main productivity drivers in the high-tech manufacturing sector was technological progress

What is also shown in Figure 2 is that the main driver of this growth was a combination of technological progress and environmental change (the TPEI component). Scale and mix effects (the OSMEI component) contributed very little. A fall in technical efficiency (the OTEI component) dragged down TFP, particularly in 2012 and 2018.

8.2.1.3 The Role of Management Characteristics and Environmental Factors

Controlling for both managers' characteristics and environmental factors is done when estimating the SFA model. The estimation results are presented in Table 4.

Table 4: Estimated Coefficients for the High Tech Manufacturing Sector, SNI21 & SNI26

Inputs	Estimate	Std.Error	z-value	p-value	Signif.
Labour	0.627	0.010	62.76	0.000	***
Capital	0.038	0.004	8.78	0.000	***
Intermediate input	0.412	0.005	80.28	0.000	***
(Intercept)	4.436	0.033	133.82	0.000	***
Managerial Characteristics					
Age	0.282	0.087	3.22	0.001	**
Female	3.392	1.649	2.06	0.040	*
Married	-8.656	3.100	-2.79	0.005	**
Immigrant	-0.488	1.275	-0.38	0.702	
Second-generation immigrant	3.022	1.276	2.36	0.018	*
Upper Secondary school degree	-5.545	1.931	-2.87	0.004	**
Post Upper Secondary school degree	0.073	0.955	0.08	0.940	
Number of children	1.348	0.442	3.05	0.002	**
Net Income	-0.001	0.0003	-3.42	0.001	***
Z (Intercept)	-31.267	11.088	-2.82	0.005	**
Environmental factors					
North Sweden	-0.078	0.0242	-3.2188	0.001	**
Major Cities in Sweden	0.074	0.0147	5.0149	0.000	***
Time trend	0.021	0.0019	11.0088	0.000	***
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	8.698	3.0642	2.8386	0.005	**
$\gamma \equiv \sigma_u^2/\sigma^2$	0.981	0.0065	151.5139	0.000	***

* indicate significance at *** = 1 per cent level, ** = 5 per cent level and * = 10 per cent level.

In the last row in Table 4, the estimate of the γ parameter is presented. This parameter can be viewed as a measure of the amount of noise in the results. A value close to one indicates that the noise component is small. In the high-tech manufacturing sector, the estimate of γ is 0.98, indicating that the noise component in the results is small.

Table 4 presents the results in different categories of variables. First, the estimated coefficients of the log-inputs are presented. As seen from the results, these estimates all have the expected positive sign, meaning they contribute positively to observed production and are significant at the one per cent level. The second set of estimated coefficients concerns the managerial characteristics. The 'dependent variable' in this part of the analysis is inefficiency. Therefore, a positive estimate indicates that a manager with that characteristic is more inefficient or, in other words, less efficient.

For example, the estimated coefficient of age is positive and significant, indicating that older managers are less efficient than younger ones, i.e. older managers make, in our vocabulary, worse decisions.[13] The other estimated coefficients indicate that: being a female is not associated with differences in efficiency; married managers tend to be more efficient, possibly because they have been forced to develop the communication and conflict resolution skills that are crucial for managing teams effectively; the fact that a manager was born outside of Sweden do not relate significantly to efficiency; managers born to parents who have immigrated (i.e., second-generation immigrants) tend to be less efficient; managers who have only been educated to upper secondary school are more efficient than managers who are less educated; a post-upper secondary school education has no significant relation to efficiency; managers with many children are less efficient than managers with fewer children; and highly-paid managers tend to be more efficient than lower paid managers, supporting the hypothesis that income correlates with unobserved management ability.

As for the coefficients of the environmental variables, a positive coefficient estimate indicates that a given set of inputs can be used to produce more output in that environment than elsewhere. Not surprisingly, the estimated coefficients in Table 5 indicate that given inputs cannot be used to produce as much output in the harsh environment of the North, and that given inputs can be used to produce more output in more densely populated metropolitan areas. Both coefficients are statistically significant.

