Misallocation of labor and capital in Finland's business sector

Editor: Timo Kuosmanen
Authors: Sheng Dai, Natalia Kuosmanen, Timo Kuosmanen, Tero Kuusi, Juuso Liesiö, Terhi Maczulskij

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Abstract

Misallocation of labor and capital has attracted considerable interest in economics, however, there is little empirical evidence from Finland's business sector. This project examined misallocation by applying modern methods of economics and statistics to the register data of Statistics Finland on business enterprises in Finland.

The main results of the study can be summarized as follows: 1) The current allocation of resources is far from optimal from a societal point of view. 2) The efficiency of resource allocation between companies deteriorated during the study period 2000-2018. 3) Misallocation of labor correlates statistically significantly with the characteristics of enterprises such as the age, size, equity-debt ratio, and foreign ownership. 4) The majority of the companies considered operate capital intensively than would be efficient from a societal perspective.

Based on the results, more efficient allocation of resources to high-productivity firms could significantly increase productivity. Although startups are, on average, more productive than exiting firms, many startups are unable to take advantage of the competitive advantage due to high productivity to expand their operation. On the other hand, the results suggest that the allocation of labor input across firms is less efficient than the allocation of capital, especially for startups and small firms. Increasing labor mobility and wage competition could be practical means to improve the allocation of labor across firms.

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Työn ja pääoman tehoton kohdentuminen Suomen yrityssektorilla

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Julkaisija	Valtioneuvoston kanslia

Tekijä/t	Sheng Dai, Natalia Kuosmanen, Tero Kuusi, Timo Kuosmanen, Juuso Liesiö, Terhi Maczulskij
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Tiivistelmä

Työ- ja pääoma resurssien kohdentumisen tehokkuuden kohdentumisesta Suomen yrityssektorilla on olemassa varsin niukasti tutkimustietoa. Hankkeessa tutkittiin työn ja pääoman allokaation tehokkuutta soveltamalla moderneja talous- ja tilastotieteen menetelmiä Tilastokeskuksen ylläpitämiin yritystason rekisteriaineistoihin.

Tutkimuksen keskeisimmät tulokset voidaan tiivistää seuraaviin neljään havaintoon: 1) Nykyinen resurssien allokaatio on kaukana optimaalisesta yhteiskunnan näkökulmasta tarkasteltuna. 2) Resurssien kohdentumisen tehokkuus yritysten välillä on heikentynyt tarkastelujakson 2000 – 2018 aikana. 3) Tehottomuus työvoiman kohdentumisessa korreloi tilastollisesti merkitsevästi yritysten ominaisuuksien kuten yrityksen iän, koon, vakavaraisuuden ja ulkomaalaisomistuksen kanssa. 4) Enemmistö tutkituista yrityksistä toimii pääomavaltaisemmin kuin olisi yhteiskunnan näkökulmasta tehokasta.

Tulosten perusteella työn ja pääoman nykyistä tehokkaampi kohdentuminen keskimääräistä korkeamman tuottavuustason yrityksiin voisi kasvattaa tuottavuutta merkittävästi. Vaikka uudet yritykset ovat keskimäärin tuottavampia kuin markkinoilta poistuvat yritykset, monet uudet yritykset eivät kykene hyödyntämään korkean tuottavuustason luomaa kilpailukykyetua toimintansa laajentamiseen. Toisaalta tulokset viittaavat siihen, että työpanoksen kohdentuminen yritysten kesken on tehottomampaa kuin pääoman kohdentuminen, erityisesti uusien ja pienten yritysten kohdalla. Työvoiman liikkuvuuden ja palkkakilpailun lisääminen olisivat konkreettisia keinoja työvoiman kohdentumisen tehostamiseksi.

Klausuuli

Tämä julkaisu on toteutettu osana valtioneuvoston selvitys- ja tutkimussuunnitelman toimeenpanoa. (tietokayttoon.fi) Julkaisun sisällöstä vastaavat tiedon tuottajat, eikä tekstisisältö välttämättä edusta valtioneuvoston näkemystä.

Asiasanat

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Felallokering av arbetskraft och kapital i Finland’s affärssektor

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Författare	Sheng Dai, Natalia Kuosmanen, Tero Kuusi, Timo Kuosmanen, Juuso Liesiö, Terhi Maczulskij
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Referat

Detta projekt undersökte felallokering av arbetskraft och kapital på det finländska näringslivet genom att tillämpa moderna ekonomi- och statistikmetoder på Statistikcentralens registeruppgifter om företag i Finland.

Studiens huvudresultat kan sammanfattas enligt följande: 1) Den nuvarande resursfördelningen är långt ifrån optimal ur samhällssynpunkt. 2) Effektiviteten i resursfördelningen mellan företag försämrades under studieperioden 2000-2018. 3) Felallokering av arbetskraft korrelerar statistiskt signifikant med företagens egenskaper såsom ålder, storlek, skuldsättningsgrad och utländskt ägande. 4) Majoriteten av de övervägda företagen driver kapitalintensivt än vad som skulle vara effektivt ur ett samhällsperspektiv.

Baserat på resultaten skulle en effektivare allokering av resurser till högproduktiva företag kunna öka produktiviteten avsevärt. Även om nystartade företag i genomsnitt är mer produktiva än utgående

företag, kan många nystartade företag inte dra fördel av konkurrensfördelar på grund av hög produktivitet för att utöka sin verksamhet. Allokeringen av arbetskraft mellan företag är mindre effektiv än allokeringen av kapital, särskilt för nystartade företag och små företag. Ökad arbetskraftsrörlighet och lönekonkurrens skulle kunna vara praktiska sätt att förbättra allokeringen av arbetskraft mellan företag.

Klausul Den här publikation är en del i genomförandet av statsrådets utrednings- och forskningsplan. (tietokayttoon.fi) De som producerar informationen ansvarar för innehållet i publikationen. Textinnehållet återspeglar inte nödvändigtvis statsrådets ståndpunkt

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Contents

PREFACE

Stagnation of labor productivity in Finland and in many other Western countries since the financial crisis of 2007-2008 and the resulting Great Recession has caused major concern among economists and policy makers. Several possible explanations for the slowdown of the measured productivity have been suggested, including insufficient level of investment to the human and physical capital. Mega-trends such as ageing society and urbanization affect the local labor markets, which can increase the matching problems in the job markets. The decline of the Finland's ICT sector during the first two decades of the 21st century further contributed to the productivity slowdown. Recently, the Covid-19 pandemic, Russia's invasion to Ukraine and the resulting economic sanctions have presented new unexpected challenges for many firms and industries, and Finland's national economy as a whole. The recent and ongoing crises will likely accel-erate the so-called “green transition” that is already well under way in the Finnish economy.

Better allocation of labor and capital resources is one potential approach to increase productivity. Thus far, the adverse effects of misallocation on productivity growth have attracted little attention in Finland. To shed further light on this issue, in February 2021, the Prime Minister's Office commissioned Aalto University School of Business and ETLA Economic Research to conduct the research project titled ”Allocation of labor and capital at the establishment, firm, and industry levels: Creative destruction, smart planning and effective regulation”. The research team includes Timo Kuosmanen (PI, Aalto), Juuso Liesiö (Aalto), Eeva Vilkkumaa (Aalto), Sheng Dai (Aalto), Terhi Maczulskij (co-PI, ETLA), Paolo Fornaro (ETLA), Natalia Kuosmanen (ETLA), Tero Kuusi (ETLA), and Heli Koski (ETLA). This final report presents the main results and the policy implications of this project.

The authors of the report would like to express their sincere thanks to the steering group of the project, Markku Stenborg (chair), Seppo Kangaspunta, Fransiska Pukander, Jukka Mattila, Timopekka Hakola, and the external experts Mika Maliranta and Peter Elmgren, for their helpful comments and constrictive feedback. As always, the authors assume sole responsibility for any errors in the report.

Timo Kuosmanen
May 2022

1 Introduction: labor productivity and economic wellbeing

Timo Kuosmanen

Aalto University

Abstract: The purpose of this chapter is to introduce the notion of resource misallocation and the main research questions of the project. We then elaborate the importance of labor productivity for the economic growth and wellbeing, and briefly examine the recent development of Finland's labor productivity in comparison to a group of peer countries. We conclude with a brief review of the chapters included in this volume.

1.1 Introduction

Allocation of labor and capital is a long-standing theme in economics since Adam Smith. More recently, there has been growing interest in the sources and consequences of the misallocation of resources, thanks to more comprehensive register data at the establishment and firm levels as well as improved econometric tools (e.g., Restuccia & Rogerson, 2013, 2017). Several studies have convincingly demonstrated stunningly large and persistent productivity gaps across establishments and firms, even at relatively narrowly defined industries (e.g., Hsieh & Klenow, 2009; Syverson, 2011). Foster et al. (2001, 2008) suggest that up to one half of productivity gaps in the US manufacturing industry are due to inefficient allocation of resources.

In the competitive markets, allocation improves through Schumpeterian creative destruction. In other words, the fittest firms survive and grow, whereas the weakest firms stagnate and die out, directly analogous to the evolutionary selective pressure in the nature. In contrast to the random genetic mutations, however, the firms do not allocate resources randomly by throwing dice, but spend considerable time and effort to optimize their resource allocation. In other words, the firms apply more or less intelligent design to allocate their resources. Within firms, productivity and competitiveness can improve though more efficient allocation of labor and capital between different establishments managed and operated by the firm. A firm can also acquire or merge with its competitors, expand to multiple industries, or switch activity from one industry to another. Therefore, intelligent planning by individual firm managers can affect allocation of resources not only between establishments, but also across firms and industries.

Modern information systems, artificial intelligence and machine learning tools provide means for more efficient planning and coordination within firms, but also between different firms within a supply chain or an innovation ecosystem. This can increase the risk that the evolutionary selection pressure leads to concentration of market power. In the classic example of a monopoly firm the resources of an entire industry are allocated through central planning with no competition. From the point of view of a monopoly firm, centralized decision making can improve operative efficiency through better coordination and planning, but can lead to inefficient allocation from the societal point of view. It is also well-established in the welfare economics that, without policy interventions, markets do not produce public goods or take into account externalities such as the influence of greenhouse gas emissions on global warming. Clearly, creative destruction or intelligent planning alone do not guarantee efficient allocation from the societal point of view, there is also a need for government policy and regulation.

