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Allocational Efficiency in the Swedish Economy Across Sectors and Time

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Abstract. Resource misallocation between firms can lower total factor productivity (TFP) in an economy. In this thesis I develop an approach to measuring the productivity impact from misallocation based on previous literature. Using Swedish firm-level data I estimate that the removal of factor market distortions could raise Swedish TFP by 37% and that misallocation has increased substantially in the Swedish economy over the last twenty years. A sectoral split shows this trend to be present across sectors and misallocation to move with business cycles. Additionally, I propose a new method for estimating misallocation across firms with different demand elasticities of substitution, which allows for a more comprehensive quantification of reallocative potential than previously possible.

Keywords: Sweden, misallocation, total factor productivity, factor market distortions

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1 Introduction

A key question in economics is the cause for wealth and income differences between countries. Research in macroeconomics has repeatedly stressed the large role of differences in total factor productivity (TFP), being the ability to turn factors into outputs, for causing differences in output between countries. TFP contains everything that impacts how productive specific factors are, and is commonly thought of as a function of technology, institutions, and a combination of other country-specific variables. However, factor productivity does not just depend on *how* factors are used, but *where* they are used.

Since different firms within an economy are not equally productive, the correct allocation of factors between firms becomes important. The aim of this thesis is to determine if factor misallocation is a problem in the Swedish economy, to what extent factors are misallocated in it, and what effect this misallocation has on Swedish TFP. The motivation for this analysis is that the impact of factor misallocation on Swedish TFP could be large, given that similar recent analyses of other economies reported that TFP would be up to 43% larger for the US if factors were allocated efficiently (Hsieh & Klenow (2009)), 79% larger for Portugal (Dias *et al.* (2016b)), 85% larger for South Korea (Kim *et al.* (2017)), 87% larger for China, and 128% for India (Hsieh & Klenow (2009)).

In order to measure the effect of misallocation on the Swedish economy, the thesis seeks to develop a method for measuring misallocation and its effects comparable to those used in recent literature. While it is impossible to measure misallocation directly, the aim of this method is to estimate misallocation as best as possible using available data. To this end, a model featuring imperfect competition within industries and heterogeneous productivities of individual firms is assumed. Given efficient factor markets, the marginal revenue of factors should be equal across firms in this environment. If that is not the case, then factor markets are distorted and some factors would be better allocated somewhere else, where they would create a higher marginal revenue. This dispersion of factors' firm-level marginal revenues - in the literature defined as *marginal revenue productivities* - lowers TFP and total output in an economy and is directly caused by misallocation. This means that the extent of misallocation is measurable through the amount of revenue productivity dispersion, and can be be used to calculate a potential gain in TFP if factors were efficiently allocated and revenue productivity dispersion did not exist.

Applying this method to a comprehensive dataset of the Swedish economy, a potential TFP improvement of 23% from removing factor misallocation within industries is calculated using data from 2017, which shows that misallocation is a problem in the Swedish economy, but that it seems to be a smaller problem than in some other economies. Analyzing misallocation from 1998 on shows that this misallocation in the Swedish economy has increased significantly over the last twenty years, and is currently 8.2 percentage points higher than it was in 1998. This increase in misallocation reduced TFP growth in the Swedish economy over the same time horizon by about a quarter. Such an increase in measured misallocation is a worrying development, as it suggests factor market frictions are rising, which risks damaging the Swedish economy in the long term.

In order to find out more about the distribution of misallocation in the Swedish economy, the thesis also conducts a separate analysis of the development of misallocation in ten sectors of the Swedish economy. The results of this show that while there is a large variation in misallocation across sectors, the trend of increasing misallocation over time is in fact seen across the economy. All but the two smallest sectors of the Swedish economy display a lower allocational efficiency in 2017 than they did in 1998. The sectoral analysis also confirms that shifts in the relative importance of different sectors are not the driving force behind the increase of aggregate Swedish TFP, but the increase in misallocation within each sector.

In order to provide the most comprehensive estimate possible of misallocation in the Swedish economy and to remove a limitation present in much of the literature, a novel method for estimating misallocation both between firms in the same industry as well as between firms in different industries is developed. Using this method and under conservative assumptions, the Swedish economy exhibits an additional potential TFP gain from between-industry factor reallocation of 14.7%. This suggests that both within-industry and between-industry misallocation are important, but that within-industry misallocation is a slightly larger concern for the Swedish economy.

The contribution of this thesis to the literature is two-fold. Firstly, to the best of the author's knowledge, this thesis presents the first application of this method for comprehensively studying misallocation in Sweden or a similar Scandinavian economy. Previous analyses have predominately focused on either developing economies or large ones like that of the US. The results of this thesis emphasize the point that misallocation is an issue affecting even ostensibly well functioning economies like the Swedish one. Secondly, this thesis proposes a new way of computing the total extent of misallocation in an economy which incorporates the existing model, but is also able to estimate misallocation between firms in different industries under consideration of their reduced demand substitutability, which was not previously possible within the same analysis. This method is as a result able to survey the allocational efficiency in an economy more comprehensively than previous literature.

2 Review of Relevant Literature

The literature analyzing the impact of factor misallocation on TFP from all different angles is large and it is not necessary to be aware of all of it in order to understand the approach of this thesis. The aim of this literature review is thus more to give a background to why and how the literature developed and what some recent approaches and results in it are. This section is structured the following: It will first give a general overview of the development of the literature, before focusing on extensions to the standard model of measuring misallocation in section 2.1, on the for this thesis particularly important topic of dynamic economy-wide approaches in section 2.2, and on the impact of measurement error in section 2.3.

Macroeconomics has historically approached the question of wealth gaps between countries using neo-classical growth models, which model the output in an economy through a representative firm. An important characteristic of this modeling choice is that productivity, meaning the ability to turn factors into output, differs between countries, but not within them. As a result, cross country differences in output are attributed to cross country differences in the common country-specific productivity.

The literature reviewed below takes a different approach by emphasizing the importance of within-country differences in productivity. While a dispersion of productivities within a country is natural, it becomes a problem if comparatively unproductive firms take a bigger share of the output than they should. This could be the case when, for example, an unproductive firm gets easier access to financing or is more likely to receive government contracts.

This misallocation of productive potential to unproductive firms is hard to measure, which caused two different approaches to develop in the literature. The first is to pick a specific and measurable potential cause of misallocation (say, credit market frictions) and estimate its effect, while the second tries to measure economy-wide misallocation through the unexpected dispersion in economic variables. In their overview of the misallocation literature Restuccia & Rogerson (2013) classify these two strategies as *direct* and *indirect* approaches. The fist, direct, strategy has the advantage of assessing a specific measurable factor, which means that in addition to describing that a problem exists, it can make causal inferences and give direct policy recommendations. Examples of issues analyzed using a direct approach include imperfect credit markets in Banerjee & Duflo (2005) and Amaral & Quintin (2010), trade barriers in Lileeva & Trefler (2010), and labor market policies in Lagos (2006).

However, the issue with this approach is that it is unable to quantify misallocation outside of a few very specific circumstances - once a specific cause of misallocation is lacking a measurable identifier, this method is out of luck. There is reason to believe that many causes of idiosyncratic misallocation do indeed lack this measurability. These include specific political connections, crony capitalism, and corruption. Furthermore, there may be many smaller factors causing misallocation which would missed by looking only at those easily measurable in many firms.

The second strategy, which Restuccia & Rogerson (2013) call the *indirect* approach, avoids this issue of measurability and is able to give a general overview of the extent of misallocation in an economy. It works by assuming a model of the economy without misallocation, and then measuring to what extent real world data violates some of the expected results. As the aim of this thesis is to give a comprehensive estimate of the extent of misallocation in the entire Swedish economy, this thesis uses this second strategy, and the remainder of this chapter will be discussing the literature within this approach.

Measuring misallocation by considering deviations from frictionless markets was first proposed in a tractable model by Restuccia & Rogerson (2008), where the authors assume idiosyncratic taxes on firms distorting factor markets, a modeling choice that has since then become convention in the literature. Here ”taxes” can refer to actual taxes levied by the government, but it can also refer to anything increasing factor prices, like for example political restrictions, corruption, etc. Restuccia and Rogerson argue that even if tax incomes are returned to the economy, the more heterogeneous net taxes / transfers are between firms, the more aggregate TFP is lowered. This is because the heterogeneous tax structure weakens the importance of firm-level productivity for production decisions. As a result some firms that should not produce additional output because of their low productivity suddenly find it profitable to do so because of this tax / transfer structure, while some productive firms produce less than what would be optimal for the economy.

Building on this model, the analysis in Hsieh & Klenow (2009) is easily the most important and impactful recent work in this literature. The authors formalize the model developed in Restuccia & Rogerson (2008) and apply it to data on manufacturing establishments in the United States, China, and India. Through this analysis they find that TFP could be improved by up to 50% in China and 60% in India, if both countries would exhibit a similar level of factor market distortions as the United States. While magnitude of this result has likely sparked additional interest in the topic of misallocation, possibly the largest contribution of Hsieh & Klenow (2009) to the literature is the provision of a model for analyzing misallocation that has been used by almost all works since, and forms the basis for the model developed in section 3 of this thesis.

The Hsieh & Klenow (2009) model is not the only approach to measuring economy-wide misallocation in the literature. An influential paper by Bartelsman *et al.* (2013) proposes to estimate productivity distortions by analyzing the covariance of firm size and firm productivity. They argue that since larger firms must be more productive (a feature also present in Hsieh & Klenow (2009)), and since distortions can weaken this relationship, cross-country variation in the strength of the link between size and productivity shows cross-country differences in misallocation. This idea has been around before (see for example Banerjee & Duflo (2005)), but Bartelsman *et al.* (2013) formalize the relationship and aggregate the data necessary to measure it.

In the end, the two approaches share a lot of primary assumptions, but the method proposed by Hsieh & Klenow (2009) seems to have found wider acceptance in the literature. The model of Hsieh & Klenow (2009) is also better suited for this thesis as it does not require the potentially error-prone extensive calibration of the model necessary in Bartelsman *et al.* (2013), increasing the internal validity of the analysis.