8.2.2 The Agricultural Sector

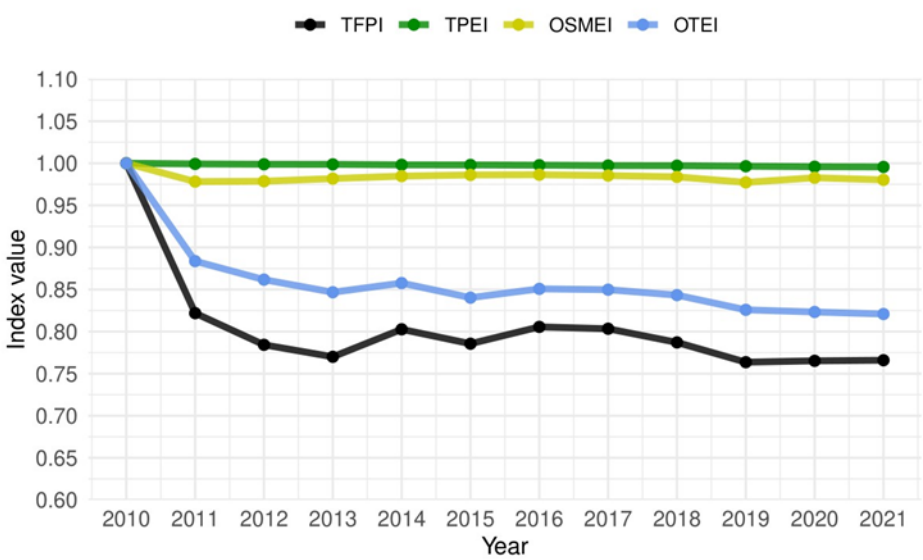
The agricultural sector is in this study defined as farming and industries directly related to farming (SNI1).

8.2.2.1 TFP Change and the Drivers of TFP Change

Figure 3 presents measures of TFP change and the estimated drivers of TFP change between 2010 and 2021 for the Agricultural sector. During this period, there was a sharp reduction in TFP (TFPI) around 2010-2011, and the sector has not recovered. The average productivity is to some extent constant around 80 per cent of the level in 2010 for the rest of the sample period, with a slight drop in TFP in 2018 and onward.

13 The value of the coefficient cannot directly be interpreted so we limit our interpretation to significance, size and direction

Figure 3: TFP and its Components, 2010-2021, Agricultural Sector



8.2.2.2 The main driver of reduced TFP is a fall in technical efficiency

Most of the drop in TFP is related to a fall in technical efficiency (OTEI). One of the reasons behind this result might be the green transition that to some extent has taken place in the agricultural sector: new EU sustainability criteria for biofuels and stricter emissions targets have influenced many farming operations, particularly in energy crop production; and bans on certain chemical pesticides and herbicides, such as endosulfan, have led many farmers to adopt alternative production practices. Another reason may be the slow uptake of the many transformative agricultural technologies that were developed in the wake of the global financial crisis (e.g., John Deere's AutoTrac & GPS-Guided Tractors, the Lely Astranaut A4 Robotic Milking System, DJI's agricultural drones, the Climate Pro system developed by The Climate Corporation, etc.).

The scale and mix component (OSMEI) has had a relatively little impact. The technical progress and environmental component (TPEI) are almost constant and around 1 for the whole period, indicating that these two aspects have also had a small influence on TFP.

8.2.2.3 The Role of Management Characteristics and Environmental Factors for the Agricultural Sector

As evident from the literature review, much of the previous research relating efficiency to managerial characteristics has been done in farming. To relate to that literature, we have chosen to report the findings related to agriculture (SNI1). The estimation results are presented in Table 5.