To design effective policy measures, it is important to gain deep understanding of the sources of the misallocation and their causal relationships. Inefficient or disproportionate policy measures can make resource allocation even worse. It is important to note that misallocation of resources at a lower level of aggregation manifests itself as technical inefficiency at the higher levels of aggregation. Therefore, to design effective policy measures, it is important to gain better understanding of how labor and capital are allocated at different levels of aggregation, including the establishments, firms, industries, as well as the national economy as a whole.

Thus far there is little empirical evidence regarding the allocation of labor and capital in Finland’s business sector. The general purpose of this report is to shed new light on this issue. The more specific research questions of this project are the following.

1.2 Research questions

The main research questions of the project are the following:

1) How efficient is the allocation of labor and capital in Finland?
2) How much could labor productivity potentially increase through better allocation?
3) What kind of factors influence efficiency of allocation?
4) What kinds of bottle necks inhibit improvement of allocation?
5) What kinds of policy measures could help to improve allocative efficiency or eliminate bottle necks?

Chapters 2-7 of this report will shed light on these questions by different methodological approaches at different levels of aggregation. To connect these developments to an appropriate historical context, the next subsections briefly review the importance of labor productivity on the economic wellbeing and the stagnation of labor productivity in Finland and its peer countries.

1.3 Contribution of labor productivity to the economic growth

The most commonly used measure of economic wellbeing, the GDP per capita, can be decomposed to the following four components

GDP per capita

=	GDP / hours worked	(mean labor productivity)
x	hours worked / number of employees	(average working time)
x	number of employees / total workforce	(employment rate)
x	total workforce / population	(dependency ratio + 1)$^{-1}$

This decomposition formally links the average labor productivity and wellbeing. If the average working time, employment rate and the dependency ratio do not change, then the economic growth can only be achieved through increased labor productivity. In our ageing population, the last component (the inverse of the dependency ratio plus one) decreases, which puts further pressure on productivity growth to sustain economic wellbeing.

It is important to note that the four components of the above decomposition are not independent, but mutually dependent. For example, increasing the average working hours per employee would likely have a negative effect on labor productivity. Therefore, the net effect of longer working hours can be positive or negative. On the other hand, retirement of the baby-boom generation born during the two decades after the World War II has increased the dependency ratio and decreased the last component of the above decomposition. Vandenbroucke (2018) has estimated that the retiring of baby boomers may cause a 2.8 percentage points decline in productivity growth in the USA between 2020 and 2040. The recent report by Valkonen & Lassila (2021) examines the economic impacts of the ageing population in Finland.

The tradeoff between the employment rate and the average labor productivity is particularly important for policy making. Finland has relatively high structural unemployment, and the need to stimulate labor market participation by various policy measures is widely recognized. Unfortunately, increasing the employment rate may affect the average labor productivity. Indeed, more active labor market participation tends to decrease the average labor productivity because the new jobs created by policy reforms are typically at the bottom of the productivity distribution. Creating more low productivity jobs helps to increase employment, but at the cost of decreasing average labor productivity. The purpose of this discussion is to highlight that labor productivity is an important means to improve economic wellbeing, but not necessarily an end in itself. Labor productivity is dependent on the other three components of the above decomposition of the GDP per capita.

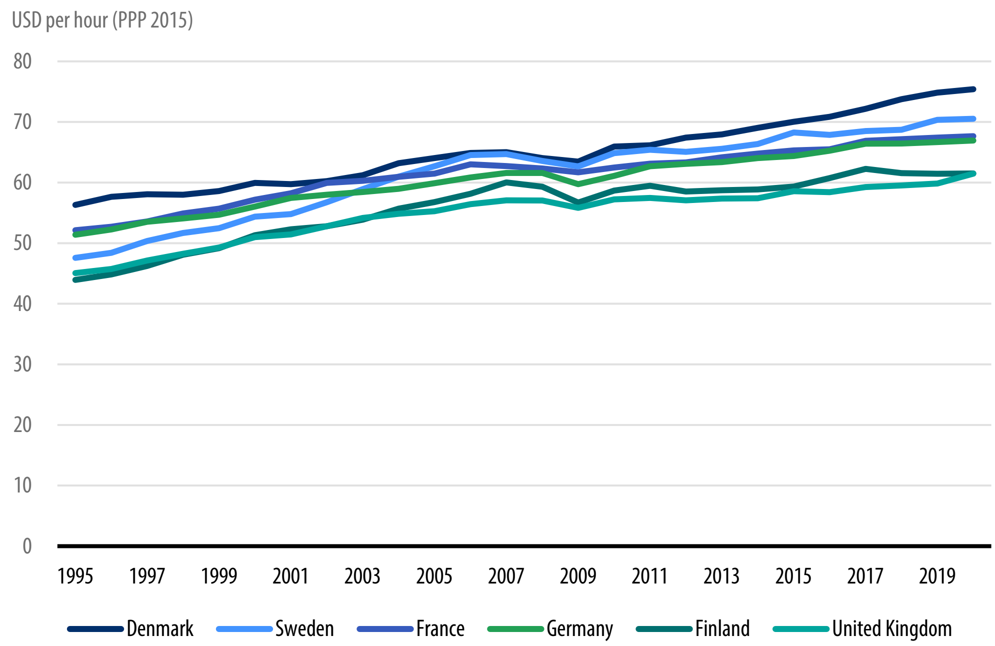
1.4 Labor productivity stagnation

Stagnation of labor productivity in Finland and in many other Western countries since the financial crisis of 2007-2008 and the resulting Great Recession has caused major concern among economists and policy makers. The popular media in Finland tends to give a rather gloomy image about the stagnation of labor productivity. It is true that the steady growth of labor productivity in the Finnish economy ground to a halt in 2007, and has stuck approximately to the same level for more than a decade. But it seems exaggerated to claim that Finland is falling behind its peer countries in Western Europe.

Figure 1 depicts the levels of labor productivity in Finland, Sweden, Denmark, France, and Germany in years 1995-2020 ($US per hour worked, using purchasing power adjusted prices of year 2015). Comparing the levels of productivity instead of productivity indices, which are sensitive to the arbitrary choice of the base year, we see that the productivity gap between Finland and other European countries was almost the same in 2020 as it was in 1995. The notable exception is Sweden, where labor productivity has grown more rapidly than in the other countries considered in Figure 1. It is misleading to conclude that Finland is doing particularly badly, it is actually Sweden that has managed to overtake France and Germany and catch up Denmark. The national currencies of Sweden and Denmark have helped these two countries to recover quicker from the financial crisis than the eurozone countries Finland, France, and Germany. However, it is also interesting to note that Finland’s labor productivity has developed along a similar trajectory with the United Kingdom.

Several possible explanations for the slowdown of the measured productivity have been suggested, including insufficient level of investment to the human and physical capital. Mega-trends such as ageing society and urbanization affect the local labor markets, which can increase the matching problems in the job markets. In Finland, the decline of the ICT sector during the first two decades of the 21st century further contributed to the productivity slowdown.

Figure 1. Labor productivity in Finland and in selected European countries 1995-2020



Source: OECD productivity statistics, https://stats.oecd.org/

One noteworthy explanation for the stagnation of the measured productivity change over time concerns the measurement challenges associated with the modern digital economy. Although digitalization can help to create new types of services and business models, and facilitate better coordination in the supply chain, the contribution of the new digital services is likely underestimated in the GDP. Brynjolfsson & Collis (2019) and Brynjolfsson et al. (2019) discuss examples of how various digital services that are nowadays available free of charge have largely replaced paid services that used to contribute to the Gross Domestic Product (GDP). To address this issue, Brynjolfsson et al. (2021) propose the so-called GDP-B approach as an attempt to accounting for the value of new and free goods.

Another possible explanation that has thus far attracted little attention concerns abatement of the greenhouse gas (GHG) emissions and the resulting growth of carbon productivity. Achieving the ambitious climate policy targets has required major capital investments to cleaner technology, and continues to do so for years to come. However, these capital investments do not necessarily increase the conventional measures of productivity such as labor productivity or total factor productivity (TFP). In Chapter 3 of this report we will argue that productivity growth has actually not stagnated, however, the growth takes place in the form of carbon productivity rather than labor productivity.

Finally, it is worth to emphasize that aggregate productivity stagnation does not uniformly concern all firms or industries in Finland. Indeed, there has been strong labor productivity growth in many firms and industries. In the interim report of this project (Fornaro et al., 2021), we showed that positive productivity growth mainly occurs in the continuing firms, however, structural change and inefficient allocation of resources contribute to the productivity slowdown at the aggregate level. We return to this discussion in Chapter 2 of this report.

1.5 Organization of the report

This report consists of eight chapters, including the present introductory chapter. In Chapter 2, Natalia Kuosmanen and Timo Kuosmanen examine empirically the contribution of resource allocation and other structural changes such as entry, exit and industry switching on the level and growth of labor productivity in Finland's business sector. They find that deteriorating resource allocation is the main culprit for the observed slowdown of labor productivity.

In Chapter 3, Natalia Kuosmanen, Timo Kuosmanen and Terhi Maczulskij extend the analysis to carbon productivity using a unique firm-level data of GHG emissions, focusing on the electricity generation industry. In contrast to labor productivity, Finland's carbon productivity shows rapid growth. The analysis of the firm-level emissions data reveals large contributions of structural change, including entry, exit, and industry switching.

In Chapter 4, Terhi Maczulskij examines the effect of export demand shock on labor productivity in Finnish exporters in manufacturing industry. The estimation results show that exogenous export demand shocks have increased labor productivity in Finnish manufacturing firms, although this effect diminished after the financial crisis. The productivity growth response to export demand shock was stronger in younger firms and in firms with higher equity-debt ratio during the financial crisis.

In Chapter 5, Natalia Kuosmanen, Sheng Dai and Timo Kuosmanen shed further light on the resource allocation by comparing the average unit costs of labor and capital with their estimated marginal products in 16 selected industries in three years. The marginal products have been estimated locally using the convex quantile regression, which is a fully non-parametric approach that does not depend on any prior functional form assumptions. The comparison reveals that the unit costs of labor tend to be lower than the corresponding marginal products, whereas the opposite holds for the capital input. Regressing the ratios of unit costs and marginal products on firm characteristics reveals significant correlations between the labor demand and firm characteristics, while no such correlations can be found for the capital input.