2.1 Endogenous Entry and Other Extensions

In the years following the publications of Restuccia & Rogerson (2008) and Hsieh & Klenow (2009) a number of authors have extended the initial model in order to show the importance of various additional mechanisms. The results of these papers are not themselves relevant for this thesis, but a short overview of this strand of literature is given below for context. Endogenous firm entry, growth, and exit models have been a large focus, with the first of these being proposed by Peters (2010). Peters argued that misallocation disincentivizes entry and therefore competition, which in turn reduces economic growth.

In contrast to the literature above, which typically made no assumptions about which firms are hit by factor market distortions, there several of these extension papers show the large effects distortions can have when they are correlated with firm productivity. In this strand of the literature, the ”taxes” levied on output are higher for highly productive firms.

Bento & Restuccia (2017) provide a model of endogenous entry and correlated distortions, but also incorporate both initial and continuous investment decisions over a firm's life cycle. They estimate that the presence of additional correlated distortions is responsible for a further 53% reduction of TFP in India.

In addition to entry decisions, there is also a literature trying to model other features that determine the impact of a given set of distortions and endogenize these mechanisms into the original model from Restuccia & Rogerson (2008). The idea is to create a connection between individual causes of factor market distortions and their economy-wide TFP impact. This is still typically done by modeling investment decisions of individuals or firms which depend on both factor market distortions as well as as other features.

Bhattacharya *et al.* (2013) study an overlapping-generations model, where individuals are born with a certain managerial ability, which they can improve through investment decisions. They find that lower-ability managers will invest less into their firm's productivity, a result that is motivated the same way as in human capital models where low-ability workers invest less into schooling. They estimate that when this dispersion in managerial ability is coupled with correlated distortions that depend on firm growth, the reduction in TFP is up to 60% larger than without this ability dispersion.

Another example of these studies of mechanisms from around the same time is Gabler & Poschke (2013), where the authors model R&D decisions of firms. They argue that if distortions impact highly productive firms more than less productive firms, this causes large distortions in investment decisions, as being productive has a lower payoff. They provide a calibrated version of this model where this mechanism alone is responsible for up to half of the total reduction in TFP from factor market distortions.

2.2 Dynamic Economy-Wide Approaches and Intersectoral Differences

This thesis attempts to map misallocation across the entire Swedish economy and over time, which is in line with multiple works in the recent literature. The first of these, Brandt *et al.* (2013), computes TFP losses from misallocation across the entire Chinese non-agricultural economy. However, the authors do not have access to firm-level data, and resort to using province-level data, although they are able to differentiate between the state and private sector. While one is able to apply the Hsieh & Klenow methodology in this instance, the authors are not able to estimate the amount of misallocation within the state / private sector within each province, only between them. As such, while they provide valuable results about state vs. non-state sectors, their estimate of an economy-wide potential TFP gain of 20% through reallocation likely severely underestimates the true extent of misallocation.

A good example of an economy-wide dynamic analysis using firm-level micro data is Dias *et al.* (2016b), where the authors estimate misallocation in the Portuguese economy in the lead up to the 2011 Eurozone crisis. They find that since 1996 up until 2011, the effects of within-industry misallocation almost doubled, with the potential TFP gain from reallocation increasing from 48% to 79%. This deterioration of allocational efficiency is according to the authors not uniform across the economy, but much stronger in the service sector.

Lastly, although the authors analyze only the manufacturing sector, Kim *et al.* (2017) provides a good example of a dynamic analysis using high-quality microdata. Here the authors estimate the development of misallocation in the manufacturing sector of South Korea from 1982 to 2007. They report potential TFP gains from reallocation of between 60% and 85%, which implies a lower misallocation in the South Korean manufacturing sector compared to those in China and India, but a higher misallocation than in the United States.

Potentially even more interesting are their dynamic results, where they report misallocation first falling throughout the 1980s, before sharply rising in the 1990s and 2000s.

The difference in allocational efficiency between sectors is a recurring topic in this literature. There are some papers that compare differences between state- and non-state-sectors which have already been discussed above. Since state-owned companies are not as much of an important factor in the Swedish economy as they are in other countries, this thesis focuses instead on differences in allocational efficiency between economic sectors.

There are two questions which receive frequent attention in the sector-specific literature. The first compares manufacturing and service sector misallocation, where consistently the service sector displays a higher measured misallocation. An example of this type of study is Dias *et al.* (2016a), where the authors find that service sector output would increase by 12% if the service sector had the same allocational efficiency as the manufacturing sector. The authors also provide possible explanations for this gap, which contain higher labor market frictions and higher price rigidity in the service sector.

The second common question in this literature addresses the agricultural sector, usually in developing economies. Gollin *et al.* (2014) shows that in most countries large differences between the productivity in agricultural and non-agricultural sectors exist and remain even when considering different ways of modeling inputs, which suggests that significant misallocation is present between these sectors.

Gollin & Udry (2019) show that there is also a large measured misallocation between firms in the agricultural sector in Africa. Combined with Gollin *et al.* (2014), this suggests large factor market distortions in developing economies' agricultural sectors. However, the authors of Gollin & Udry (2019) also find that at least three quarters of this measured misallocation inside the agricultural sector is due to measurement error.

2.3 Measurement Error

As the previous segments have shown, there is a large cross-country (and cross-paper) variation in the estimated potential gains from reallocation, with some countries like India in Hsieh & Klenow (2009) being supposedly able to more than double their TFP by eliminating factor market distortions. A very recent literature has examined the empirical importance of the issue of measurement error for these large estimates.

As mentioned in the previous subsection, Gollin & Udry (2019) show that measurement error accounts for up to three quarters of measured misallocation across farms in Africa. One might expect data quality to be low in these rural and developing regions, but Nishida *et al.* (2017) show that even analyses of manufacturing sectors can be seriously affected by measurement error. The authors of this paper give a survey of the differences in how census data, which almost all analyses are based on, is processed and cleaned. They point out that large cross-country differences exist in these processing methods. The authors apply a common cleaning technique to raw data from India and the United States and re-estimate the results from Hsieh & Klenow (2009), finding that the entire difference in allocational efficiency reported in that paper disappears, suggesting that misallocation is at a similar level in the two countries and that the possible TFP gains for India do not exist.

A recent working paper by Bils *et al.* (2020) also addresses the question of measurement error in Indian and US data. The authors develop their own model to estimate potential the TFP gains from the removal of factor market frictions, the same thing Hsieh & Klenow (2009) are estimating, but which is robust to measurement error. Using this approach, they find that potential gains from reallocation in the United States are 60% below the level reported in Hsieh & Klenow (2009).

The results of these papers show that the potential effects of measurement errors are large, which introduces serious doubts about the validity of static analyses of misallocation as well as cross-country comparisons thereof.

These recent papers present an important contribution to the literature studying misallocation, which is why they have been included in this review. It is important to note that this thesis largely avoids the issue of measurement errors by predominantly analyzing the development of dynamic estimates. This means that, while measurement errors are without question present in the data, they would only affect the results of this thesis if the extent of measurement errors significantly changes over time - for which there is little reason.

3 Theoretical Foundations for Measuring Allocational Efficiency

This thesis uses a structural method for estimating the effect misallocation has on total factor productivity (TFP) by comparing observed productivities with computed potential productivities, based on the approach taken in Hsieh & Klenow (2009) and most literature since then. The idea to express TFP losses from factor market distortions by assuming an economy with constant elasticity of substitution and constant returns to scale is taken from Hsieh & Klenow (2009). In contrast to Hsieh & Klenow, this thesis proposes building the model without specifying explicit wedges in order to show a model structure that is in the author's opinion easier to follow. As such, the definitions in sections 3.1 and 3.2 are identical to those in Hsieh & Klenow (2009), whereas the steps taken in sections 3.3 and 3.4 differ from Hsieh & Klenow (2009). In the end, both approaches rely on the same underlying idea, meaning they lead to the same result, and it is up to the reader which mathematical expression is preferred.

This sections has the aim of explaining the model while developing it and discussing some comparative statics, as the topic can be quite dense. For the reader interested in a condensed and math-focused model development using wedges see for example Kim *et al.* (2017).

3.1 The Economy

The structural model considers an economy with m industries s, in each of which n_s firms each produce a single good and compete in a monopolistic competition. This is a type of imperfect competition, where producers still constrain each other's pricing, but do so only imperfectly. This means that, as opposed to perfect competition, producers have some pricing power, so that a producer can raise prices without losing all his customers, although they will lose some. The amount of pricing power firms have depends on the elasticity of substitution between products. This elasticity is for simplicity assumed to be constant and defined as σ, which makes this a standard constant-elasticity-of-substitution (CES) model.

Customer demand in this economy is defined as:

$$P_{si} = Y_{si}^{\frac{\sigma-1}{\sigma}-1} X_s \tag{1}$$

The term X_s is an industry-specific demand shifter, which expresses how much total demand there is in an industry. This term will later cancel out when comparing potential and actual productivities, meaning it is not of importance for this model.

As a second basic assumption, the model assumes a standard constant-returns-to-scale (CRS) Cobb-Douglas production function facing each firm, with labor and capital shares differing between industries, but not firms[1]:

$$Y_{si} = A_{si}\, K_{si}^{\alpha_s}\, L_{si}^{1-\alpha_s} \tag{2}$$

Lastly, for this setup industry output is defined as a CES aggregate of individual firms' outputs:

$$Y_s = \left(\sum_{i=1}^{n_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{3}$$

This assumption, often just mentioned briefly in the literature, is worth further examination. It means that in this model total output is *not* a simple summation of firm outputs, but takes into account consumer preferences through the elasticity of substitution. This means that maximizing productivity and output actually means maximizing utility, which will become important later on.[2]

To finish the model set up, one can use (1) and (3) to define an aggregation for the price within an industry as follows:

$$P_s = \left(\sum_{i=1}^{n_s} P_{si}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{4}$$

The above equation basically weights individual prices by how much demand for that firm's product there will be, given the elasticity of substitution. The higher this elasticity, the smaller will the demand for a product with a comparatively high price be. The resulting value of P_s is such that $P_s Y_s = \sum_{i=1}^{n_s} P_{si} Y_{si}$.