Table 5. Estimated Coefficients for the Agricultural sector, SNI1

Inputs	Estimate	Std.Error	z-value	p-value	Significance
Labour	0.528	0.0023	231.75	0.000	***
Capital	0.194	0.0007	266.35	0.000	***
Intermediate input	0.394	0.0008	492.86	0.000	***
(Intercept)	3.744	0.0062	606.67	0.000	***
Managerial Characteristics					
Age	0.285	0.0035	82.49	0.000	***
Female	1.974	0.0315	62.66	0.000	***
Married	-0.738	0.0131	-56.32	0.000	***
Immigrant	0.987	0.0271	36.42	0.000	***
Second-generation immigrant	0.403	0.0144	27.87	0.000	***
Upper Secondary school degree	-0.331	0.0182	-18.20	0.000	***
Post Upper Secondary school degree	0.538	0.0156	34.54	0.000	***
Number of children	-0.165	0.0221	-7.47	0.000	***
Net Income	-0.0001	0.0000	-69.59	0.000	***
Z (Intercept)	-21.915	0.3056	-71.71	0.000	**
Environmental factors					
North Sweden	-0.069	0.0034	-20.2965	0.000	***
Major Cities in Sweden	0.066	0.0039	17.0981	0.000	***
Time trend	-0.0003	0.0003	-1.0716	0.2839	
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	3.711	0.0563	65.9401	0.000	***
$\gamma \equiv \sigma_u^2/\sigma^2$	0.944	0.0009	1038.5320	0.000	***

Our estimate of γ is 0.94, indicating that there is relatively little statistical noise in our analysis. The estimation results for the agriculture sector indicate that labour, capital, and intermediate inputs all contribute positively to production and are statistically significant. Among them, labour has the highest elasticity, highlighting its essential role in agricultural output, while capital and intermediate inputs also play important roles.

Regarding managerial characteristics, age is positively associated with inefficiency, suggesting that younger managers tend to be more efficient. A possible explanation could be that older farmers may struggle to adopt new technologies, leading to reduced efficiency (Featherstone et al., 1997; Rasmussen, 2010; Koirala et al., 2016; Bozo˘glu & Ceyhan, 2007; Battese & Coelli, 1995; Bozo˘glu & Ceyhan, 2007). Female managers exhibit lower efficiency levels (Danso-Abbeam et al., 2020; FAO, 2011; Kilic et al., 2015). Some studies suggest gender disparities in agriculture are primarily driven by unequal access to resources rather than differences in skills (Dadzie & Dasmani, 2010; Moock, 1976; Saito et al., 1994). Firms managed by immigrants or second-generation immigrants tend to exhibit lower efficiency, possibly due to adaptation challenges. Education plays a mixed role, as having only an upper secondary school degree is linked to lower inefficiency. However, post-upper secondary education is positively linked to inefficiency (0.5376), reinforcing the notion that practical experience matters more in agriculture than formal education (Hong et al., 2019; D. A. Ali et al., 2020). Managers who are married and those who have more children tend to be more efficient. Net income, on the other hand, has a strong negative relationship with inefficiency, suggesting that highly paid managers might be operating more efficient farms, possibly due to risk compensation or alternative income structures (Matolcsy & Wright, 2011; Amornkitvikai & Harvie, 2011)

Environmental factors also play a role, with farms located in northern Sweden being at a disadvantage, which is expected given lower temperatures and shorter growing seasons. Conversely, being located in a major Swedish city is advantageous. The time trend variable is not significant, indicating no clear pattern over time. Overall, these results highlight the critical influence of managerial characteristics and environmental conditions on agricultural production, consistent with previous research emphasising experience, access to resources, and location as key determinants of productivity in farming