In Chapter 6, Sheng Dai, Timo Kuosmanen and Juuso Liesiö further utilize the quantiles estimated in Chapter 5 to examine how the optimal allocation of labor and capital would look like and how much the output and productivity could potentially increase through better allocation. The current allocation is compared with the random allocations and with the optimal allocations subject to four alternative sets of constraints. The results suggest that the allocation could improve by concentrating more resources on the most productive deciles of firms, but not necessarily to the top decile. In most industries, the current allocation turns out as a far cry from the optimal allocation, barely competitive with the random allocations. The results of this chapter suggest that there is great potential to increase productivity through more efficient allocation of resources.

In Chapter 7 Tero Kuusi examines resource allocation of Finnish innovative firms and their workers by applying a general equilibrium growth model. Kuusi finds that the optimal policy drives out low-quality, low-productivity firms to make room for high-quality firms that have growth potential that has not yet materialized. Policies that foster such creative destruction can boost economic growth in the long run. Selective policies that discriminate between high- and low-quality firms are the most efficient in achieving optimal allocation, but improvements in allocation are possible even if perfect discrimination is not feasible.

Finally, in Chapter 8 Timo Kuosmanen draws together the findings of Chapters 2-7 and discusses their policy implications. The discussion of this chapter focuses on the three themes. First, the observed changes in the allocation of resources is examined form the perspective of the size distribution of firms and the corresponding employment shares. Second, the voluntary job switching of employees as a means to reallocate labor input to more productive firms. And third, the industry switching of firms as a means to reallocate labor and capital resources as well as entrepreneurial skills and experience from deteriorating industries to growth industries.

Appendices 1 and 2 provide additional empirical results concerning industries that were considered in the study, but for the sake of brevity were not explicitly discussed in the report.

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2 Structural change decomposition of labor productivity

Natalia Kuosmanen [1], Timo Kuosmanen [2]

1) ETLA Economic Research, 2) Aalto University

Abstract: This chapter examines possible sources of productivity stagnation by decomposing the productivity change to the components that describe the structural change. We apply a novel productivity decomposition by Kuosmanen and Kuosmanen (2021) which ensures consistent aggregation of firms to industry and sector levels, and also explicitly captures the effect of firms that switch from one industry to another. We empirically examine the business sector of Finland and the manufacturing, construction, information and communications, and the service industries in years 2000-2018, divided to three sub-periods. We find that the structural change has had a major contribution to the productivity development. Firm entry, exit, and industry switching had generally positive effect on productivity growth in most industries and time periods considered. The main culprit for the stagnated labor productivity is the negative Olley-Pakes reallocation effect, which offsets and nullifies the otherwise positive productivity dynamics.

2.1 Introduction

Structural change is nowadays understood as an important source of productivity growth at the aggregate level (e.g., Syverson, 2011). The first systematic productivity decompositions that allow one to break down the aggregate productivity growth of an industry into components that capture the contributions of entry and exit of firms were introduced by Baily et al. (1992) and Griliches and Regev (1995). On the other hand, Olley and Pakes (1996) drew attention to the reallocation of resources across firms. Several studies have further extended the Olley-Pakes decomposition to capture entry and exit of firms, most notably, Maliranta (2003), Böckerman and Maliranta (2007), Diewert and Fox (2009), Hyytinen and Maliranta (2013), Melitz and Polanec (2015), and Maliranta and Määttänen (2015). In all these studies firms are classified into mutually exclusive groups of surviving firms, new entrants, and exiting firms.

Recently Bruhn et al. (2021) present sharp critique of the typical practice of performing productivity decompositions based on log-transformed productivity measures. They argue that the use of logs may lead to inaccurate aggregate growth rates as well as inaccurate estimates of the microsources of aggregate growth. Using firm-level data from the French manufacturing sector during the 2009-2018 period, the authors empirically demonstrate that the magnitude of the log-induced distortions is substantial. The recent study by Fornaro et al. (2021) reveals similar log-induced distortions in Finland. Alternative decomposition formulas also yield somewhat contradictory results. This motivates us to further examine the contribution of structural change on the stagnation of labor productivity in Finland.

While the use of logs can be problematic in the present context, Kuosmanen and Kuosmanen (2021) argue that the main source of the problem is the inconsistent aggregation of firms' productivity to aggregate levels of the industry or a sector. Aggregate productivity of an industry or a sector can be computed in two alternative ways. The first approach is to sum the inputs and outputs of firms to form the industry aggregates, and subsequently compute industry productivity using the aggregate inputs and outputs. The second approach is to first compute the firm-level productivity measures, and subsequently use a share-weighted average to compute the industry productivity. Consistent aggregation requires that these two approaches yield the same results: the order in which one performs the aggregation and productivity computations should not matter. However, the use of any arbitrary share-weighted average does not guarantee consistent aggregation.

The recent article by Kuosmanen and Kuosmanen (2021) argues that the geometric mean or harmonic mean would be inconsistent with the summation of the firm-level inputs and outputs to the aggregate level of the industry. In the case of labor productivity, it is easy to prove that consistent aggregation requires the use of weighted average, and that the employment shares are the correct share weights (see Section 2.2). Importantly, the common use of the share weighted average of log-productivity of firms is subject to a significant aggregation bias because the average of log-productivities is not the same as the logarithm of the average.

Another notable practical limitation of the log-productivity is that it is undefined whenever the inputs or outputs are negative or equal to zero. However, value added of a firm can be negative: excluding such highly unproductive firms from the outset can cause sample selection bias, especially during the turbulent times such as the financial crisis.

To address these issues, in this chapter we apply the theoretically consistent productivity decomposition by Kuosmanen and Kuosmanen (2021), applying it to labor productivity of the business sector in Finland. Section 2.2 introduces the decomposition formally. Section 2.3 describes the data sources and variables. Section 2.4 presents the decomposition results for the business sector of Finland. Section 2.5 subsequently focuses more specifically on manufacturing, construction, information and communication, and service industries. Section 2.6 presents our concluding remarks.

2.2 Aggregation-consistent stuctural change decomposition

Denote the labor productivity of firm *i* in period *t* as $p_{it} = y_{it} / l_{it}$ where y_{it} denotes the value added and l_{it} is the labor input. Aggregate productivity of the industry in period *t* is defined as

$$P_t = \frac{\sum_i y_{it}}{\sum_i l_{it}}.$$

Consistent aggregation of firm-level productivity measures to the industry or sector levels requires that the industry productivity is computed as a weighted average of firm-level productivity measures

$$P_t = \frac{\sum_i y_{it}}{\sum_i l_{it}} = \sum_{i=1}^{N_t} \left(\frac{l_{it}}{\sum_j l_{jt}} \right) p_{it} = \sum_{i=1}^{N_t} s_{it} p_{it} \,, \tag{2.1}$$

where $s_{it} = \frac{l_{it}}{\sum_j l_{jt}}$ is the employment share of firm *i* in period *t*. Clearly, if the wrong share-weights are used, the weighted average of firms' productivity does not equal the aggregate productivity of the industry. Further, it is easy to verify that the weighted average of log-productivities does not equal the log-productivity of the industry. When the objective is to gain insights on productivity impacts of structural change, in our view, the first step is to ensure that the aggregate productivity is correctly measured. Otherwise the aggregation bias can distort the decomposition and give a misleading picture of the contribution of structural change to aggregate productivity growth.

Using the results by Olley and Pakes (1996), equation (2.1) can be rewritten as

$$P_t = \overline{p}_t + \sum_{i=1}^{N_t} (s_{it} - \overline{s}_t)(p_{it} - \overline{p}_t)\,, \tag{2.2}$$

where the right-hand side of equation (2.2) breaks down the industry-level productivity to two components: the first one is the unweighted mean productivity of all firms and the second covariance term captures the impact of resource allocation across firms. In the context of total factor productivity, Olley and Pakes (1996) present an extensive discussion of how market competition between firms leads to an improved allocation over time as more productive firms increase their market share and less productive firms decline. In the present context of labor productivity, however, it is worth to note that market competition does not necessarily favor firms that have the highest labor productivity if it is achieved at the cost of excessive capital intensity.

Kuosmanen and Kuosmanen (2021) depart from (2.2), breaking down the unweighted mean productivity $\overline{p}_t$ to account for the contributions of entering and exiting firms as well as the firms that switch from one industry to another. Considering the nested sub-samples of continuing firms *S* and the continuing firms that continue to operate in the same industry *Sn*, they introduce the following simple decomposition:

Industry productivity (P_t)

= Productivity of non-switching surviving firms ($\overline{p}_{Sn,t}$)

+ Industry switch effect ($\overline{p}_{S,t} - \overline{p}_{Sn,t}$)

+ Entry and exit effect ($\overline{p}_t - \overline{p}_{S,t}$)

+ Reallocation effect ($P_t - \overline{p}_t$)

or equivalently,

$$P_t = \overline{p}_{Sn,t} + \left(\overline{p}_{S,t} - \overline{p}_{Sn,t}\right) + \left(\overline{p}_t - \overline{p}_{S,t}\right) + \left(P_t - \overline{p}_t\right). \tag{2.3}$$

The subscripts *S* and *Sn* refer to the sub-groups of continuing firms and continuing firms in the same industry, respectively.[1] By using the nested sub-groups, and by noting the equivalence of the Olley-Pakes allocation component of equation (2.2) and the last component of equation (3), the decomposition of Kuosmanen and Kuosmanen

[1] In this study, we use the Finnish TOL 2008 industry classification at the 5-digit level, which is based on the 4-digit European NACE industry classification, but provides a more detailed classification of some industries of interest.

(2021) effectively eliminate the share weights *s* from equation (2.3). Obviously the share weights are an important driver of industry productivity, but it is unnecessary to state them explicitly in the decomposition formula.

The original Olley-Pakes decomposition was stated in terms of the level of productivity. To decompose productivity changes, Kuosmanen and Kuosmanen re-state equation (2.3) as

$$\frac{P_t}{P_{t-1}} = \frac{\overline{p}_{Sn,t}}{\overline{p}_{Sn,t-1}} + \left[\frac{\overline{p}_{S,t}}{\overline{p}_{S,t-1}} - \frac{\overline{p}_{Sn,t}}{\overline{p}_{Sn,t-1}}\right] + \left[\frac{\overline{p}_t}{\overline{p}_{t-1}} - \frac{\overline{p}_{S,t}}{\overline{p}_{S,t-1}}\right] + \left[\frac{P_t}{P_{t-1}} - \frac{\overline{p}_t}{\overline{p}_{t-1}}\right]. \qquad (2.4)$$

This allows one to first calculate the changes in labor productivity separately at the firm-level and for the sub-groups of firms, and then add up the four components to arrive at the industry productivity growth, preserving the original interpretation of the components. Again, it is easy to verify that the sum of the four components on the right-hand side of (2.4) equals the aggregate productivity ratio on the left-hand side. The fact that the new decomposition applies to both the level of productivity and productivity growth is one of its appealing properties. Kuosmanen and Kuosmanen (2021) argue that their proposed decomposition provides a natural and intuitive extension of the static Olley-Pakes decomposition to the dynamic setting of productivity growth, where all components can be expressed as percentage changes.