This is a very standard way of modelling an economy, similar to those used in most other misallocation papers and going back to work such as Hart (1982). As such, lengthy intermediate steps are skipped and basic results are transferred from those papers in order to focus fully on developing the theory of measuring allocational efficiency.

[1] Hsieh & Klenow (2009) also show that similar overall results are achieved by relaxing this assumption, although the inferred cause for distortions would shift from input to output distortions.

[2] This is essentially a simplifying assumption. In reality, industry output will, under consideration of an outside option, depend on the demand for consumption of that industry's goods, which depends on the potential utility from that consumption. As long as the outside option as well as purchasing power is exogenous, it suffices to model industry output through industry utility.

3.2 Physical Productivity and Revenue Productivity

The central variable of interest in the misallocation literature, and this thesis, is the total factor productivity (TFP). This variable, to put it simply, measures the efficiency at which inputs are converted into physical output. Using the Cobb-Douglas production function from equation (2), TFP_{si} can be defined as:

$$\text{TFP}_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \tag{5}$$

The central assumption in the misallocation literature is that TFP_{si} will differ naturally between firms in an economy. This is necessary for misallocation to be an economic issue, as if all firms were equally productive, it would not matter which firm used how many factors. Dispersion in TFP_{si} is also quite a reasonable assumption, as different firms with differentiated products likely also use different production technologies.

Now if the idea is to simply maximize physical output in the economy, it would be enough to shift all productive factors to the firm with the highest TFP (since the CRS production function assumed in (2) means that there is no decrease in marginal output of the firm from doing this). This is where the assumption of imperfect competition comes in. Because customers care about having a mix of different products, an economy only producing one product might maximize output, but it would not be maximizing utility. Instead, the maximization of utility (our output of interest) needs to take into account consumer preferences, which in a market environment express themselves through prices.

The inclusion of prices is where the concept of revenue productivity becomes important. As opposed to physical productivity, revenue productivity (denoted TFPR_{si}) can be defined as the efficiency of turning inputs into revenue. Define TFPR_{si} as:

$$\text{TFPR}_{si} = P_{si} A_{si} = \frac{P_{si} Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \tag{6}$$

TFPR_{si} can be understood as a measure for how much revenue firms make from their factors. The key difference of revenue productivity compared to physical productivity is that while the latter is exogenous, revenue productivity depends on price, which itself is inversely related to demand. This means that as a firm increases its output it uses the same amount of factors for each additional unit of output, but it will earn less revenue for each additional unit of output because of equation (1). This means that with increasing output a firm's TFPR_{si} will fall.

Given the standard firm profit maximization problem, firms will increase output until the marginal revenue of their factors equals those factor's marginal costs. The model assumes for simplicity that factor costs are linear, meaning that marginal costs are the same as average costs. Marginal revenue itself is based on two things, the marginal physical output and the price. Because of the CRS production function in (2) marginal output equals average output. Firms add additional factors following the factor elasticity of substitution (the α in their production function). Firms will add factors and thereby increase output until average factor costs equal the marginal revenue - which is expressed through a firm's TFPR_{si}.

As factor prices are determined in a market they are the same for all firms. As each firm produces output until their revenue productivity TFPR_{si} equals their combined factor prices, this means that also all revenue productivities of firms in the same industry are equal.

3.3 Effects of Misallocation

The meaning of factor misallocation, as it is used in this literature, is simply that factors are not where they should be. This throws up the question of where should factors be? Grouping all factors at the firm with the highest physical productivity would maximize output, but it would not maximize utility, as consumers have somewhat rigid preferences with a limited degree of substitutability between different firms' products. Instead, factors should be allocated so as to maximize utility, which would happen naturally in an economy where markets function without frictions. In such an economy, the interplay of imperfect competition and differing physical productivities places factors optimally between firms.

In the previous section, this was an assumed state of the world, leading to revenue productivities being equal between firms. However, if something causes firms to either not behave according to their maximization problem or to face higher factor costs than other firms do, then factors are suddenly no longer allocated efficiently.

How does this misallocation affect the industry-wide productivity TFP_s and utility? The concept of revenue productivity allows for a quantification of this question, for which two relationships will first be established below.

First, if a firm is using fewer factors than they should (for example because inefficient capital markets or political interventions make a factor more expensive for this specific firm) then its output will decrease proportionally. Using (1), an output decrease causes a price increase, because customers dislike substituting other products for the reduced output. This increase in P_{si} causes the revenue productivity of the firm to go up, as the remaining factors now produce higher-valued output. Since the distortions impact only this firm, revenue productivities are no longer equal across firms in the industry. This means that distortions cause misallocation, which in turn causes a dispersion of the revenue productivities of firms within an industry.

Second, TFP and TFPR exist not just at the firm level, one can define the terms analogously at the industry level:

$$\text{TFP}_s = A_s = \frac{Y_s}{K_s^{\alpha_s} L_s^{1-\alpha_s}} \tag{7}$$

$$\text{TFPR}_s = P_s A_s = \frac{P_s Y_s}{K_s^{\alpha_s} L_s^{1-\alpha_s}} \tag{8}$$

Recall from (3) that industry output is defined through the utility of that output, meaning that industry-level productivity TFP_s can be understood as the ability to turn factors into utility, while such a definition does not hold for firm-level TFP_{si}.

In order to find the effect of misallocation on industry TFP_s, one can develop an expression for TFP_s that is dependent on the dispersion of firm revenue productivities. Start by expressing TFP_s using (8):

$$\text{TFP}_s = \frac{\text{TFPR}_s}{P_s} \tag{9}$$

Express firm-level prices P_{si} using the definition of firm-level TFPR_{si} from (6):

$$P_{si} = \frac{\text{TFPR}_{si}}{\text{TFP}_{si}} \tag{10}$$

Insert the above equation into the industry price index P_s defined in (4):

$$P_s = \left(\sum_{i=1}^{n_s} \left(\frac{\text{TFPR}_{si}}{\text{TFP}_{si}} \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{11}$$

Having established this, simply use the expression for P_s found in (11) as the denominator in (9). This results in an expression for TFP_s dependent on revenue productivity dispersion and physical productivities:

$$\text{TFP}_s = \left(\sum_{i=1}^{n_s} \left(\text{TFP}_{si} \frac{\text{TFPR}_s}{\text{TFPR}_{si}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{12}$$

This now expresses total industry TFP_s as a weighted sum of firm level TFP_{si}, as well as an expression for the distance of firm-level revenue productivity from industry level revenue productivity. There are two ways that TFPR_{si} dispersion can lower industry-level TFP.

The first is through the weighting of the individual terms, which depends on σ. As a mathematical reminder, increased dispersion in the terms of a weighted sum reduces that sum if the weighting function is concave and increases the sum if the weighting function is convex. This has the - perhaps surprising - effect that in cases with a high elasticity of substitution dispersion in for example physical productivities actually *increases* aggregate productivity. The intuitive reason for this is simple: Keeping all else equal, in an economy where consumers are easily able to switch between different firm's products, some firms being more productive than others means that consumers can predominantly get their consumption from these productive firms. This causes more factors to be allocated to productive firms, raising overall productivity. However, this mechanism only contributes to aggregate TFP when $\sigma > 2$, for $\sigma < 2$ aggregate TFP will be reduced by dispersion.

The second, and usually more important, mechanism is that revenue productivities between firms differ for the reasons explained above. The negative effect of this dispersion can be quantified by using the ratio of industry-wide TFPR to firm-level TFPR. If all factors were allocated efficiently, then as established above revenue productivities would not vary and $\text{TFPR}_s = \text{TFPR}_{si}$, which reduces (12) to:

$$\text{TFP}_s^* = \left(\sum_{i=1}^{n_s} (\text{TFP}_{si})^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{13}$$

Comparing these two values now allows to estimate the TFP gains from a theoretically optimal allocation of resources between firms in a sector. Define ΔTFP_s^* as the industry-specific multiplier that would be applied to current TFP_s if no dispersion in TFPR_{si} would exist:

$$\Delta\text{TFP}_s^* = \frac{\text{TFP}_s^*}{\text{TFP}_s} = \left(\frac{\sum_{i=1}^{n_s} (\text{TFP}_{si})^{\sigma-1}}{\sum_{i=1}^{n_s} \left(\text{TFP}_{si} \frac{\text{TFPR}_s}{\text{TFPR}_{si}} \right)^{\sigma-1}} \right)^{\frac{1}{\sigma-1}} \tag{14}$$

The above equation is the key equation used for the empirical estimation in the upcoming chapters. Note that the higher productivity in TFP_s^* is caused only by the absence of factor market frictions. In the remainder of the thesis, whenever *reallocation* is mentioned, what is meant is not a social planner moving factors around, but exactly this - a higher TFP caused by the absence of factor market distortions.

3.4 Measurability and Economy-Wide Aggregation

The expression in (14) now needs to be made measurable using firm-level data one commonly has access to. This importantly means that neither prices P_{si} nor quantities Y_{si} are observable, simply because most firm-level data stems from financial reporting where such information is not included.