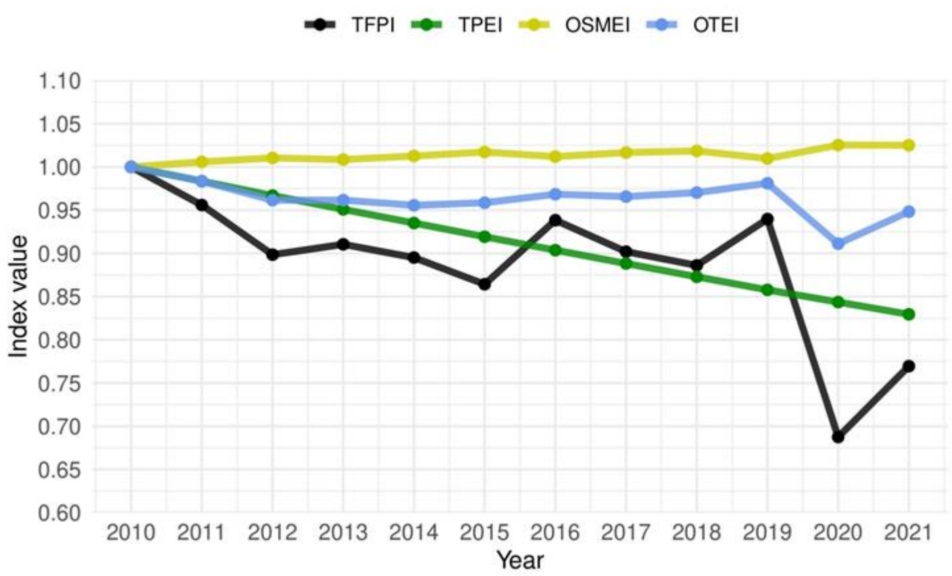
8.2.3 The Transport Sector

The transport sector covers train, public transport, taxi, and freight transport by road (SNI49). Thus, transport by sea and air is not included.

8.2.3.1 Technological regress makes productivity decline

Figure 4 presents measures of TFP change and the estimated drivers of TFP change for the transport sector between 2010 and 2021 for the transport sector.

Figure 4: TFP and its Components, 2010-2021, Transport Sector



The sector has maintained an average productivity level of around 87 per cent of the 2010 benchmark, with a significant drop in 2020 and only partial recovery afterwards. Improvements in scale and mix efficiency (OSMEI) have not been large enough to offset a slight fall in output-oriented technical efficiency (OTEI) and a large fall in the technical progress and environmental change component (TPEI). The large fall in this last component reflects what is widely recognised as a deterioration in the quality of low-traffic roads and a decline in the quality of railroad infrastructure. While production continues, it appears that the lack of investment in infrastructure renewal and upkeep has led to a gradual reduction in the production environment. The development of new transport technologies has not been sufficient to overcome this deterioration. The problem is most likely more acute in remote areas of Northern Sweden, where, for example, the Malmbanan railway (the Iron Ore Line) is in a particularly fragile state.

8.2.3.2 The Role of Management Characteristics and Environmental Factors in the Transport Sector

Table 6 sheds light on key determinants of productivity within the transport sector. The results share several similarities with those observed in the High-Tech Manufacturing Sector, for example, the statistical noise component γ is close to one (0.985), indicating that the present noise is low

Table 6 Productivity within the transport sector.

Inputs	Estimate	Std.Error	z-value	p-value	Significance
Labour	0.4368	0.002	279.62	0.000	***
Capital	0.110	0.001	159.20	0.000	***
Intermediate input	0.538	0.001	429.77	0.000	***
(Intercept)	4.028	0.006	701.66	0.000	***
Managerial Characteristics					
Age	0.752	0.020	37.82	0.000	***
Female	5.330	0.220	24.28	0.000	***
Married	-1.917	0.054	-35.41	0.000	***
Immigrant	12.870	0.375	34.35	0.000	***
Second generation immigrant	0.841	0.074	11.34	0.000	***
Upper Secondary School degree	-1.861	0.044	-42.58	0.000	***
Post Upper Secondary School degree	1.401	0.169	8.28	0.000	***
Number of children	2.116	0.068	30.88	0.000	***
Net Income	-0.0003	0.0000	-33.15	0.000	***
Z (Intercept)	-74.192	1.969	-37.68	0.000	***
Environmental factors					
North Sweden	-0.028	0.0029	-9.8080	0.000	***
Major Cities in Sweden	-0.088	0.0021	-42.4824	0.000	***
Time trend	-0.017	0.0003	-60.6480	0.000	***
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	6.956	0.1654	42.0487	0.000	***
$\gamma \equiv \sigma_u^2/\sigma^2$	0.985	0.0004	2433.9445	0.000	***

* indicate significance on *** = 1 per cent level, ** = 5 per cent level and * = 10 per cent level.