2.3 Data

The analysis of this chapter makes use of the Financial Statement Data Panel of Statistics Finland. [2] This register data of firms contains the most essential profit and loss account and balance sheet data of all enterprises in virtually all all industries in Finland. All enterprises employing at least 20 persons are included in the direct data collection. The data of smaller enterprises and non-respondent enterprises are derived from administrative records (Business taxation register). To restrict attention on the business enterprises relevant for productivity, we exclude from the outset enterprises classified as housing company, voluntary association, foundation, pension fund, mortgage society, state or municipality, registered religious community, students' union or association, governmental institution, decedent's estate, bankrupt’s estate, state-

[2] As for more information on data, see https://taika.stat.fi/en/aineistokuvaus.html#!?dataid=FIRM_19862020_jua_FSSpaneeli_001.xml.

owned or municipally-owned public utility, and other suchlike non-profit organizations and associations.

To compute labor productivity, we use value added (thousand euros) and number of employees (full-time equivalent units). We exclude observations with missing values and observations with zero employees because labor productivity cannot be computed for those observations. All nominal values are deflated to the constant prices of the year 2010 using the GDP deflator of Statistics Finland.

The time period of this study ranges from 2000 to 2018. To gain insight on structural changes, we specifically analyze productivity changes in the following time periods:

2000–2005 (the growth period),
2006–2012 (the Great Recession),
2013–2018 (the follow-up recession and slow recovery).

The choice of these periods is justified by the following reasons. First, instead of focusing on yearly changes, considering longer time periods enables us to better capture the productivity impacts of structural changes such as entry, exit, and industry switching. Second, Statistics Finland conducted major revisions to the Financial Statement Data Panel in years 2006 and 2013, which may potentially cause difficulties in comparison of the data across these three sub-periods. Thirdly, the second sub-period covers to a large extent the period of Great Recession, which refers to the global recession in 2007-2009 that started from the subprime mortgage crisis in the USA and subsequently led to the European Debt Crisis. According to the seasonally adjusted quarterly real GDP data, the Finnish economy was initially in recession from the first quarter of 2008 until the second quarter of 2009, but there was also a follow-up recession from the second quarter of 2012 until the first quarter of 2015, which overlaps with the third sub-period of our study.

2.4 Business sector of Finland

In this section we first consider the entire business sector of Finland. More specifically, the following analysis covers all industries, except the following: primary production (01-05), financial intermediation (65-672), public administration and defence (75), public education units (80), activities of organisations (91) and extra-territorial organizations and bodies (98). According to Statistics Finland: "*These industries are not* *checked by Statistics Finland and the data are of poor quality*".[3] Therefore, we henceforth exclude these industries from further analysis, noting that inclusion of those industries would change the results only marginally.

Let us first consider the levels of labor productivity in the four sub-groups of firms: firms continued to operate within the same industry (Same industry), surviving firms that switched industry during the time period considered (Industry switch), firms that exited the business sector during the time period (Exit), and firms that entered the business sector during the period (Entry). Table 1 reports the average levels of labor productivity in these four sub-groups in the first and the last year of the three sub-periods 2000–2005, 2006–2012 and 2013–2018. All productivity figures are expressed in 1000 € per worker (in 2010 prices). To gain understanding of the relative sizes of the four sub-groups of firms in the sample, the right-most columns report their relative shares in percentage.

Table 1. Average levels of labor productivity (1000 € per worker, in 2010 prices) in the sub-groups of firms; the shares of firms in the groups of surviving firms, switching firms and entering and exiting firms (in percentage).

Period	Levels				Group shares (%)			
	Same industry	Industry switch	Exit	Entry	Same industry	Industry switch	Exit	Entry
2000	47.6	48.4	44.3		64.8	4.5	30.7	
2005	53.9	76.9		52.2	61.2	4.3		34.5
2006	58.5	66.9	56.0		54.7	8.8	36.5	
2012	54.8	51.9		57.0	49.7	8.0		42.3
2013	50.0	42.2	45.7		62.3	2.4	35.3	
2018	65.0	72.8		129.4	70.7	2.8		26.6

Note: The number of firms in the sample varied over this period as follows: 201,943 (2000); 213,768 (2005); 223,555 (2006); 245,992 (2012); 247,205 (2013); and 217,795 (2018).

During the period 2000-2005, labor productivity developed favorably in all sub-groups. The average productivity of firms continuing in the same industry increased from 48 thousand to more than 77 thousand euros per worker. In the sub-group of firms that switched from one industry to another, labor productivity increased even more rapidly,

[3] See the data description at: https://taika.stat.fi/en/aineistokuvaus.html#!?dataid=FIRM_19862020_jua_FSSpaneeli_001.xml

however, this group is relatively small and included only approximately 4 percent of all firms. Note that the exiting firms are only observed at the beginning of the time period, whereas the entering firms are observed at the end of the period: alternative productivity decompositions mainly differ in terms of how the counterfactual productivity change of these sub-groups is estimated. It is encouraging to observe that the productivity of entering firms was considerably higher than that of the exiting firms, and that the relative shares of the entering and exiting firms were rather large, almost one third of all observations.

During the time period of 2006-2012, the global recession that started from the financial crisis in the USA and subsequently lead to the European debt crisis had major adverse effect on labor productivity in Finland. The average labor productivity of continuing firms decreased, particularly in the sub-group of switching firms. Note also that the relative share of switching firms almost doubled compared to the previous sub-period. Fortunately, the entering firms had slightly higher level of productivity than the exiting firms, however, the entering firms achieved lower productivity level than the continuing firms.

In the last sub-period of 2013-2018, the average labor productivity returned to a more positive trajectory. In the sub-groups of continuing firms, average labor productivity increased considerably, especially in the sub-group of industry switchers. During this period, the exiting firms had a lower average labor productivity, but in particular, the group of entering firms had a notably larger average productivity than any other sub-group.

Next, we consider the average yearly change of labor productivity in the three sub-periods. Using the decomposition presented in the previous sub-section, we make use of the classification of firms to four sub-groups, but also take into account changes in the labor shares of firms to capture the Olley-Pakes reallocation component. Table 2 summarizes the results.

The first column of Table 2 indicates the aggregate productivity change of the business sector in Finland. There was modest productivity growth in the first sub-period 2000-2005, but during the second sub-period 2006-2012 labor productivity declined rather remarkably. In the third sub-period 2013-2018 productivity of the business sector recovered, but did not reach the pre-recession levels. Decomposing the aggregate productivity to its components helps to shed light on the underlying structural dynamics.

Table 2. Average change in labor productivity (% per year) in the business sector of Finland and its four components

	Business sector of Finland	Continuing firms in the same industry	Industry switch effect	Entry and exit effect	Reallocation effect
2000–2005	0.46	= 2.67	+0.61	+0.04	-2.86
2006–2012	-2.12	= -1.06	-0.42	+0.66	-1.31
2013–2018	1.94	= 5.99	+0.27	+7.83	-12.15

The second column indicates the average labor productivity growth in the subgroup of continuing firms that remain in the same industry according to the 5-digit TOL 2008 industry classification. These average productivity figures can be interpreted as the baseline productivity change in the absence of structural changes. Table 2 indicates that the average productivity growth of continuing firms notably exceeded that of the business sector in all three time periods, especially in the first and the last sub-periods. In other words, there has been strong productivity growth at the firm level, despite the stagnation at the aggregate level.

The third and fourth columns indicate the incremental contribution due to industry switching of continuing firms (third column) and the entry and exit of firms (fourth column). Recall that the industry switching is a novel component that has not been considered in any previous structural change decompositions. We find that industry switching had a small but noteworthy positive contribution to aggregate productivity growth in the first and the third sub-period, however, industry switching had a negative effect on productivity growth during the crisis years of the second sub-period. In contrast, the entry and exit effect was positive in all time periods, and particularly strong during the third sub-period, thanks to high average productivity of entering firms during that period (compare with Table 1).

The right-most column of Table 2 reports the Olley-Pakes reallocation effect, which can be interpreted as the change in the covariance of the employment shares and the firm-level productivity measures. The reallocation effect is negative in all time periods, and in practice cancels out the productivity growth of continuing firms and the positive contributions of industry switching and the entry and exit. Our decomposition results point to the deteriorating resource allocation as the main culprit of the stagnated labor productivity of Finland's business sector. To gain further insight, we next examine the structural change components at a more detailed level of 1-digit industries.

2.5 Industry-level decompositions

This section zooms from the aggregate level of the business sector to more specific industries at the 1-digit and 2-digit NACE/TOL levels. We consider the following four industries:

Manufacturing (C)

Construction industry (F)

Information and communication industry (J)

Service industries (69-96)

It is worth noting that when we focus on a more narrowly specified industries, the classification of firms to the sub-groups of entering, exiting, and switching firms changes to some extent compared to the previous analysis of the business sector. When decomposing aggregate productivity change, we can only account for firms that operate in the given industry or sector of interest, even if the entering firms come from another industry or exiting firms continue to operate in another industry. For example, if an ICT manufacturing firm switches to the ICT services, this firm will be classified as industry switcher within the business sector, however, it will be treated as an exiting firm in the analysis of the manufacturing industry. The industry switch effect will only include firms that switch withing the manufacturing industries. This is worth keeping in mind when interpreting the decomposition results. For the sake of brevity, we here focus on the decomposition of productivity change in these four industries: the average levels of productivity of the sub-groups and their relative shares are reported in Appendix 1.

Table 3 reports the productivity decomposition for the manufacturing industries (C). This industry had productivity decline already in the first sub-period, which further deteriorated during the crises of the second sub-period. The main culprit is the negative Olley-Pakes reallocation component, analogous to Table 2, but fortunately it is relatively small in the last sub-period. Industry switching and the entry and exit had small positive contributions in most sub-periods considered, the positive entry component was particularly notable during the last sub-period.