Looking at (14), in order to estimate the effect of misallocation one needs to measure firm-level physical and revenue productivities, as well as industry-level revenue productivities. Given that the calculation of revenue productivities (equations (6) and (8)) only needs data on revenues, labor, and capital, all of which one does have access to, calculating TFPR_{si} and TFP_s is not an issue.[3]

In order to be able to express the physical firm productivity TFP_{si} using available data, multiply both sides of (1) by Y_{si} and rearrange to get:

$$Y_{si} = \left(\frac{P_{si}Y_{si}}{X_s}\right)^{\frac{\sigma}{\sigma-1}} \tag{15}$$

Now all that is left is putting the above expression as the numerator into (5), which results in an expression for TFP_{si} that is measurable using observable firm-level data:

$$\text{TFP}_{si} = \frac{1}{X_s^{\frac{\sigma}{\sigma-1}}} \; \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \tag{16}$$

Again, note that the left term including the industry demand shifter cancels out in (14) when dividing TFP_s^* by TFP_s. Having found an expression for industry-wide productivity, all that is left is to aggregate the industry-wide results at the level of the economy. An aggregation of productivities simply means weighing the productivity in each industry by this industry's share of total factor expenses, defined as λ_s, which expresses the importance of this industry for the economy:

$$\Delta TFP^* = (\Delta TFP_1^*)^{\lambda_1} + (\Delta TFP_2^*)^{\lambda_2} + ... + (\Delta TFP_m^*)^{\lambda_m} \tag{17}$$

The resulting term, ΔTFP^*, gives the number with which economy-wide TFP would be multiplied with if all factor market distortions would be removed such that revenue productivities would equalize across firms in each industry. All percentage results reported in sections 5 and 6 display $(\Delta TFP^* - 1)$, being the percentage increase in current TFP from the removal of factor market distortions.

[3]These equations also need values for α_s, which can either be assumed or calculated from the data, and σ, which is typically assumed at a certain value based on previous literature, like Broda & Weinstein (2006).

4 Data

The empirical analysis in the upcoming chapters is primarily based on the Serrano dataset, which contains historical financial reporting data of all Swedish firms. The data originates from the Swedish Companies Registration Office, Statistics Sweden (SCB), and the private Bisnode Group Register. The dataset is supplied by the Swedish House of Finance.

Two things are of note regarding this data, especially compared to data commonly used in this literature, which are this dataset's data quality and comprehensiveness. Data quality is an important factor, especially as mismeasurement has a direct impact on my results[4]. Corrections and imputations have been applied to the Serrano data, which is an important step, as most data is self-reported and can contain mistakes. Data quality in Scandinavia is generally high, and with the strict corrections applied, this data can be assumed to have somewhat higher quality than those used in most other literature. As a result, only minor necessary data cleaning is performed.

Most papers look at a specific sector like agriculture in Gollin & Udry (2019) or manufacturing in Hsieh & Klenow (2009), which is often due to the lack of reliable data from other sectors. Serrano contains data on all legal entities in Sweden, which is an advantage, as it allows for a comprehensive look on the Swedish economy. Analyses of specific sectors are of course still possible and are presented in section 5.3.

This completeness is a welcome characteristic, but it remains important to only analyze those entities that can be assumed to exhibit the production and demand functions described in the previous section. For this reason, all non-firm entities are exluded, as well as firms in the financial sector. Overly small firms are also excluded, since the model presented likely does not hold for them. Section 7.2 discusses this decision in more detail. For the purpose of this analysis, an ”overly” small firm is one where value added, fixed tangible assets, or labor costs do not exceed 10,000 SEK in a given year.

For computing firm-level and aggregate productivities, information on value added, wage payments, and total fixed capital is used for the years 1998 until 2017, the last year data was available at the time of writing. Note that in the model developed in section 3, the only inputs to producing revenue are capital and labor. In reality, firms also use a variety of intermediate goods. For this reason, and in line with the literature including Hsieh & Klenow (2009), the analysis uses reported firm-level value added instead of reported firm revenue. Value added simply subtracts all intermediate goods bought by a firm from its revenues, leaving capital and labor as the remaining inputs.

[4] See section 8 for a discussion of measurement error

Table 1 shows descriptive statistics on firms included in this analysis for the years 1998 and 2017, which corresponds to the beginning and end of the sample period. The variation in the values presented is as expected, both across industries as well as over time. Two tables containing additional descriptive statistics can be found in Appendix A.

Table 1: Descriptive statistics on firm averages (in thousand SEK) by sector and year

1998	Sector	Capital	Labor expenses	Value added	n
	Agriculture, Forestry, and Fishing	48	72	144	17
	Construction	75	187	194	83
	Electricity and Water Supply	722	60	186	179
	Extraction of Minerals	324	94	145	23
	Hospitality	67	72	95	57
	Manufacturing	137	99	153	1587
	Services	79	152	182	154
	Technology, Media, and Communications	383	252	373	120
	Trade and Retail	69	87	120	460
	Transport	97	67	92	272
2017	**Sector**	**Capital**	**Labor expenses**	**Value added**	**n**
	Agriculture, Forestry, and Fishing	289	37	82	70
	Construction	52	102	126	428
	Electricity and Water Supply	1532	92	307	262
	Extraction of Minerals	1661	195	776	32
	Hospitality	57	61	79	254
	Manufacturing	180	138	238	1638
	Services	184	308	414	338
	Technology, Media, and Communications	500	353	626	136
	Trade and Retail	79	135	202	814
	Transport	115	75	99	712

5 State and Trends of Swedish Misallocation

Using the Swedish firm-level data discussed above and the model from section 3, this section estimates the improvements in Swedish total factor productivity (TFP) that could be realized through an optimal allocation of resources.

In order to ensure a certain level of comparability with previous literature, an elasticity of substitution of $\sigma = 3$ is chosen, which reflects the conservative choice of most other works (including Hsieh & Klenow (2009)). Note that not all authors support this assumption, for example Brandt *et al.* (2013) assume an elasticity of substitution at $\sigma = 1.5$, although they consider factor distortions between industries and not within them. The value of σ is important, as setting it too high will make the potential gains from reallocation appear larger than they actually are and vice versa. However, the absolute value of potential TFP improvements has only limited policy relevance and comparative analyses (as the one in this thesis) are not affected by the choice of σ. As such the exact value of σ is ultimately only relevant for cross-comparisons with other literature, so it is set at a level that facilitates this comparison.[5]

5.1 Estimation of Productivity Gains from Reallocation

This first empirical result is computed using the model on the Swedish firm level data from 2017, the last year with available data. The estimation procedure can be grouped in three steps explained in detail below; the computation of preliminary firm- and industry-level terms, the estimation of industry-level actual and optimal productivities, and the economy-wide aggregation of potential TFP improvements. All computations are performed using the software R.

First, after the initial data selection described in the previous section, firm-level TFPR_{si} and industry-level TFPR_s are computed, using the expressions found in (6) and (8), for convenience displayed again below:

$$\text{TFPR}_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}$$

$$\text{TFPR}_{s} = \frac{P_{s}Y_{s}}{K_{s}^{\alpha_s} L_{s}^{1-\alpha_s}}$$

[5] The choice of σ is further discussed in section 7.1.

The firm- and industry-level TFPRs are straightforward to compute. Capital and labor are directly measured using variables for fixed capital and labor expenses[6] described in section 4 and the α_s can be estimated through the labor share of expenses in each industry. Also note that the product $P_{si}Y_{si}$ in the numerator simply equals revenues, measured as value added.

In addition to revenue productivities, the last preliminary result needed are the firm-level physical productivities TFP_{si}, which are computed using equation (16):

$$\text{TFP}_{si} = \frac{1}{X_s^{\frac{\sigma}{\sigma-1}}} \; \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}}$$

Similarly to above, the computation of firm-level TFP_{si} contains value added, capital, and labor terms, with the addition of the assumed σ and an industry-specific demand shifter term X_s. Note however that this term does not have to be specified correctly, as it cancels out when later taking the ratio of optimal to actual TFP_s. For simplicity, it is thus set at $X_s = 1$ for the estimation procedure.

Using the results from these preliminary computations, in a second step actual productivity in an industry (TFP_s) and its optimal counterpart TFP_s^* are computed (equations (12) and (13) in the model):

$$\text{TFP}_s = \left(\sum_{i=1}^{n_s} \left(\text{TFP}_{si} \frac{\text{TFPR}_s}{\text{TFPR}_{si}} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$$

$$\text{TFP}_s^* = \left(\sum_{i=1}^{n_s} (\text{TFP}_{si})^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$$

In a third step, dividing the optimal TFP_s^* with the actual TFP_s calculates the industry-specific potential gains from reallocation ΔTFP_s^*. Lastly, these ΔTFP_s^* are aggregated economy-wide weighted by each industry's factor expense share λ_s using equation (17), which then gives a value for ΔTFP^*, the total potential TFP gain from reallocation:

$$\Delta TFP^* = (\Delta TFP_1^*)^{\lambda_1} + (\Delta TFP_2^*)^{\lambda_2} + ... + (\Delta TFP_m^*)^{\lambda_m}$$

[6]Using labor expenses as a measure for the factor labor is a somewhat conservative assumption, as there could in theory be distortions directly affecting labor expenses which are correlated with firm-specific deviations from the industry-wide α, which would then not be picked up by this approach. The assumption is necessary as there are no good measures for the number of full-time employees or for human capital held by employees, but it means that the total effect from misallocation might still be underestimated.

Applying these steps to the Swedish data described in the previous section leads to the result that the total potential TFP gain for the Swedish economy is currently at $\Delta \text{TFP}_s^* = 1.23$. This means that a removal of factor market distortions would cause capital and labor to move between firms such that Swedish total factor productivity would rise by approximately 23%.

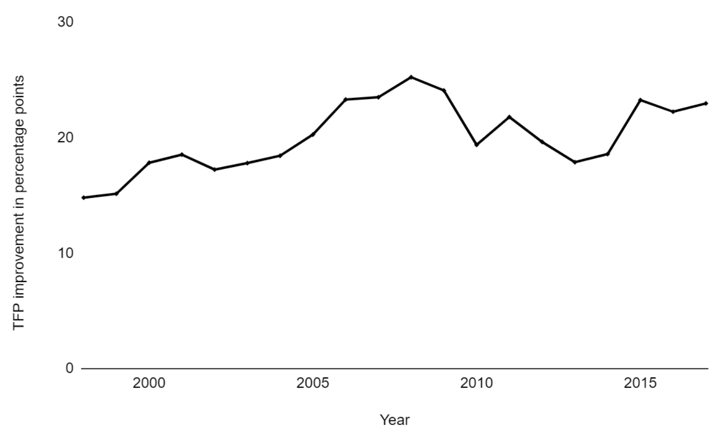
This substantial difference between actual and optimal productivity is caused by factor markets not working correctly, which suggests a substantial opportunity for TFP increases from improving factor markets. The magnitude of the Swedish economy's potential TFP gains is comparable, if perhaps a bit lower, to those found in similar literature. This suggests that misallocation in the Swedish economy exists and is an important, but slightly smaller issue than it is in some other countries.