The results show that labour, capital, and intermediate inputs significantly contribute to output within the transport sector. Labour (0.44) plays a crucial role, though its impact is lower compared to intermediate inputs (0.54), which have the highest influence on output. Capital investment (0.1099) is also positively associated with output, but to a lesser extent. The strong significance levels indicate that these inputs are key drivers of performance in the transport industry.

Similar to high-tech manufacturing, managerial traits in the transport sector reveal that older and female managers exhibit a strong positive correlation with inefficiency (i.e., they are less efficient). In contrast, managers who are married tend to be more efficient. Regarding educational background, having a post-upper secondary school degree does not appear to correlate with efficiency, suggesting that practical experience may be more valuable than formal education in the sector. Moreover, managers who identify as immigrants and those with children are positively associated with inefficiency, potentially due to structural barriers or additional responsibilities affecting efficiency. Interestingly, net income correlates negatively with inefficiency, which may suggest that higher-paid managers enhance firm performance.

The results for environmental variables reveal that being located in Northern Sweden negatively affects output; this may be due to the poor state of railway infrastructure in the region. Moreover, in contrast to high-tech manufacturing, being situated in a major Swedish city also correlates negatively with output; this may be due to the poor quality of low-traffic roads. The negative time trend coefficient suggests a gradual decline in productivity over time, potentially pointing to industry-wide challenges such as increased regulations, evolving market conditions, or rising operational costs. Lastly, our estimate of γ (0.9852) is very close to 1, signifying that the noise component in the model is minimal.

9. Conclusion and concluding remarks

A first and important finding relates to the use of partial productivity measures as a proxy for TFP. In many studies, there is a claim that labour productivity, for example, is highly correlated with TFP. We found that this is the case in most sectors. For example, the correlation between labour productivity and our TFP index is perfect in the computer programming sector. However, in other sectors, such as in specialised construction activities, the correlation between labour productivity and our TFP index is less than 0.5. Thus, using partial productivity measures as a proxy for total factor productivity can be hazardous and point policymakers in the wrong direction.

Heterogeneity in what is driving productivity

The sectoral analysis shows that there is sector heterogeneity.[14] While the high-tech manufacturing sector shows a large increase in productivity, mainly driven by technological progress and a more favourable production environment, the Transport sector shows the opposite. The decline in TFP in the transport sector is to a large extent related to the same component, i.e. technical progress and the production environment. We conjecture that these particular results are driven by a lack of reinvestment and maintenance in the sector. If capital, in this case, roads and rail tracks, is not maintained, then less can be produced with the same amount of inputs (e.g., due to standstills or lower possible speed on the roads). In contrast, productivity declines in the agriculture sector were mainly driven by increased technical inefficiency. A possible, speculative explanation could be that a lot of farms had switched over to eco-production. Another possibility is that many farmers were relatively slow to adopt new technologies that were developed in the wake of the global financial crisis.

Manager characteristics have different importance for different sectors

Our analysis has identified that managerial characteristics and environmental factors are important in shaping productivity and inefficiency. We found that the strength (significance), direction and/or magnitude of the correlation differed between sectors. For example, the age variable has a significant correlation for all three sectors. It is almost the same in size for the high-tech manufacturing and the agricultural sector, but almost twice the size in the transport sector. The variable 'number of kids' also significantly correlates with efficiency for all three sectors at the 5 per cent level. While it is positive and significant for the high-tech manufacturing sector, it is negative and significant for the agricultural sector. Thus, our results highlight the heterogeneity of the sectors regarding managerial characteristics. One interpretation of these results is that there is no such thing as a universally 'good manager' – it is a good manager in a specific sector. Finally, our results show that production environmental conditions also play a major role, with urban areas benefiting from, e.g. larger markets, access to technology, and better infrastructure, while more remote or challenging environments experience lower productivity levels.

[14] This is also evident from the online appendix sections A and B where results for all industries, except for those left out due to too few observations and to data issues, are presented.