Table 4 examines the construction industry (F). This industry exhibited productivity growth in all three sub-periods, including the second sub-period of 2006-2012. In this sub-period the productivity of continuing firms declined, but the positive Olley-Pakes reallocation component offset the negative effect. The reallocation component became negative in the last sub-period, but then the strong growth of the continuing firms and the entry of high-productivity firms maintained the growth of this industry.

Table 3. Manufacturing industry (C): Average change in labor productivity (% per year) and its four components

	Manufacturing industry	Continuing firms in the same industry	Industry switch effect	Entry and exit effect	Reallocation effect
2000–2005	-1.20	= 2.67	+0.05	+0.15	-4.08
2006–2012	-4.80	= -1.19	-0.19	+0.13	-3.55
2013–2018	2.86	= 1.37	+0.08	+1.85	-0.44

Table 4. Construction industry (F): Average change in labor productivity (% per year) and its four components

	Construction industry	Continuing firms in the same industry	Industry switch effect	Entry and exit effect	Reallocation effect
2000–2005	2.02	= 1.83	+0.05	+0.19	-0.05
2006–2012	0.34	= -0.62	-0.53	+0.38	+1.12
2013–2018	1.24	= 3.19	-0.08	+6.68	-8.55

The ICT-industry (J) also managed to maintain productivity growth in all three sub-periods, as indicated by Table 5. Interestingly, the industry switching had a major positive contribution in all three sub-periods, especially during 2000-2005. In contrast, the entry and exit effect was negative during the first two sub-periods. There was an extremely large positive contribution of entry and exit in the last sub-period, but unfortunately it was offset by the negative reallocation effect. Note that many firms in this industry were closely linked to the supply chain of Nokia Corporation, the world's largest mobile phone manufacturer from 1998 till 2011, which started to rapidly losing its market share towards the end of the second sub-period of this study. The downfall of Nokia resulted as major restructuring of this industry. Hence, it is not surprising to see double-digit structural change components in the last sub-period reported in Table 5.

Table 5. Information and communication industry (J): Average change in labor productivity (% per year) and its four components

	ICT-industry	Continuing firms in the same industry	Industry switch effect	Entry and exit effect	Reallocation effect
2000–2005	1.79	= 1.59	+1.29	-1.06	-0.03
2006–2012	0.08	= -0.22	+0.18	-0.07	+0.20
2013–2018	2.34	= 0.73	+0.42	+17.06	-15.87

Table 6. Service industries (69-96): Average change in labor productivity (% per year) and its four components

	Service industries	Continuing firms in the same industry	Industry switch effect	Entry and exit effect	Reallocation effect
2000–2005	1.79	= 2.74	+0.02	-0.53	-0.44
2006–2012	-0.39	= -0.14	-0.15	-0.01	-0.09
2013–2018	0.82	= 0.54	+0.18	+11.69	-11.58

Finally, we consider service industries 69-96, which include such industries as legal and accounting activities, management consulting, architectural and engineering activities, research and development, advertising and market research, education, health care, public administration and defence, among others. Recall that most of these service industries were excluded from the analysis of the business sector in Section 2.4. For the sake of completeness, we here extend the productivity analysis to cover the service sector as well.

Table 6 presents the labor productivity decomposition of the service industries. The overall picture does not differ much from the pattern observed in other industries. The continuing firms serve as the main engine of growth, and the components of structural change are relatively small in the service sector, except for the last sub-period 2013-2018. In that period we observe a pattern of large positive entry and exit effect offset by large negative reallocation effect, very similar to the ICT-industry. We suspect that this pattern may be related to the major restructuring of Finland's ICT sector observed in Table 5: although industries 69-96 do not span the core ICT services, these service industries are heavy users of the ICT services and as such part of the broader digital economy of Finland.

2.6 Conclusions

While structural change has been recognized as an important driver of productivity growth at the aggregate levels of industries and sectors, most commonly used decompositions are prone to aggregation errors and log-induced bias, which can blur both the overall picture about productivity change and its structural change components. To address this issue, Kuosmanen and Kuosmanen (2021) proposed an aggregation-consistent decomposition that applies to both levels and the change of productivity, and also explicitly considers the productivity effect of firms that switch from one industry to another. In this chapter we have applied this approach to examine labor productivity in Finland's business sector and in four one-digit industries during the period 2000-2018.

We find that structural change has had a major contribution to labor productivity in Finland. The entry and exit of firms as well as industry switching contributed to productivity growth in most periods and industries considered. Indeed, relatively large shares of entering, exiting and switching firms point towards dynamic renewal of Finland's business sector, especially during the years of the Great Recession. However, the negative contribution of the Olley-Pakes reallocation component tends to offset and nullify the positive contributions in most sectors and periods considered. Indeed, we find the deteriorated resource allocation as the main culprit for the stagnated labor productivity.

The negative reallocation component does not necessarily mean that workers have moved from high-productivity firms to low-productivity firms. A more likely explanation for the negative reallocation effect is that workers remained in their jobs despite the entry of new high-productivity firms, which failed to attract workers to increase their market share. According to the popular media, many firms in Finland have faced difficulties in finding skilled workers. Indeed, the mismatch of skills and experience can be one impediment of growth. On the other hand, the labor market in Finland remains rather rigid and heavily regulated, which can affect the competition between firms for the high-skill workforce. Finally, it is not self-evident that the high-productivity startups need workforce to grow if their superior productivity performance is based on highly automated, capital intensive technology. As we noted in Section 2.2, market competition does not necessarily reward firms that achieve high level of labor productivity; firms' competitiveness is more closely related to the total factor productivity that also takes into account the capital inputs.

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3 Carbon productivity and structural change in electricity generation

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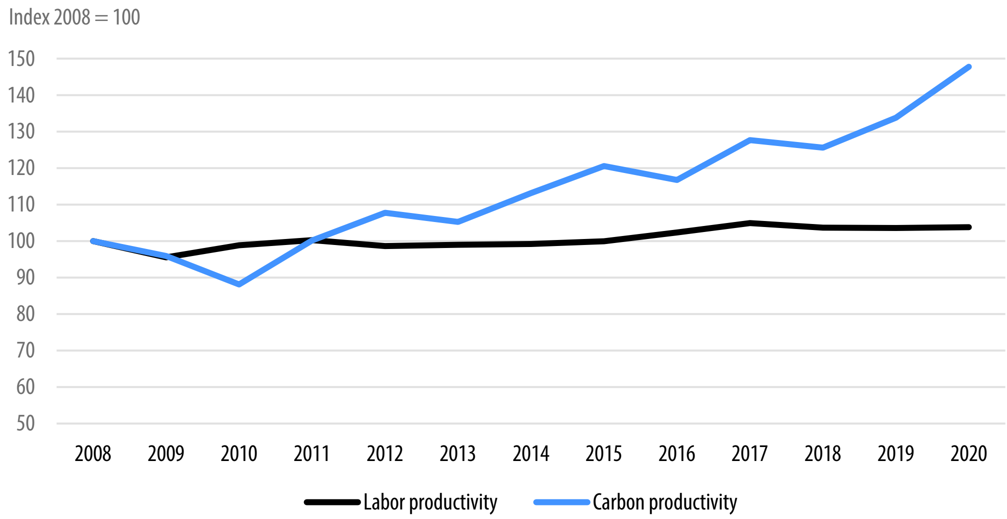
Abstract: This chapter examines the contribution of structural change on carbon productivity growth by decomposing the change of carbon productivity in Finland's electricity generation industry. Previous carbon productivity decompositions consider technical progress and efficiency change at the regional and industry levels. To our knowledge, this study is the first attempt to quantify the structural change effects using firm-level data of green-house gas emissions. Our empirical results indicate major growth of carbon productivity, influenced by rather radical structural changes in this industry.

3.1 Introduction

Mitigating climate change through reduction of green-house gas (GHG) emissions has been a major policy objective since the early 1990s. The use of fossil fuels such as coal, oil, and natural gas is the main source of GHG emissions. The first commitment period of the Kyoto Protocol started in 2008, and since then, a significant proportion of capital investments has been devoted to GHG abatement in the EU and other Annex I parties to the agreement. While reducing the use of fossil fuels is clearly necessary to mitigate the climate change and Finland's dependence on imported energy, there is an opportunity cost.

The fact that conventional labor productivity and total factor productivity measures overlook the great achievements in the GHG abatement may at least partly explain the productivity stagnation. To illustrate the tradeoff, Figure 2 depicts two partial productivity indices (2008=100), the labor productivity (value added per worker) and carbon productivity (value added per tonne of GHG) for the period 2008–2020 in Finland. While labor productivity in Finland has stagnated close to its 2007 level for more than a decade, carbon productivity shows a strong growth trend during 2008–2020, with the average growth rate of 4 percent per year. Figure 2 illustrates that there has been major productivity growth in terms of carbon productivity, but the conventional productivity statistics such as labor productivity or total factor productivity fail to capture this growth.

Figure 2. Labor productivity (black line) and carbon productivity (blue line) in Finland in 2008-2020.



Source: Eurostat and own calculations based on Eurostat data.

Understanding the development of carbon intensity (i.e., GHG emissions per value added) and its inverse carbon productivity (i.e., value added per tonne of GHG) has attracted considerable research attention at the aggregate levels of countries, regions and industries (e.g., He and Su, 2011; Ekins et al., 2012). A number of studies decompose the changes in carbon intensity or carbon productivity to such underlying components as technical change and efficiency change (e.g., Liu and Ang, 2003; Zhou and Ang, 2008; Meng and Niu, 2012; Lin and Du, 2014; Hu and Liu, 2016), applying insights from index decomposition analysis and/or production theory. To our knowledge, however, the contribution of structural changes such as entry and exit of producers or the reallocation of emissions between producers has not been investigated before. This chapter fills the gap by applying the novel decomposition introduced by Kuosmanen and Kuosmanen (2021) to carbon productivity using unique firm-level emissions data of Finnish firms.