5.2 Trend of Swedish Misallocation

More interesting than computing the one-period gains from moving to an optimal allocation is a dynamic analysis of how these potential gains have changed over time. Through showing how these gains have evolved, one is able to show how misallocation in the Swedish economy itself has changed over time. This is particularly interesting from not just a descriptive, but also from a policy-making perspective, as it gives a range in which misallocation can move in an economy. While full allocational efficiency may never be reached, historical figures show what degree of efficiency definitely is within reach.

The dynamic analysis uses all available data on the Swedish economy, from 1998 until 2017. For each year the entire analysis above is repeated separately, the results of which are displayed in figure 1.

Figure 1: Potential TFP improvements from reallocation in the Swedish economy over time



As one would expect, large year-to-year jumps are uncommon in the results, instead the economy seems to be following trends spanning multiple years. There is a visible upward trend in measured misallocation from 1998 to the financial crisis in 2008, after which measured misallocation fell and has been slightly more volatile since. The smallest value of potential TFP improvements observed is 14.8 percent in 1998, the first included period, while the largest is 25.3 percent in 2008, which means that misallocation in the Swedish economy almost doubled between 1998 and 2008. Today, at 23 percent, misallocation still remains at a much higher level than it did twenty years ago.

Given that between 1998 and 2017 Swedish TFP increased by almost 20% (Feenstra *et al.* (2015)), these results imply that an increasing misallocation in the Swedish economy ate up about a quarter of the improvement in TFP over the last twenty years.

5.3 Misallocation by Sector

Next to the aggregated results of the previous two sections, knowing how misallocated the different sectors of the Swedish economy are and if any of them are driving the above results is necessary to understand the development of Swedish misallocation. Furthermore, in the context of an economy-wide analysis over time, shifts in the importance of sectors could potentially explain shifts in aggregate misallocation, even when sector-level allocational efficiencies do not change.

For this analysis the economy is split into ten broad sectors based on each firm's SNI industry classification. The above analysis is then redone, and similar to the economy-wide aggregation defined in section 3.4, the computed TFP gain in each four-digit industry is now aggregated at a sector level instead. This approach basically corresponds to pretending the economy consisted only of one sector at a time, which results in sector-specific estimates of misallocation. Note that aggregating at a sector-level first does not impact the overall estimation. When the sector-level results are themselves aggregated, one gets the same economy-wide misallocation measure as before.

Table 2 presents the estimated potential TFP improvement from moving to an optimal factor allocation for each sector in both 1998 and 2017. Figure 2 shows the dynamic development of each sector's measured allocational efficiency over time. Detailed results on all sector and year combinations can be found in Appendix B.[7]

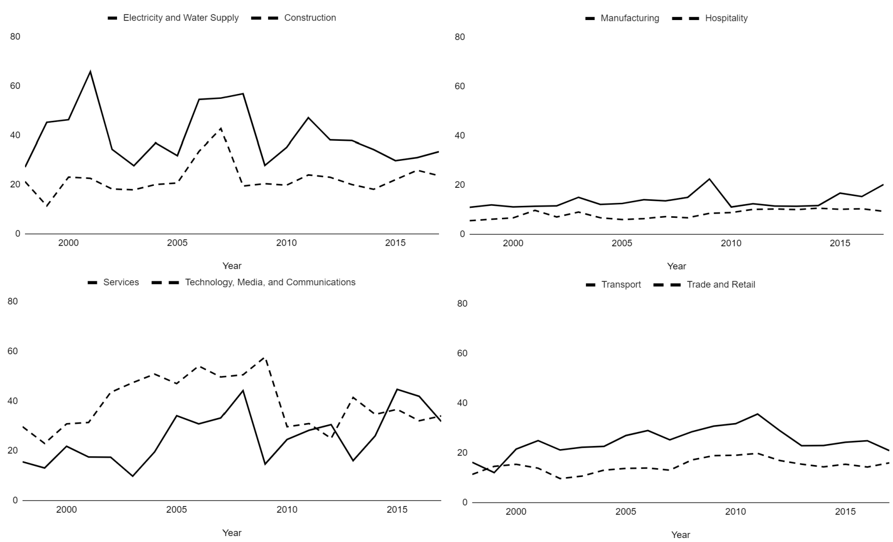
[7] Note that the agricultural and mining sectors have been excluded from the graphs and are bearing a special mark in the table, as small sample sizes in these sectors increase the possibility of mismeasurement and cause a high volatility of measured misallocation. These two sectors also represent less than 3 percent of the Swedish economy, meaning their estimated misallocation impacts aggregate results only marginally. Also note that the small values in the mining sector reported in the table are driven by the small amount of firms in many of the industries in this sector. If an industry only contains one firm, no gains from reallocation can be achieved, so the presence of many single-firm industries in the mining sector lowers the measured potential for reallocation in this sector.

Table 2: Potential percentage TFP improvement by sector

Sector	1998	2017
Agriculture, Forestry, and Fishing†	26.4	15.7
Construction	21.3	23.7
Electricity and Water Supply	27.2	33.4
Extraction of Minerals†	2.2	1.9
Hospitality	5.5	9.4
Manufacturing	11.0	20.3
Services	15.6	31.8
Technology, Media, and Comm.	29.7	34.0
Trade and Retail	11.4	16.0
Transport	16.3	21.0

† denotes small sample sizes

Figure 2: Potential percentage TFP improvement by sector over time

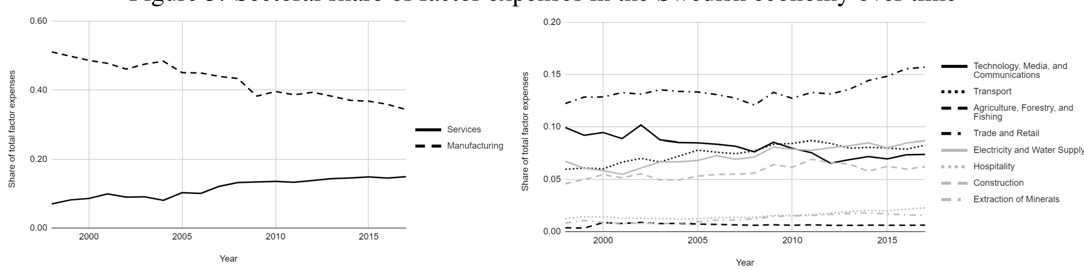


The first conclusion from these figures and the table is that there is a large amount of difference in allocational efficiency between sectors in the Swedish economy. Some, like the manufacturing or hospitality sectors, exhibit consistently low potential improvements from reallocation. Others, like the transport sector, have a higher measured misallocation, but exhibit low volatility over time. Yet other sectors, like services and technology, have both comparatively high misallocation and frequent changes in their measured misallocation over time. This shows the importance of the sectoral decomposition; Looking purely at economy-wide aggregates would miss the existing large sectoral differences in allocational efficiency.

Despite the volatility, many sectors exhibit a slight upward trend in their measured misallocation over time. This can be seen most strikingly in table 2, where all sectors with sufficiently large sample sizes have larger potential TFP improvements in 2017 than they did in 1998. This suggests that the increasing misallocation in the Swedish economy is indeed an economy-wide phenomenon, and is not limited to certain sectors.

Lastly, this sectoral split allows an estimation of the extent to which shifts in the relative importance of sectors could explain the worsening of allocational efficiency in the Swedish economy over the last twenty years. Figure 3 shows the development of this importance of different sectors for the economy by displaying each sector's share of total factor expenses. Graphing total factor expenses is motivated by this variable being the basis for the economy-wide aggregation in the used model, meaning that shifts in factor expense shares will directly translate into shifts in aggregate potential TFP gains. The left graph compares the manufacturing and service sectors to highlight their respective changes, while the right one includes all other sectors. Note that the scale of the two graphs differs for readability.

Figure 3: Sectoral share of factor expenses in the Swedish economy over time

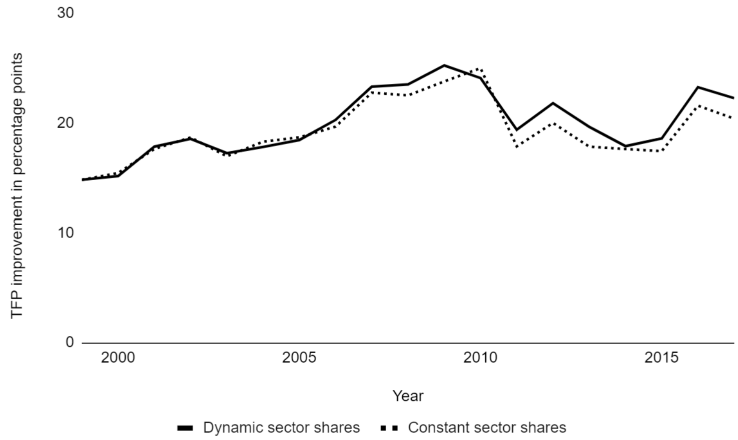


As in other developed countries, the manufacturing sector has seen a relative decline in importance over the past twenty years, in this dataset from 51% of total expenses to only 34% at the end of the sample period. At the same time, the service sector has more than doubled in importance, from 7% to 15%. This value might still seem surprisingly low, one might have expected the service sector to occupy a bigger share of the economy. However, note that many of the sectors that are counted as services in analyses applying a three-way agriculture-manufacturing-services-split are counted as their own sectors here, for example hospitality and retail.