Concluding remarks - Several possible extensions

This report has aimed to adopt an index approach that can serve as a starting point for several extensions. There are several areas where we, due to time constraints, have left problems unsolved or just glanced at them. Four of these areas are:

How to aggregate sectors or geographical dimensions

Firstly, we feel there may be some value in aggregating sector-specific results into an overall economy-wide measure of productivity performance. Policy-makers might find it useful to compare such a measure with other existing measures of overall economic performance, such as GDP. Other aggregations include combining sectors or industries in geographical areas. We do not at present have a clear-cut answer on how this should be done, but we are quite confident that the methods used in this report could be adapted for this purpose. Among other things, this future research will need to determine exactly how the importance of each sector should be reflected in the aggregated measure of TFP.

Room for improvement

Secondly, we have not delved deeper into modelling issues in specific sectors. As indicated by the estimated γ parameters, our model works well for some sectors but could be improved for others. These improvements could, for example, involve using different functional forms, using alternative definitions of inputs and outputs based on more detailed sector-wise data sources, and handling the passage of time in a more flexible way in order to disentangle technical progress from changes in the production environment. One such possible extension is to divide capital into tangible and intangible capital.

Selection of managers

Thirdly, another extension would be to consult management researchers to get a better understanding of management research regarding the selection and interpretation of managerial characteristics. We, as economists, have selected variables based on previous literature and, to some extent, data availability, but we recognise that management researchers can potentially provide further insights.

Access to codes

Finally, this report comes with the code that was used for the computations. We encourage researchers and civil servants at authorities, ministries, regions and municipalities that have the ambition to study productivity to use this code to apply our methods (or other methods that are consistent with ours) to other datasets. We have in the report shown, and discussed, that many of the methods that are currently used by statistical agencies have flaws that make them less useful for policy-makers who want to study how measures of productivity, i.e., measures of output volume divided by measures of input volume, are changing across space and over time. The R-codes are available to download from https://www.bth.se/staff/jonas-mansson-jpm/.

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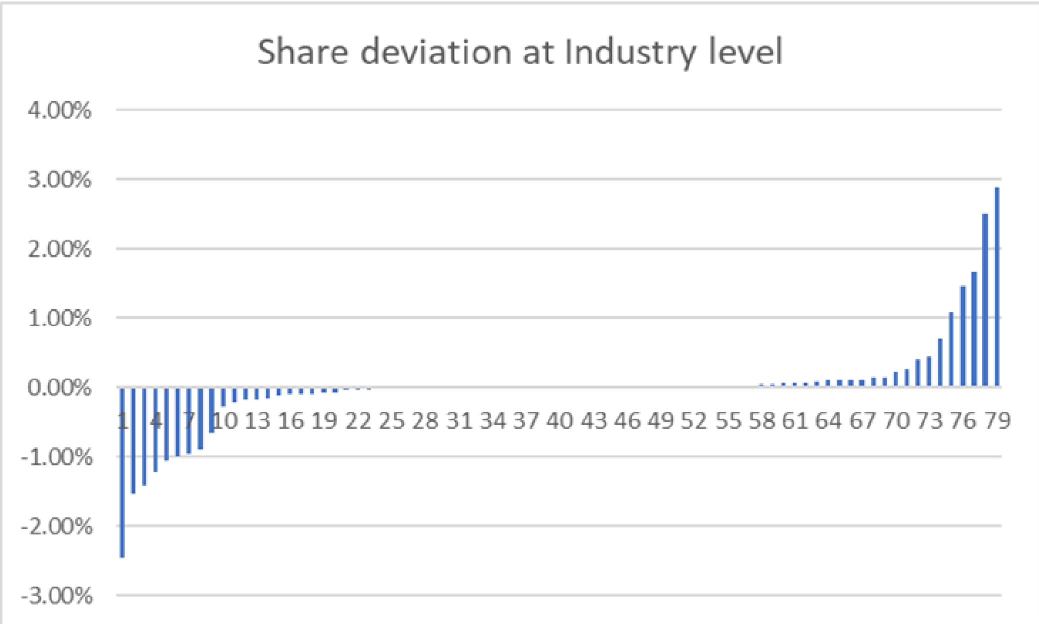
Appendix A: Data reduction and external validity