The energy industry is one of the main contributors of the GHG emissions in Finland as well as in other industrialized countries. Since the energy generation is subject to the European emissions trading scheme, the GHG emissions are routinely recorded and monitored at the firm-level. Therefore, in this chapter we focus attention on the electricity generation industry, which has the NACE code *3511 Production of electricity*. In the Finnish TOL 2008 classification, this industry is further divided to the following 5-digit industries:

35111 Production of electricity with hydropower and wind power

35112 Separate production of electricity with thermal power

35113 Combined heat and power production

35114 Production of electricity with nuclear power

35115 Heat and power production for industry

The detailed 5-digit industry classification of Finland enables us to examine the structural changes in the electricity generation industry. Due to stricter GHG emissions standards and increasing prices of the emissions rights in the European emissions trading system (ETS), the share of renewable energy has sharply increased in Finland's energy portfolio. The growing wind-power industry has also attracted considerably entry of new firms. As for continuing energy companies, as the share of renewables in a firm's energy portfolio exceeds that of other energy sources, the TOL classification of the firm is changed to 35111. Such change of industry classification is referred to as industry switching. While the combined heat and power production has conventionally been seen as an efficient way to utilize by-production, this industry has faced serious difficulties to replace coal as a fuel. Besides, entry, exit, and industry switching, reallocation of emissions and emissions rights between the firms forms one important source of structural change.

The rest of this chapter is organized as follows. In Section 3.2 we introduce a structural change decomposition of carbon productivity, adapted from the recent article by Kuosmanen and Kuosmanen (2021). Section 3.3 introduces the data used in this chapter. Section 3.4 presents and discusses our main empirical results. Section 3.5 concludes.

3.2 Structural change decomposition of carbon productivity

In order to decompose aggregate carbon productivity of an industry into different components, we adopt the productivity decomposition developed by Kuosmanen and Kuosmanen (2021) to carbon productivity. Denote the carbon productivity of firm *i* in period *t* as c_{it} and aggregate carbon productivity of the industry in period *t* as C_t. Following the similar logic used in labor productivity decomposition presented in Chapter

2, the aggregate carbon productivity of an industry can be defined as the sum of four components as follows:

Industry carbon productivity (C_t)

= Carbon productivity of non-switching continuing firms ($\overline{c}_{Sn,t}$)

+ Effect of industry switching ($\overline{c}_{S,t} - \overline{c}_{Sn,t}$)

+ Entry and exit effect ($\overline{c}_t - \overline{c}_{S,t}$)

+ Reallocation effect ($C_t - \overline{c}_t$)

or equivalently,

$$C_t = \overline{c}_{Sn,t} + (\overline{c}_{S,t} - \overline{c}_{Sn,t}) + (\overline{c}_t - \overline{c}_{S,t}) + (C_t - \overline{c}_t). \quad (3.1)$$

As a result, the first component in equation (3.1) is the average carbon productivity of non-switching continuing firms. The second component captures the effect of industry switching that is very common in many industries. The third component captures the productivity impact of entry and exit and the fourth component captures allocation of GHG emissions between the firms.

3.3 Data

The analysis is based on the annual national greenhouse gas inventory of Statistics Finland[4]. In addition to firm-level emission data from GHG inventory we utilize the Financial Statement Data Panel. The statistics comprise industry-specific data and describe enterprises operating in Finland. The panel includes profit and loss account variables and balance sheet data.

For computing carbon productivity at firm level, we use value added in euros (deflated using the GDP price deflator) and GHG in tonnes of GHG emissions (CO_2 equivalents). Note that to be able to compute carbon productivity the measured GHG emissions must be strictly positive. Therefore, firms that only produce renewable electricity through hydro, solar or wind power and do not have any direct GHG emissions are excluded from the sample. On the other hand, firms that specialize in renewable energy

[4] For further information about the GHG inventory, please see the website: https://www.tilastokeskus.fi/tup/khkinv/index.html.

but also generate some proportion of electricity using fossil fuels are included in the following analysis.

As noted in the Introduction, we focus on the 4-digit NACE industry 3511 Production of electricity and its five sub-industries according to the Finnish TOL 2008 industry classification. The time period of this study ranges from 2000 to 2019. Similar to the labor productivity analysis presented in Chapter 2, we here examine carbon productivity changes in three time periods:

1) 2000–2006 (the growth period),
2) 2007–2012 (the Great Recession),
3) 2013–2019 (the follow-up recession and slow recovery).

3.4 Results

Let us first compare the average levels of carbon productivity in the sub-groups of continuing, industry-switching, entering and exiting firms. The left part of Table 7 presents the carbon productivity levels (1000 € per tonne of GHG in 2015 prices) for these four sub-groups of firms during the three subperiods: 2000–2006, 2007–2012 and 2013–2019. The right part of Table 7 presents the relative shares of firms in those sub-groups.

During the first period 2000-2006, the electricity generation industry experienced major structural change in the form of entry, exit, and industry-switching: see the four columns on the right-hand side of the table. Approximately one third of the firms continued within the same 5-digit industry within electricity generation, one third of firms switched to a different 5-digit industry within electricity generation, and almost one third of firms exited the energy generation industry and were replaced by new entrants. The average levels of carbon productivity were low among the continuing firms, especially the industry-switchers. In contrast the average carbon productivity was high both in the groups of exiting and entering groups.

In the second sub-period the industry structure was more stable as almost 75 percent of firms observed in 2007 continued to operate in the same 5-digit TOL industry in 2012. In this sub-group of continuing firms, the average level of carbon productivity was relatively high already in 2007, and continued to grow strongly. In the group of entering firms, the average carbon productivity was slightly negative due to negative value added. Note that the negative value added of startups might relate to subsidized production: the Finnish government introduced feed-in tariffs for the renewable wind, wood, and biogas production in 2011.

Table 7. Electricity generation: average levels of carbon productivity (1000 € per tonne of CO2 eq. in 2015 prices) of continuing, switching, entering and exiting firms and their relative shares (in %).

Period	Levels (1000 € per tonne)				Shares (%)			
	Same industry	Industry switch	Exit	Entry	Same industry	Industry switch	Exit	Entry
2000	0.67	-0.56	8.58		36.7	33.3	30.0	
2006	0.21	0.00		16.39	32.4	23.5		44.1
2007	4.16	0.11	0.03		74.4	12.8	12.8	
2012	10.71	0.99		-0.07	69.0	11.9		19.0
2013	7.69	1.28	-1.16		72.1	11.6	16.3	
2019	2.32	0.30		1.89	64.6	4.2		31.3

The sample includes 64 obeservations in 2000–2006, 81 in 2007–2012, and 91 in 2013–2019.

In the last sub-period 2013-2019, the share of continuing firms remained high, but the industry attracted new firms: almost one third of the firms in 2019 had entered this industry after 2013. In the sub-group of continuing firms, the average level of carbon productivity decreased, both for firms that continued in the same industry and those that switched industry. The average carbon productivity was negative in the in the group of exiting firms; we suspect that many firms subsidized by the feed-in tariffs that entered during the second sub-period remained unprofitable and had to exit during the third sub-period.

Now, how do the structural changes observed in Table 7 influence carbon productivity growth of the industry? Table 8 presents the average change in carbon productivity of the industry (% per year) and its structural change components for the three sub-periods. We find that carbon productivity growth of the electricity generation industry was positive in all sub-periods, with the largest growth rate in 2007–2012. However, the engine of growth varied considerably between the sub-periods, and the structural change effects play a major role.

Table 8. Electricity generation: average change in carbon productivity (% per year) and its structural change components.

	Energy industry	Continuing firms in the same industry	Industry switch effect	Entry and exit effect	Reallocation effect
2000–2006	6.15	= -11.50	+17.74	+23.25	-23.34
2007–2012	10.37	= 31.53	+0.58	-3.87	-17.88
2013–2019	5.42	= -11.63	+0.36	+0.97	+15.72

In the first sub-period, the largest contributions to carbon productivity growth came from the entry and exit of firms and the industry switching of continuing firms. In contrast, carbon productivity of the continuing firms in the same industry deteriorated, as did the allocation of GHG emissions between the firms. During this period, the prices of emissions rights were relatively low in the European ETS.

In sharp contrast, the continuing firms in the same industry managed to improve their carbon productivity massively during the second sub-period of 2007-2012. This is likely due to relatively high electricity prices during this period that benefited the established producers. In contrast, the entry and exit effect became negative, which may be associated with the subsidized renewable production that started in 2011. The allocation of GHG emissions continued to deteriorate during this period.

In the last sub-period situation is completely different. Carbon productivity of the continuing firms in the same industry falls surprisingly sharply. The entry, exit, and industry switching have positive contributions. Most remarkably, the reallocation effect becomes large and positive. We suspect that this remarkable improvement in the allocation of GHG emissions is due to the increased price of emissions rights in the ETS, which increased the costs of fossil fuels towards the end of the last sub-period.

3.5 Conclusions

According to a commonly held view shared by economists and policy makers, Finland's productivity growth has stagnated to since 2007. However, the commonly used measures of labor productivity and total factor productivity overlook the great progress achieved in carbon productivity. The vast investments to GHG abatement do have an opportunity cost, which has likely contributed to the observed productivity stagnation. Fortunately labor productivity did not decline as a result of the vast investments to GHG abatement.

This study is a first attempt to shed light on the role of structural changes in the carbon productivity growth in the electricity generation industry. Using a unique firm-level data of GHG emissions and a novel structural change decomposition, we find that entry and exit of firms as well as industry switching had very large impacts on carbon productivity growth especially during the first sub-period 2000-2006 considered in this chapter. The allocation of GHG emissions deteriorated during the first two sub-periods, but became the main driver of carbon productivity growth during the most recent sub-period 2013-2019. This likely relates to the fact that the price of emission rights in the ETS has sharply increased in the recent years. In addition, the price of electricity and the fuel costs have been highly volatile during this time period, which can cause large swings in the structural change components as well.

In light of the ongoing green transition and Finland’s ambitious target of carbon neutrality by the year 2035, we expect to see further growth of carbon productivity, not only in electricity generation but also in manufacturing industries. This can cause major structural changes in all energy intensive industries. How to support productivity growth and the green transition simultaneously is a major policy challenge, which clearly requires further attention. We hope that this chapter presents a valuable step in this direction, showing how the established tools of productivity analysis can be adapted to carbon productivity. Further research is clearly needed in this direction.

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4 Trade shock, firm-level characteristics and productivity

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Abstract: This chapter examines the effect of export demand shock on the labor productivity in Finnish manufacturing exporters. The analysis utilizes various administrative registers combined with information on world trade flows. The adjustment to trade shock is examined separately for three distinct periods, namely 1999-2007, 2007-2011 and 2011-2016. Our estimation results show that exogenous export demand shock increases labor productivity in Finnish manufacturing firms, although this effect diminished after the financial crisis. The productivity growth response to export demand shock was stronger in younger firms and firms with higher equity ratios during the financial crisis.