From figure 2 above it is clear that the service sector exhibits a consistently higher measured misallocation than the manufacturing sector. The sectoral shift between the two will cause the higher misallocation in the service sector to be weighted more when aggregating results. To determine whether this or other sectoral shifts drive the measured increase in economy-wide misallocation, as a counterfactual the model is recomputed for every year while keeping the sector expense shares constant at their 1998 levels. Figure

4 presents the results of this counterfactual analysis as well as the results of the original analysis. A table with exact results for all years can be found in Appendix B.

Figure 4: Potential TFP improvements from reallocation in the Swedish economy over time



The dashed line shows how misallocation would have developed at constant 1998 factor shares, which means that the difference between the dashed and solid lines shows the impact of sectoral shifts. It is clear from this presentation that sectoral shifts account at best for a small part of the increase in misallocation in the Swedish economy. This is confirmed when looking at the exact numbers; Of a total increase in measured misallocation of 8.2 percentage points, sectoral shifts account for only 0.5 percentage points.

In conclusion, the sector-specific analysis shows that increased factor misallocation in Sweden over the last twenty years was predominately driven by increased misallocation in each of the economy's most important sectors. The manufacturing and service sectors both saw large declines in allocational efficiency, while transport, retail, technology, media & communications, and utilities all experienced smaller, but economically significant, declines in their allocational efficiency. Only the small sectors of agriculture, mining, construction, and hospitality do not show a clear time trend in their allocational efficiency.

6 Inter-Industry Reallocation

An implicit assumption of the present model, reaching back to Hsieh & Klenow (2009) and being part of all literature since, is that a reallocation of factors is only possible between firms in the same industry. The practical reason for this assumption is the limited ability to know the differing sizes of the demand elasticity of substitution between different firms, a topic discussed in detail in section 7.1. The model instead assumes a common elasticity of substitution between similar firms. In order for this assumption of a common elasticity to hold, factors, and through them demand, can only shift between firms whose activities are very close to each other. Take a simple example for why this is; It is certainly much easier to move factors of production and demand between two ice cream makers than between an ice cream maker and say a law firm.

The problematic result of this assumption is that only the reallocation potential within narrowly defined groups is assessed - for Hsieh & Klenow (2009) and most following literature, including this thesis, those firms sharing the same four digit industry classification. This ignores both possible reallocation between closely linked industries (i.e. an ice cream maker and a frozen foods producer) as well as long-term reallocation possibilities, where changing consumption and investment patterns do allow for reallocation between more distant industries.

This thesis proposes a novel approach to approximate these additional potential gains from reallocation, while accounting for the decreased substitutability between products of more distant types of firms.

Multiple values for the elasticity of substitution are ill suited to being modeled simultaneously using the standard model developed in section 3 or any other model mentioned in the literature review of section 2. The reason is that the presented model works through weighting the relative distance between a firm's TFPR and that of the industry by a factor expressing the impact of dispersion on industry TFP. This factor is given by $\sigma - 1$, meaning it depends on the demand elasticity of substitution. Combining firms from multiple industries means that there now are different levels of demand substitutability $\sigma_0, \sigma_1, \ldots$ between these firms, with σ_0 denoting the elasticity of substitution within an industry, σ_1 the elasticity of substitution between closely linked industries, etc. Since this model is not modeling individual reallocative moves between two specific firms, but instead remains agnostic to the specifics of which firm transfers demand and factors to which one, the common σ used in the model has to be an aggregate of the individual $\sigma_0, \sigma_1, \ldots$.

Clearly, this aggregate has to depend on between which firms potentials for reallocation exist - if most reallocation would happen between industries, the aggregate would need to be closer to σ_1 and vice versa.

However, reallocative potential is precisely what this entire calculation is attempting to establish, meaning that one needs to find an aggregate $\overline{\sigma}$ by comparing results from a computation depending on this very same aggregate $\overline{\sigma}$. This is clearly not possible, meaning that a reallocation with multiple demand elasticities of substitution cannot be modeled simultaneously.

In addition to this inability to perform a simultaneous estimation, one also cannot simply estimate once only the reallocation between firms within the same industries and once of all firms and aggregate the two. This is because an estimation using all firms will count some of the same reallocative potential that would also be counted in the within-industry analysis. This double-counting is not possible to control for given that one does not know which reallocative moves have already taken place, as discussed above.

In order to avoid these pitfalls, this thesis proposes a sequential estimation approach, which first estimates within-industry misallocation using a σ_0, and then redefines individual industries as single homogeneous productive units in order to estimate between-industry misallocation using a $\sigma_1 < \sigma_0$. In order to show the validity of this approach, first consider that all potential reallocative moves can be grouped either into within-industry reallocation, or between-industry reallocation. If one can show that the reallocative potential of each can be assessed separately, and that the combination of the two covers all reallocative moves, then their aggregate will cover the entire reallocative potential.

Recall that reallocative potential, as calculated in (14) (and displayed again below for convenience), is caused by a dispersion of revenue productivities.

$$\Delta \mathrm{TFP}_s^* = \frac{\mathrm{TFP}_s^*}{\mathrm{TFP}_s} = \left(\frac{\sum_{i=1}^{n_s} (\mathrm{TFP}_{si})^{\sigma-1}}{\sum_{i=1}^{n_s} \left(\mathrm{TFP}_{si} \frac{\mathrm{TFPR}_s}{\mathrm{TFPR}_{si}} \right)^{\sigma-1}} \right)^{\frac{1}{\sigma-1}} \tag{18}$$

This dispersion is in turn caused by factor market distortions varying factor prices across firms, which then impacts the firm's profit maximization function. The potential reallocative potential estimated in this thesis is then calculated by hypothetically eliminating those factor market distortions. This elimination of distortions then causes all firms within an industry to exhibit the same revenue productivity. However, this is all one knows. One does not know which firms actually have which factors in the optimum allocation. If one did know this, one could simply combine the firms from different industries after they had their factors reallocated within each industry and compute the additional between-industry TFP improvement.

This thesis proposes that one can still do this even without knowing individual firms' factors by utilizing the known distribution of factors between firms in the optimal allocation, which is such that marginal revenue products of all firms are equal:

$$\text{TFPR}_{s1} = \text{TFPR}_{s2} = ... = \text{TFPR}_{sn_s} \tag{19}$$

This means that *any* factor movement into or out of an industry s with removed factor distortions is immediately reallocated such that marginal revenue products are equal again between firms. In a way, without factor market distortions, firms in an industry behave such that one can see the entire industry as a single productive unit.

By treating each reallocated industry as a firm, it is possible to apply exactly the same steps as one did at a firm level to calculate possible TFP improvements between these productive units - only that now, industries are productive units, instead of firms. When in the course of this process the TFPR_s of an industry is equalized with that of other industries, this TFPR_s shift is followed at the same rate by all firms' TFPR_{si} in each industry.

It is clear that in the first step, when computing within-industry reallocation gains, only the reallocative potential within an industry is considered, and that in the second step there is no more within-industry reallocative potential, which means the second step can only estimate between-industry reallocation. As after performing both steps no more factor market distortions exist, neither for firms in the same industry nor between industries, this sequential approach[8] must estimate the entire allocation potential that exists.

Applying this sequential method to the Swedish data from 2017 for multiple clustering levels results in estimates for additional reallocative potential as displayed in table 3.

A couple notes on the calculation are warranted. In the absence of good data, the σ have been chosen very conservatively, reducing by half for every step up in granularity. To understand this σ progression intuitively, at a three-digit level σ is smaller than two, so aggregate TFP will no longer experience the positive effect from physical productivity dispersion described in section 3.3. At a two-digit and sector level σ is even below one, meaning that a price rise in a unit at that level actually increases the relative

[8]For completeness: This sequential order of the estimation is not actually required for the computation, but it is conceptually much easier to understand. One could alternatively also reallocate between industries first, which has the harder to follow assumption that factors can flow freely between more distant firms, but still face distortions between closely related firms. As distortions are still present within industries, no within-industry reallocative potential would be counted in this between-industry reallocation. Industry-wide TFPR would experience a level shift as it is equalized with the TFPR of other industries, which would apply uniformly to individual firms. This uniform TFPR shift will actually change the aggregate ratio of firm TFPR to industry TFPR, but the impact of this on the amount of measured misallocation is counteracted by the change in the industry-level factor expense share in the economy caused by between-industry reallocation, which shows that the aggregate economy-wide measured misallocation is unchanged by the order of the steps. Leaving the conceptual side, computationally, one could even estimate the two completely separately, given that reallocation within a unit does not actually change the observed variables, meaning the amount of factors and created revenue in that unit (it only improves TFP and output, which we do not observe).

amount spent on products of that unit, as customers are so hesitant to switch that the price effect dominates the quantity effect.

Table 3: Potential additional percentage TFP improvement across industries

Step	Homogeneous unit	Reallocation across	σ	Reallocative potential
1	Firms	4-digit industries	3	23.0%
2	4-digit industries	3-digit industries	1.5	2.8%
3	3-digit industries	Sectors	0.75	10.2%
4	Sectors	Economy	0.38	1.7%

The result displayed give the additional improvement in TFP from reallocation at each step. In total, measured misallocation is almost 15 percentage points higher when employing this approach, bringing the total estimated potential for TFP improvements from removing factor misallocation in the Swedish economy up from 23% to 37.7%.

This is a substantial amount of additional reallocative potential, especially considering that the elasticities of substitution were chosen somewhat conservatively. This result suggests two things. First, misallocation in the Swedish economy is about 50% higher than a standard approach would estimate it, which strengthens the result of this thesis that factor misallocation is an important concern for the Swedish economy. Second, the importance of between-industry factor market distortions is significant for both policymakers seeking to stimulate economic growth as well as researchers attempting to estimate possible TFP gains in an economy.

7 Discussion

This section first discusses the results of the main empirical analysis, before focusing on model assumptions in section 7.1, model applicability in 7.2, and potential underlying result drivers in section 7.3.