With external validity, we mean how well the final sample represents the original sample. To get some information about the final sample's external validity, we compared the final and original samples in two dimensions. The first comparison relates to industry representativeness. In Figure 5, the differences between the original sample and the final sample at the industry level are presented.[15]

Figure 5: Over- and under-representation by industry



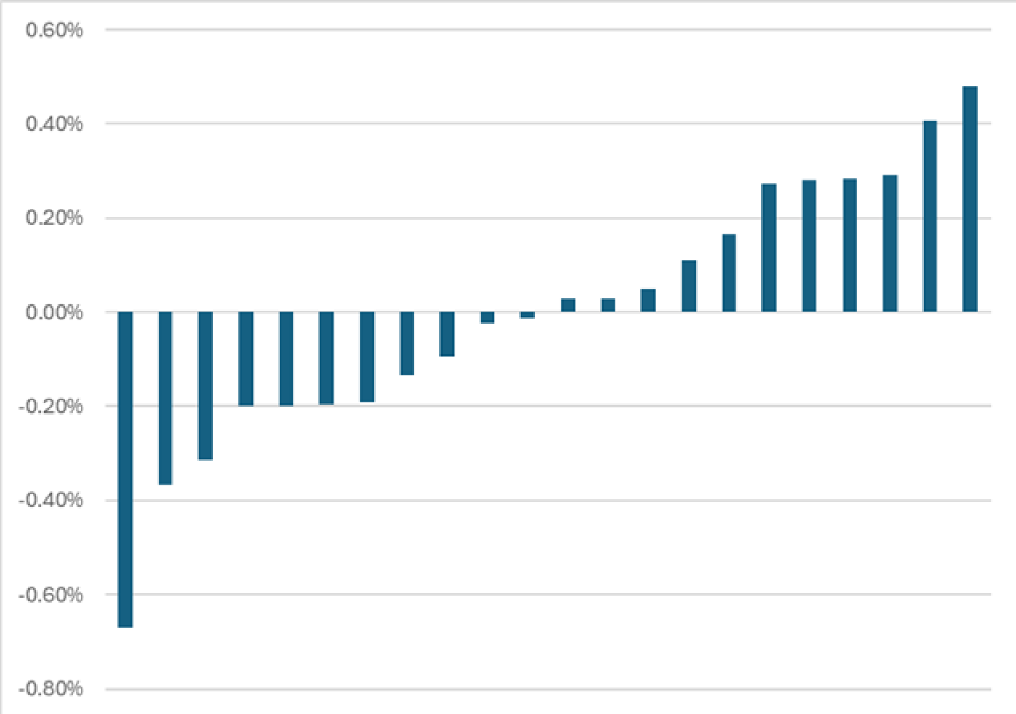
In Figure 5, under- and over-representation is measured on the vertical axis. A value less than zero indicates that the original sample has a smaller share than the final sample (underrepresentation), and a positive number indicates that the final sample has a higher share than the original sample (over-representation). Industries are indicated on the horizontal axis. As illustrated in Figure 5 there are some industries that are overrepresented and others that are under-represented in the final sample. A negative value in Figure 5 indicates that the final sample contains a smaller share than the original sample and is thus under-represented in the final sample. The industries that to the largest extent are under-represented are farming and forestry, which both have a share below -6 percentage points (NACE 1 and 2). The industry that has the largest over-representation is construction work (NACE 43), where the share in the final sample is around eight per cent higher than in the original sample. However, overall, the

[15] To compute the real value we used a sector-wise producer price index (PPI) from Statistics Sweden. For some sectors at SNI digit level 2, information was missing. For them, the PPI was replaced with the Swedish average. Finally, there were missing data for some years. If data were missing for one or two years, the PPI value was imputed using the average of the year before missing and the year after missing. If more than one year was missing, the PPI was taken from the industry NACE 1 digit level.

difference on the industry level is small. Only 17 industries deviate more than +/- one percentage point from the original sample, which, at least, gives motivation to the fact that this is a representative sample on the industry level.