4.1 Introduction

There has been a strong stagnation in labor productivity in Finland since the financial crisis of 2008. This could be due to a mismatch of labor, lack of firm-level innovation, or insufficient physical investments. The labor productivity decline was particularly strong in the manufacturing industry in 2000-2012, whereas after 2013, labor productivity was positive (Chapter 2.5). Accordingly, a high share of manufacturing firms operates in international trade. Interestingly, however, increased import competition typically leads to improved productivity (e.g., Bloom, Draca and Van Reenen, 2013; Auer, Degen and Fischer, 2013; Syverson, 2011, for a review). The first objective of this chapter is to examine the causal effect of export demand shock on labor productivity in Finnish manufacturing firms. Our novel evidence shows that an increase in world market size increased labor productivity between 1999 and 2011, though this positive effect diminished in the years after the financial crisis.

The second objective is to examine the association of firm-level characteristics with labor productivity and whether the productivity growth response to export demand shock varies by different firm-level characteristics, such as age and size. The overall literature on the associations of different firm-level characteristics and productivity growth is extensive (e.g., Syverson, 2011). Our aim is not to provide a comprehensive review of this research, but rather to highlight a few salient papers that are relevant to our study. First, the empirical literature on productivity at the firm-level considers size one of the main sources of heterogeneity in firm performance. Large firms are often found to be more productive than small ones, although reverse findings have also been presented. A recent theory and empirical evidence even suggests that smaller firms are more productive than larger firms (e.g., Dhawan 2001, Diaz and Sanchez, 2008). Although small firms have a lower survival probability, they might undertake actions that make them more efficient when facing market uncertainties and capital constraints. The higher level of flexibility and non-hierarchical structure of smaller firms might be related to their managerial ability to adjust and use capital and labor more efficiently. Halkos and Tzeremes (2007) argue that there is an indirect effect of firm size on firm productivity because size conditions the effect of internal factors on productivity. We find only a modest positive size-productivity relationship for the period 2007-2011.

Second, productivity may vary by firm age. Young firms have higher failure rates, but conditional on survival, younger firms grow faster compared to older firms (e.g., Haltiwanger, Jarmin and Miranda, 2013). At least to some extent, the firm age-growth relationship could be explained by the composition of the workforce in younger firms employing younger and innovative employees (Ouimet and Zarutskie, 2014). Our results support the notion that younger firms show higher productivity growth after 2011.

Third, there is a literature linking R&D (research and development) and product innovation with productivity (Syverson, 2011, for a review). Bloom and Van Reenen (2002) show that patents increase firm-level productivity, but market uncertainty reduces this positive effect. Cainelli, Evangelista and Savona (2006) find that there is a positive association between innovation and productivity in the service sector. Hall, Lotti and Mairesse (2013) report that R&D and ICT are both positively associated with labor productivity. Our results point to interesting differences in results regarding patents in times of economic up- and downturns. Accordingly, the number of patents reduced the positive effect of export demand shock during the financial crisis.

Fourth, a firm's financial strength is related to productivity and growth. Huynh and Petrunia (2010) show that financial factors (e.g., leverage) are positively related to the growth of new young firms. Coriceli et al. (2012) find that productivity growth increases with leverage until it reaches a critical threshold beyond which leverage lowers productivity. Earlier studies have also found that industries and firms that are more dependent on external banking finance grow significantly less during economic crises (e.g., Görg and Spaliara, 2014). We note that firms with higher financial strength (as measured by the equity ratio) have approximately 1.5% lower annual labor productivity growth compared to firms with lower equity. However, positive productivity growth as a response to export demand shock was stronger within firms that had better financial situation during the financial crisis.

Lastly, there are many studies showing that foreign-owned firms are more productive than domestic enterprises (see Xu, Liu and Abdoh, 2022, for a recent literature review). There are many potential mechanisms through which foreign ownership could affect firm productivity. For example, foreign-owned firms tend to have higher innovation (e.g., R&D investments), greater telecommunication usage, superior management practices, and more efficient financial support (Xu, Liu and Abdoh, 2022, for a review). When many of these potential channels, such as innovation and equity ratio, are controlled for in models, we do not find any clear connection between foreign ownership and productivity level.

In the next section, we present the register datasets used in our empirical analysis, describing the main independent variables and measure for labor productivity. Then, we present our empirical model and carry out an econometric analysis to estimate the effect of export demand shock on labor productivity in Finnish exporting firms in manufacturing industry. Finally, we conclude our paper by setting the findings in a larger context.

4.2 Data and variables

This analysis makes extensive use of various administrative registers from Statistics Finland, which are linked together using unique firm identification codes. The main data are the Financial Statement panel data, which are intended for research use, including firms' most essential profit and loss accounts and balance sheet data. Especially value added and other provisional variables are comparable over time. The data exhaustively cover all independent business enterprises in almost all industries for the years 1999-2016. All enterprises with at least 20 employees are included in the direct data collection, and the data of mainly smaller enterprises and non-respondent enterprises are derived from administrative records (business taxation registers). The data include information on, for instance, industry, number of personnel, value added, research and development expenses, investments, sales, equity ratios, and quick and current ratios.

To these data we match information on age, foreign ownership, and region from the Statistics of the Business Register. In addition, we include the number of domestic and EU patents based on information provided by the Finnish patent and register office.

To measure an exogenous export demand shock instrument, we utilize two additional data sources. The first is Finnish customs data, which cover both the exports and imports of goods at the firm level. These data include the total values of imports and exports to/from all partner countries. The goods are categorized at the most detailed goods category (8-digit level) based on the CN (Combined Nomenclature). The UN's Comtrade database is a comprehensive register of all export and import flows between country pairs and includes goods classifications up to the 6-digit HS2002 level. The second data we use are the Comtrade database, which in connection to the Finnish customs data are used to calculate for each good – reporting country pair the total imports from the world market and the imports from Finland. The export demand shock instrument is calculated only for firms that are engaged with international trade that employed at least 10 employees in the initial year.

The outcome variable is labor productivity, which is measured as the value added per employee. The baseline specifications include firm-level characteristics, that are hypothesized to be associated with productivity. These include:

- Firm size (number of employees/100)
- Firm age (in years)
- Indicator for foreign ownership (over 50% of the firm is foreign owned)

In addition, we use three variables that describe firm innovation. These are:

- External R&D expenditures (in euros)
- Number of domestic and EU patents
- Investment expenditure (in euros)

Total investment expenditures include investments in software, increases in machinery and equipment and increases in buildings and structures. As a measure for firm financial strength, we use:

- An indicator for equity ratio, measured as the below or above sector-specific median equity (Aghion et al. 2019).

Finally, the model is augmented with additional controls for:

- Industry (9 indicators)
- Region (19 indicators).

The information on region is based on the 19 NUTS (Nomenclature of Territorial Units for Statistics). It is important to control for region, as evidence shows large disparities in productivity performance across Finnish regions (Böckerman and Maliranta, 2007).

The information on detailed industry in the manufacturing sector is based on the Standard Industrial Classification and is aggregated and categorized into 9 groups based on a 2-digit classification. These categories are food products and beverages; textiles, wearing and leather products; wood, pulp and paper products; chemicals, rubber and non-metallic products; metal products; machinery and equipment; electrical and optical equipment; transport equipment; and furniture and recycling.

As suggested by Aghion et al. (2019), the export demand shock for firm *f* between *t* and t_0 is constructed as:

$$\Delta D_{ft} = \sum_{js} w_{fjst_0} \frac{Mj{,}s{,}t - Mj{,}s{,}t0}{\frac{1}{2}(Mj{,}s{,}t + Mj{,}s{,}t0)}, \tag{4.1}$$

where weight *w* represents firm *f*'s initial (t0) share of sales of product *s*, at the HS6 level, to destination country *j*, and M_{jst} is the world export flow of product s to destination *j* in time *t*. This is quite similar to a standard shift-share, or “Bartik” variable.

An increase in world market size could affect Finnish firms in numerous ways. If firm *f* initially exported a high share of product *s*, then an increase in the world demand of product *s* could affect domestic firm to export more. In contrast, an increase in world demand could increase low-wage import competition (e.g., from China), which could decrease domestic prices (e.g., Nilsson Hakkala and Pan, 2019; Auer et al. 2013), exporting and/or sales, and employment. The firm’s improved/dinimished performance could also lead to changes in labor productivity through different channels. The effect of export demand shock on labor productivity could thus be positive or negative.

4.3 Method

We study how various firm-level characteristics are associated with the firm’s productivity growth for the years 1999–2016. This time frame includes three distinct periods that we examine separately: 1999-2007, 2007-2011 and 2011-2016. The first period includes China’s WTO membership, the second period includes the financial crisis period, and the third period includes the peak of the Greek government debt crisis. With our data, the first estimation strategy is described by:

$$\Delta y_{ft} = \sum_{k=1}^{n} \beta_k x_{kt0} + \gamma \Delta D_{ft} + \theta_r + \alpha_s + \varepsilon_{ft}, \tag{4.2}$$

where Δy_{ft} represents the difference in log of productivity of firm f between years t and t_0 (e.g., between 2007 and 1999), and x_k is a vector of firm characteristics measured in year t_0 (e.g., in 1999). Parameter γ captures the effect of export demand shock on productivity, and parameters β_k capture the associations of other firm-level characteristics with productivity. Parameter θ_r captures the region effects, α_s captures the sector effects, and ε_{ft} is an error term. The standard errors are clustered at the firm-level.

Heterogeneity of the effects of export demand shock is next examined by including interaction terms between the shock variable D_{ft} and other firm-level controls in vector x_k:

$$\Delta y_{ft} = \sum_{k=1}^{n} \beta_k x_{kt0} + \gamma \Delta D_{ft} + \sum_{k=1}^{n} \delta_k (x_{kt0} \times D_{ft}) + \theta_r + \alpha_s + \varepsilon_{ft}, \qquad (4.3)$$

where parameters δ_k capture, for example, whether the effect of export demand shock on firm's productivity growth differs by age, size, or financial strength.