The most important result of the empirical analysis is the increase in Swedish misallocation over time, given that the static result is not robust to measurement error or a mis-specification of σ. This upward trend of measured misallocation is surprising, given that there is no clear reason for why misallocation would have increased. At the same time, this observation fits with recent literature, where an increase in measured misallocation is also seen in other developed economies, like in Dias *et al.* (2016a) for Portugal or in Kim *et al.* (2017) for South Korea.

This increase of misallocation over time suggests that inefficiencies and factor market distortions are increasing in the Swedish economy. This is an important result, as these inefficiencies can lower long-term growth and dynamism in the Swedish economy.

In addition to the trend of overall decreasing allocational efficiency, changes in measured misallocation seem to follow changes in GDP, meaning they move together with business cycles. However, from this movement alone it is not possible to determine what is driving the relationship between misallocation and business cycles, only that misallocation does depend in some way on what is happening in the economy.

One interesting point is that the sectoral split shows some sectors reacting much stronger to these business cycle fluctuations than others, which can be seen especially well around the time of the financial crisis and economic recession of 2008-2009. This is a particularly important observation for the question of whether the business cycle relationship is primarily revenue driven or factor price driven. If the co-movement of measured misallocation and economic growth were factor-price driven, for example by business cycles altering the cost of capital, one might expect all sectors to be impacted. However, the opposite is observed and primarily those sectors with assumed demand shocks in a crisis, like manufacturing and construction, show a change in measured misallocation. Potentially, this could be due to negative demand shocks eliminating the most unproductive firms, causing remaining firms' revenue productivities to lie closer together. However, the decrease in measured misallocation in a crisis could also work through crises perhaps "equalizing" revenue productivity across firms by reducing revenues from the most productive firms more than less productive ones. Either way, further research is required in order to answer this question and confirm one or both mechanisms.

The examination of individual sectors also allows comparisons with results in other literature, which are usually sector-specific. Addressing the seminal paper first, Hsieh & Klenow (2009) report a potential TFP gain in the manufacturing sector of 42.9% for the United States, 86.6% in China, and 127.5% for India in 2005. The potential TFP gain in the manufacturing sector in Sweden for the same year is only 12.5%. However, this striking difference in measured misallocation between the US and Sweden is indicative at best of actual differences in allocational efficiency, and could just as well be driven by differences in data quality.[9]

Another comparable result of this thesis is the difference in allocational efficiency between Swedish manufacturing and service sectors, which is found to be about 11.5%. This result is almost exactly the same as in Dias *et al.* (2016b), who find a difference of 12%. Similar to Dias *et al.* (2016a), Swedish service sector allocational efficiency also fell more sharply over time than that of the whole economy.

7.1 Importance of Imperfect Competition

The largest and most important assumption in this model is that of having a market characterized by imperfect competition. Without this assumption, there would be no potential for reallocating factors across firms, as in a monopoly customer demand cannot shift, and in perfect competition only the most productive firm would exist and produce all output. The assumption of imperfect competition is also more than reasonable, given that in any economy many firms can be observed, each of them with a slightly differentiated product.

As a result of assumed imperfect competition the magnitude of the computed results is highly dependent on the assumed demand elasticity of substitution σ. Different values of σ scale the TFP improvements to be gained from an optimal allocation of resources up or down. The economic reason for this scaling effect can be demonstrated as follows: Even firms with low physical productivity can persist because consumers like to consume some of their product and cannot perfectly substitute their demand for this product with the consumption of a different firm's product. If this substitution were easier, more consumption could be reallocated to the most productive firms. This would also mean a large reallocation of capital and labor to productive firms, increasing overall productivity in the economy. If, on the other hand, substitution is assumed to be very difficult, the same reallocation to more productive firms would carry a much larger utility loss for consumers.

Ideally, one would use year- and industry-specific σ in order to approximate the true heterogeneity of σ the closest, or even discard the assumption of any homogeneity in elasticities of substitution and

[9] See section 8 and Nishida *et al.* (2017) for a further exploration of the importance of measurement error.

use fully heterogeneous σ, which would approach economic reality the closest. Unfortunately, it is not possible to collect economy-wide data on consumer preferences between all firm's products, leaving this as a hypothetical exercise.

Since the actual size of σ is uncertain, static results have low validity. However, as long as the true σ does not change over time, the dynamic analyses presented in this thesis remain valid and informative irrespective of the σ chosen.

7.2 Small Firms

Besides firms in the financial sector and non-firm entities, the empirical analysis importantly excludes small firms, defined at an arbitrary threshold of having less than 10,000 SEK in value added, fixed assets, or labor expenses. This section explains the cause for this exclusion by highlighting two reasons this model is unfit to analyze small firms. The first reason comes from having assumed a production function with constant returns to scale (CRS). While that is a reasonable assumption for, say, an industrial firm controlling two plants instead of one, it is less so for a skilled carpenter who can at most work in one workshop at a time. Adding the likelihood of small firms to exhibit large measured differences in physical productivity, for example one carpenter being more skilled than another, and the model would suggest gains from reallocation to be much larger than they actually are.

The second reason not to analyze small firms lies in data quality. Small firms have to follow less strict accounting and auditing standards, which likely lowers their quality of reporting. Additionally, some small firms might include a large share of informal labor, conduct business in private residences, or use special tax deductions. These possibilities suggest that misreported data and resulting measurement errors will be much more common among small firms.

As a result of these reasons, the inclusion of small firms should bias the estimate for the TFP gains from misallocation upward. This is in line with the empirical outcome observed when including all small firms, where potential gains from reallocation jump from an estimated 23% to 121%. This result not only confirms the reservations described above around including small firms, it also underlines the magnitude of the potential biases that can be introduced when the model is applied to entities which do not fulfill the necessary assumptions.

7.3 Potential Explanations

This model, being descriptive in nature, is unable to give causal inferences. As such, it is impossible to know why measured misallocation in the Swedish economy increased, although one can speculate about the reasons. As part of the interpretation of the observed results, the paragraphs below give a brief overview and discussions of possible reasons.

First, there is a possibility that the underlying model is mis-specified, or that mismeasurement in the data drives results. This is generally a valid criticism of much of the literature, especially of those works comparing allocational efficiency across countries (see Nishida *et al.* (2017)). As a result, the absolute value of potential TFP improvements from equalizing firm TFPR cannot be treated as a precise estimate, since the amount of measurement error is unknown, as is the ”true” elasticity of substitution. Similarly, the degree to which a production function in the real world would exhibit constant returns to scale is likely not what the model assumes.

However, while this makes static results somewhat unreliable, none of these shortcomings impact the validity of the dynamic analysis, unless they are themselves dynamic, i.e. changing over time. When comparing misallocation across time periods, the effect of static biases gets canceled out. It is far less certain that any of the aforementioned biases would have changed over time, which in turn suggests that something within the Swedish economy changed and drove up misallocation.

Following the common line of interpretation in the literature, misallocation is caused by firms facing heterogeneous taxes on capital or labor. The meaning of taxes in this context is wide and includes anything that causes differing factor costs between firms. Typically political favors are mentioned in this context, but those can be assumed to be not as big of a determinant for economic success in the Swedish one economy. Instead, factor market frictions, and especially informational asymmetries, are a possibility worth considering. It is for example possible that next to incumbent firms with very predictable earnings, newer or growing firms have much more difficult to predict earnings, causing financial institutions to demand a higher cost of capital from them. This relationship could also have been strengthened by increased regulation in the banking sector over the last twenty years. In this scenario, an increased dynamism is causing lower allocational efficiency in an economy, a link that would be interesting for future work to establish, especially since it could impact interpretations of differences in misallocation between developing and developed economies.

On the opposite end of the spectrum of possible explanations, it could be that factors have become less mobile during the last twenty years. This could be modeled through increasing costs of gaining or shedding capital or labor, which in turn means that much larger revenue productivity differences between firms would be needed order for reallocation to be happening naturally. A lower factor mobility could be due to, for example, additional labor regulation as in Lagos (2006).

A last possibility is that the relationship between measured misallocation and business cycles is a driving force in the observed increase. If one assumes that misallocation is related to inefficiencies in the economy, and that economic crashes have cleansing effects, we might just currently observe an inefficient economy awaiting a cleansing crash. This result, if true, would be an important addition to the literature connecting business cycles to economic efficiency and would support the ”cleansing” theory of recessions. From an academic perspective, all of these explanations would be interesting to explore in further research.

8 Limitations and Validity

This section gives an overview of the limitations of the approach used in this thesis, many of which have already been mentioned in other sections. Likely the largest and most important limitation to any analysis using dispersion as a strategy for identifying an effect is the amount of measurement error present in the data. This topic has already been discussed in section 2.3 in the context of Nishida *et al.* (2017) and Bils *et al.* (2020), both of which show large potential impacts from inaccurate measurement and insufficient cleaning of the data. The mechanism through which measurement error impacts results can be understood as follows. Recall that misallocation is computed through the dispersion of revenue productivities, which themselves are calculated using the raw firm-level data. The more this data is misreported, the larger is the variation in this data, and the larger is the computed dispersion in revenue productivities, which biases the potential TFP gains from reallocation upward.

That being said, there are two reasons for why measurement error is likely a smaller issue in this thesis than it is elsewhere in the literature. First, the Swedish firm-level dataset can be seen relatively more trustworthy and well-kept than the data from a developing economy might be. The second, and more important, reason is that this thesis performs an analysis over time. Whereas measurement error often varies between countries and between the statistical institutions aggregating the data, there is no clear reason that there should be any change in measurement error over time.

It is important to realize that, even in the absence of measurement error, the magnitude of possible productivity improvement from an optimal allocation is still at best a rough estimate. There are a number of assumptions necessary in order to compute this estimate which can have distorting effects. Likely the largest of these, as discussed before, is the degree of demand substitutability between firms. This degree to which consumers prefer one firm's products over those of another likely varies between sectors and between firms, and perhaps even over time. The model has assumed a common and static demand elasticity of substitution, meaning that for those firms / industries / periods where substitutability is lower, the model overestimates the potential for reallocation, and when substitutability is higher, it underestimates it.