As for the industries, counties are also under- and overrepresented. However, the difference between the original sample and the final sample at the county level is small. The maximum under-representation is for Stockholm County, where the original sample contains 0.67 percentage points more observations than the final sample. The most overrepresented county is Östergötland, which in the original sample has 0.48 percentage points fewer observations compared to the final sample. Figure 6 illustrates the difference between samples at the county level.

Figure 6: Over and under-representation, by county



A final word regarding the external validity is related to size. Our sample consists of firms that have one or more employees. Compared to the original sample and Sweden as a whole, this means that our final sample is not valid as a replacement for the whole Swedish economy. Small firms without employees are a very big part of the Swedish economy. We will, in the future, make attempts to include these firms, however, present data limitations prevent us from doing so in this study. Finally, as shown above, the sample we are using is fairly representative regarding industry and geographical representation

Appendix B: Summary of previous research on management characteristics influence on efficiency

Table 7 Summary of previous research

Manager Characteristics	Key Studies
Education	Alvarez and Crespi (2003); Zaabouti and Ben Mohamed (2025); Addo and Salhofer (2022); Amare et al. (2020); Ahmed et al. (2019); Servan-Mori, Chivardi, Mendoza, and Nigenda (2018); Dadzie and Dasmani (2010); Hong et al. (2019); Acheson (1975); D. A. Ali et al. (2020); Kirkley, Squires, and Strand (1998); Mundlak (1961); Kauko (2009); Ben Mohamed et al. (2021); Kisaka et al. (2014); Sherlund, Barrett, and Adesina (2002); Ajibefun and Daramola (2003); Cosh, Fu, and Hughes (2007); Xu, Zhang, and Zhang (2018); Bender, Bloom, Card, Van Reenen, and Wolter (2018); Khan, Ali, Ahmad, Abid, and Kusch-Brandt (2022); Bhasin and Akpalu (2002)
Age and Experience	Alvarez and Crespi (2003); Kirkley et al. (1998); Zaabouti and Ben Mohamed (2025); Addo and Salhofer (2022); Renner et al. (2005); Sultan and Crispim (2018); Ram Jat and San Sebastian (2013); Dadzie and Dasmani (2010); Karagiannis and Sarris (2005); Madau (2007); Villano and Fleming (2006); Chen et al. (2009); Featherstone et al. (1997); Rasmussen (2010); Koirala et al. (2016); Sherlund et al. (2002); Ajibefun and Daramola (2003); Narcisse, Antoine, and Chrysostome (2019); Crossland, Zyung, Hiller, and Hambrick (2014); Wang and Wong (2016); Manevska-Tasevska, Hansson, and Labajova (2017); Leza et al. (2016); Bhasin and Akpalu (2002); Bozoˇglu and Ceyhan (2007); Battese and Coelli (1995)
Gender	Amare et al. (2020); Qian et al. (2024); Dadzie and Dasmani (2010); Moock (1976); Saito et al. (1994); Danso-Abbeam et al. (2020); FAO (2011); Kilic et al. (2015); Akresh (2005); D. Ali, Bowen, Deininger, and Duponchel (2016); Seymour (2017); Ma et al. (2017); Tan et al. (2010); Gutierrez-Romero et al. (2021); Makheti (2017); Sengupta et al. (2015); Narcisse et al. (2019)
Remuneration(income)	Matolcsy and Wright (2011); Amornkitvikai and Harvie (2011); Zaabouti and Ben Mohamed (2025); Firth, Leung, Rui, and Na (2015)

Tillväxtanalys
Myndigheten för tillväxtpolitiska utvärderingar och analyser

Tillväxtanalys
Studentplan 3, 831 40 Östersund
Telefon: 010-447 44 00
E-post: info@tillvaxtanalys.se
Webb: www.tillvaxtanalys.se