The demand elasticity of substitution is just one aspect of the wider potential limitation of a possible model mis-specification. This thesis describes an economic phenomenon across almost all sectors of an economy over the time span of twenty years. Across this enormous amount of different economic activity, it seems likely that some of the underlying assumptions, like the degree of constant returns to scale or the degree of imperfect competition, do vary across industries, time, or both.

However, while all these factors could and likely do impact the results of this thesis to some extent, it is much less clear that any of them might be changing across time in such a way as to be driving the main results. This means that while the results may not be understood as an exact estimate, their qualitative conclusion of increasing misallocation in the Swedish economy over time likely has a high internal validity.

A further limitation of this analysis is that only the profit maximization problem of the firm is considered. Previous literature like Bento & Restuccia (2017) show that factor misallocation can also impact a variety of other firm decisions. By keeping these decision around entry and investment exogenous, this thesis potentially still somewhat underestimates the total effect of misallocation on Swedish TFP.

The external validity of this thesis extends mostly to similar economies as Sweden's, which first and foremost includes the Scandinavian countries. Since measured misallocation seemed to closely follow economic development, the results might also apply to other Western industrialized nations with similar recent economic histories as Sweden.

9 Conclusion

This thesis explains the theory of misallocation and develops a method for estimating the potential total factor productivity (TFP) gains from removing allocational inefficiencies. It shows that Swedish TFP would be 23% higher if factor markets would efficiently allocate resources within industries, and, more importantly, that this measure for misallocation has been rising substantially within the last twenty years, suggesting a worsening of the functioning of Swedish factor markets. Performing a sectoral split shows that aggregate results are not driven by a specific sector or by shifts in the importance of sectors. Instead, a decrease in allocational efficiency has taken place across sectors, suggesting the problem is one impacting the wider Swedish economy. Lastly, the thesis adds to the theory and literature of factor misallocation by estimating the potential additional TFP effects from reallocating resources not just within industries, but also between industries, all while incorporating the different demand elasticities of substitution present. It finds that through this analysis, the potential TFP gain in the Swedish economy from reallocation is 14.7 percentage points higher than if one would only compute within-industry misallocation using the standard model, bringing the total estimate for the potential Swedish TFP gain from reallocation to 37.7%.

For policymakers, the results presented in this thesis suggest that misallocation is a problem in the Swedish economy and that it seems to be getting worse. This should be seen as the first indication of an important phenomenon that needs to be understood better. The economic significance of this increasing misallocation in the Swedish economy is large - just as an eight percentage point decrease in Swedish GDP would be concerning, the equivalent loss estimated from misallocation is as well.

From an academic perspective, the phenomenon of factor misallocation is still only starting to be understood. In addition to approaches which measure the level of misallocation in an economy, of which this thesis is an example, additional empirical research is needed to give inferences about the causes of misallocation. An economy like the Swedish one is an ideal candidate for further research into this area, given the availability of high-quality and comprehensive data. This thesis has shown the problem of factor misallocation existing and worsening in Sweden, and provides a good starting point for this future research.

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A Appendix: Descriptive Statistics

This appendix contains two additional descriptive statistics of potential interest on the data used in this thesis. Table 4 displays the share of each sector of total expenses in the Swedish economy. Table 5 shows the number of observations in each period.

Table 4: Share of total factor expenses by sector and year

Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Agriculture, Forestry, Fishing	0.4	0.3	0.9	0.8	0.9	0.8	0.8	0.7	0.7	0.7
Construction	4.6	5.0	5.5	5.2	5.5	5.0	5.0	5.3	5.5	5.5
Electricity and Water Supply	6.7	6.1	5.8	5.5	6.1	6.7	6.7	6.8	7.3	6.9
Extraction of Minerals	0.8	1.1	0.9	0.8	0.8	0.8	0.8	0.9	1.1	1.1
Hospitality	1.3	1.4	1.4	1.3	1.3	1.2	1.2	1.2	1.3	1.4
Manufacturing	51.1	49.8	48.6	47.8	46.1	47.6	48.4	45.1	45.0	44.0
Services	7.0	8.1	8.6	9.9	9.0	9.0	8.0	10.2	10.1	12.1
Technology, Media, Comm.	9.9	9.2	9.5	8.9	10.2	8.8	8.5	8.5	8.4	8.2
Trade and Retail	12.2	12.8	12.9	13.3	13.1	13.5	13.4	13.3	13.1	12.7
Transport	6.0	6.1	6.0	6.6	7.0	6.7	7.2	7.8	7.6	7.5
Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Agriculture, Forestry, Fishing	0.6	0.7	0.6	0.7	0.6	0.6	0.6	0.6	0.6	0.6
Construction	5.6	6.4	6.2	6.9	6.6	6.5	5.8	6.3	6.0	6.2
Electricity and Water Supply	7.2	8.1	7.9	7.8	8.0	8.2	8.5	8.0	8.5	8.7
Extraction of Minerals	1.2	1.5	1.5	1.6	1.7	1.7	1.8	1.7	1.6	1.6
Hospitality	1.4	1.6	1.5	1.6	1.8	1.9	2.0	2.0	2.2	2.3
Manufacturing	43.4	38.3	39.6	38.7	39.4	38.3	37.1	36.8	35.9	34.4
Services	13.2	13.3	13.5	13.3	13.8	14.3	14.5	14.8	14.5	14.9
Technology, Media, Comm.	7.6	8.6	8.0	7.6	6.6	6.9	7.2	7.0	7.4	7.4
Trade and Retail	12.1	13.3	12.7	13.3	13.1	13.6	14.4	14.8	15.6	15.7
Transport	7.7	8.4	8.4	8.7	8.4	8.0	8.1	8.0	7.9	8.3

Table 5: Total observations per year

Year	n
1998	2952
1999	3130
2000	3320
2001	3402
2002	3423
2003	3414
2004	3420
2005	3472
2006	3608
2007	3836
2008	3966
2009	3874
2010	3946
2011	4061
2012	4075
2013	4103
2014	4108
2015	4269
2016	4455
2017	4684

Note that the increase in observations over time displayed in table 5 is unlikely to be driving the results, as there is nothing in the model that would predict new entrants to be less efficiently allocated. In fact, one might expect the opposite to be true, with new entrants generally assumed to remove inefficiencies in existing systems. Nonetheless, even if new entrants were connected to rising inefficiencies, it would not devalue the results of this thesis.

B Appendix: Additional Sector-specific Results

This appendix contains two tables presenting additional detailed results. Table 6 is specifying the exact size of possible TFP improvements for each sector and year. Table 7 gives the estimated possible TFP improvement for each year when holding sector shares fixed at 1998 levels.

Table 6: Potential percentage TFP improvements by sector

Sector	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Agriculture, Forestry, Fishing	26.4	51.0	84.3	107.3	28.4	9.6	12.0	14.4	14.4	49.3
Construction	21.3	11.4	23.1	22.6	18.3	17.9	20.1	20.7	33.6	42.7
Electricity and Water Supply	27.2	45.3	46.3	65.8	34.4	27.7	37.0	31.8	54.6	55.1
Extraction of Minerals	2.2	8.9	4.8	14.4	18.4	17.5	16.6	25.7	12.4	12.5
Hospitality	5.5	6.1	6.7	9.7	7.1	9.0	6.7	6.0	6.4	7.2
Manufacturing	11.0	12.0	11.1	11.4	11.6	15.0	12.2	12.5	14.1	13.6
Services	15.6	13.1	21.8	17.5	17.4	9.8	19.6	34.1	30.8	33.2
Technology, Media, Comm.	29.7	23.0	30.8	31.4	43.5	47.4	50.8	47.0	54.1	49.7
Trade and Retail	11.4	14.6	15.5	13.9	9.7	10.7	13.1	13.8	13.9	13.1
Transport	16.3	12.1	21.6	25.0	21.2	22.3	22.7	27.1	29.1	25.3

Sector	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Agriculture, Forestry, Fishing	53.8	31.5	53.3	12.6	15.6	18.9	15.7	15.9	15.4	15.7
Construction	19.5	20.4	19.8	24.0	23.0	20.1	18.1	22.0	25.9	23.7
Electricity and Water Supply	56.9	27.9	35.2	47.1	38.1	37.9	34.3	29.8	31.0	33.4
Extraction of Minerals	4.2	4.3	4.3	3.5	4.8	4.1	4.9	3.8	2.3	1.9
Hospitality	6.7	8.5	8.8	10.1	10.3	10.0	10.6	10.2	10.4	9.4
Manufacturing	15.0	22.5	11.1	12.4	11.5	11.4	11.7	16.7	15.4	20.3
Services	44.2	14.7	24.6	28.3	30.5	16.0	26.0	44.7	41.9	31.8
Technology, Media, Comm.	50.6	57.7	29.7	31.0	25.0	41.5	34.7	36.7	32.1	34.0
Trade and Retail	17.2	19.0	19.1	19.9	17.0	15.5	14.4	15.5	14.4	16.0
Transport	28.6	30.9	31.8	35.7	29.1	23.0	23.0	24.4	24.9	21.0

Table 7: Economy-wide TFP improvement potential in percent depending on sector expense shares

Year	Actual expense shares	1998 expense shares
1998	14.8	14.8
1999	15.2	15.4
2000	17.8	17.6
2001	18.6	18.7
2002	17.2	17.0
2003	17.8	18.3
2004	18.4	18.7
2005	20.3	19.7
2006	23.3	22.8
2007	23.5	22.5
2008	25.3	23.8
2009	24.1	25.0
2010	19.4	17.9
2011	21.8	20.0
2012	19.6	17.8
2013	17.9	17.6
2014	18.6	17.4
2015	23.3	21.6
2016	22.3	20.4
2017	23.0	22.5