4.4 Results

Table 9 reports the descriptive statistics of the variables. The means of all firm-level factors are measured in year t_0 (1999, 2007 or 2011) except for productivity growth, which shows the difference in log of productivity between years *t* and t_0. Accordingly, export demand shock is measured as described in equation (4.1). The euro values for R&D expenditures and investments are deflated to 2016 prices using the cost-of-living index.

Table 9 shows clear labor productivity growth in Finnish manufacturing export firms between 1999-2007 (3.4% annually) and 2011-2016 (1.4% annually). The labor productivity growth was negative during the financial crisis (1.4% annually). The equity ratio is approximately 41%, which is considered as the sufficient level. The firms were, on average, 15 years old in 1999 and 25 years old in 2011. The number of employees vary between 119 and 155. In 1999, 11% of the exporting firms were foreign-owned, and this share increased to 17% in 2011. The firms all have approximately less than 1 patent. However, patents tend to accumulate in the same firms. Further examination reveals that only 6-8% of the firms in our sample have at least 1 patent. There is also heterogeneity in the number of patents across different manufacturing sectors. For example, in 2011, approximately 16% of firms had patents that operated in the machinery and equipment or electrical and optical equipment sectors.

Table 9. Means of the variables

	1999	2007	2011
Productivity growth	0.272	-0.049	0.071
Initial productivity	10.7	11.0	11.0
Shock	0.179	0.023	-0.035
Equity ratio	39.4	41.8	41.0
Age of firm (in years)	15.3	23.4	25.1
Size (employees)	119	155	146
At least one patent	0.06	0.07	0.08
Sum of patents	0.06	0.49	0.50
Foreign ownership	0.11	0.16	0.17
R&D expenditure (€)	131931	935524	1818208
Investments (€)	874608	2441598	1324203
Food products and beverages	0.04	0.05	0.05
Textiles, wearing and leather products	0.07	0.06	0.05
Wood, pulp and paper products	0.20	0.17	0.16
Chemicals, rubber and non-metallic mineral products	0.15	0.16	0.18
Metal products	0.15	0.16	0.16
Machinery and equipment	0.16	0.19	0.19
Electrical and optical equipment	0.10	0.11	0.11
Transport equipment	0.05	0.04	0.05
Furniture and recycling	0.08	0.06	0.05
Uusimaa region	0.26	0.24	0.24
N	1602	1571	1398

Note: The mean of difference in log of labor productivity is measured between 1999-2007 (Column 1), 2007-2011 (Column 2007) or 2011-2016 (Column 3).

R&D expenditures have increased over time, whereas the money spent on investments was the highest in 2007 (2.4 mil. Euros), just before the financial crisis. A high share of manufacturing export firms operate in the wood, pulp, and paper products sector (16-20%), machinery and equipment (16-19%), metal products (16%), and chemicals, rubber, and non-metallic mineral products (15-18%). Finally, approximately one-fourth of the firms operate in the Uusimaa region. The sample size is approximately 1,400-1,600 firms annually.

Next, we focus on the empirical analysis in which we add all the variables in the model simultaneously. Equation (4.2) is estimated by OLS (ordinary least squares), and the results are represented in Table 10. The coefficients for sector and region indicators are omitted from the table to save space. Our main findings show that export demand shock has increased labor productivity in Finnish manufacturing firms. The estimates are statistically and economically significant for the periods of 1999-2007 and 2007-2011, but no longer statistically significant for the period of 2011-2016.

Table 10. The effect of export demand shock on labor productivity growth

	1999-2007	2007-2011	2011-2016
Shock	0.343 (0.163) **	0.309 (0.127) **	0.124 (0.173)
Equity ratio	-0.117 (0.030) ***	-0.025 (0.030)	-0.072 (0.029) **
Age of firm	0.000 (0.001)	0.000 (0.001)	-0.003 (0.001) ***
Size/100	-0.002 (0.007)	0.010 (0.004) **	0.007 (0.005)
Sum of patents	-0.041 (0.040)	-0.011 (0.002) ***	0.012 (0.007) *
Foreign ownership	-0.064 (0.054)	0.016 (0.043)	-0.045 (0.050)
Log (R&D expenditure)	-0.001 (0.003)	-0.004 (0.003)	-0.002 (0.003)
Log (Investments)	0.004 (0.003)	-0.005 (0.004)	0.000 (0.004)
N	1604	1507	1398
R^2	0.06	0.05	0.07

Note: Dependent variable is difference in log of labor productivity. Firm-level factors are measured in year t_0. Other controls include region and sector indicators. Standard errors are clustered at the firm-level. *** (p < 0.010), ** (p < 0.050) and * (p < 0.100).

Higher initial financial strength of the firm is negatively related to labor productivity for 1999-2007 and 2011-2016. In terms of effect size, firms above the sector-specific median equity ratio have approximately 1.5% lower annual labor productivity growth compared to firms below the sector-specific median equity ratio.

Older firms show lower productivity growth after 2011. However, the size of the association is economically negligible. One additional year of firm age is associated with a 0.06% annual decrease in labor productivity. Larger firms (as measured by the number of employees) show higher productivity growth, and this positive relationship is statistically significant at the conventional level only during 2007-2011.

There is also an interesting heterogeneity in the results regarding patents. The initial number of patents is negatively associated with labor productivity growth during the financial crisis (0.3% annually), but positively related to labor productivity growth after the financial crisis (0.2% annually). Finally, the estimates for foreign ownership, R&D expenditures and investments are statistically insignificant in each specification.

Table 11. The heterogeneity in the effect of export demand shock on labor productivity growth

	1999-2007	2007-2011	2011-2016
Equity ratio × Shock	-0.375 (0.206) *	0.612 (0.227) ***	0.183 (0.316)
Age of firm × Shock	0.001 (0.006)	-0.017 (0.006) ***	-0.012 (0.009)
Size/100 × Shock	-0.002 (0.012)	0.032 (0.034)	-0.035 (0.023)
Sum of patents × Shock	0.126 (0.151)	-0.110 (0.021) ***	0.048 (0.013) ***
Foreign ownership × Shock	0.212 (0.310)	0.408 (0.335)	-0.425 (0.396)
Log (R&D exp.) × Shock	-0.002 (0.017)	0.010 (0.022)	-0.032 (0.040)
Log (Investments) × Shock	-0.024 (0.013)	0.017 (0.042)	0.067 (0.031) **
N	1604	1571	1398
R^2	0.07	0.06	0.08

Note: Dependent variable is difference in log of labor productivity. Firm-level factors are measured in year t_0. Other controls include region and sector indicators. Standard errors are clustered at the firm-level. *** ($p < 0.010$), ** ($p < 0.050$) and * ($p < 0.100$).

Table 11 reports the interaction coefficients from equation (4.3). The results show that labor productivity growth, as a response to export demand shock, was lower in firms with higher equity ratios in 1999-2007. However, the effect of export demand shock on labor productivity was higher in firms with higher equity ratios during the financial crisis. These results indicate that labor productivity growth, as a response to export demand shock, was higher in younger firms during the financial crisis. The results also show that numerous patents diminished the positive trade shock effect on labor productivity between 2007 and 2011.

There is heterogeneity in the effects of the shock on firm's labor productivity for 2011-2016. The results suggest that the positive association between export demand shock and productivity was higher in firms with a higher level of innovation, as measured by the number of patents and total investments. However, the results of the interaction coefficients should be treated with caution, as the direct effect of export demand shock is statistically insignificant.

4.5 Extensions

To explore the robustness of the baseline estimates, we have estimated several additional specifications. First, the financial strength of the firm is allowed to enter productivity function in a more flexible manner. As suggested by Coricelli et al. (2012), productivity may increase with leverage (e.g., equity ratio) until it reaches a critical threshold value beyond which leverage is negatively associated with productivity. Therefore, we tested nonlinearity by including a firm-level equity ratio and its quadratic term in the model. Interestingly, there is a U-shaped relationship between equity ratio and labor productivity growth for the period of 2011-2016. The coefficients for firm-level equity ratio and its quadratic term are -0.00397 and 0.0000261, respectively (these results are not reported in the tables). This finding suggests that the initial negative relationship between equity ratio and productivity growth becomes positive after reaching the critical minimum of 76.1%, which is well above the average equity ratio of 41% (see, Table 9, Column 3).

Second, we used alternative measures for financial strength of the firm as independent variables. Instead of equity ratio, the model was augmented with quick or current ratio, which are both available in the Financial Statement data. Quick ratio measures a firm's short-term liquidity position, indicating how well the firm is able to meet its short-term obligations with its most liquid assets. Current ratio is quite similar, except that it measures whether a firm has enough resources to meet its longer-term (usually within a year) obligations. The results using quick and current ratio were comparable with the ones using equity ratio as a measure for financial strength of the firm (these results are not reported in the tables). Only for 2007-2011, the interaction term between trade shock and quick ratio was statistically insignificant at the conventional level.

Third, total investments are disaggregated into three different categories: investments in software (IT), increases in machinery and equipment and increases in buildings and structures. Syverson (2011) suggests that different capital inputs may affect productivity differently. Cainelli et al. (2006) also find that productivity is especially linked to innovation expenditures devoted to the acquisition and internal development of new software. The three investments variables are included in the model simultaneously. The results for 2007-2011 show that the positive effect of trade shock on firm's labor productivity is higher in firms that initially invested more on buildings and structures. Accordingly, the positive interaction coefficient between trade shock and investments (Table 11, Column 3) is driven by increases in machinery and equipment (the results are not reported in the tables).

Fourth, we included additional control variable into the models to account for potential cost competitiveness. Therefore, we augmented the model with the firm-level unit labor costs, using information on salaries, indirect employee costs, and total sales. The results remained robust to our main findings (these results are not reported in the tables).

4.6 Conclusions

Previous empirical evidence shows that import competition may increase productivity (e.g., Bloom, Draca and Van Reenen, 2013; Auer, Degen and Fischer, 2013, Syverson, 2011, for a review). Novel evidence from Finland indicates that an increase in world market size has improved labor productivity in Finnish manufacturing firms. However, this positive effect diminished after the financial crisis. There are many potential channels through which increased export demand shock affects productivity. For example, increased import competition may case less-productive firms to cease exporting. Trade competition may also decrease total export value, lead to changes in firm's product portfolio (e.g., Nilsson Hakkala and Pao, 2019), trigger price cuts (e.g., Nilsson Hakkala and Pao, 2019; Auer et al., 2013), decrease employment (e.g., Auer et al., 2013; Autor, Dorn and Hanson, 2013), or affect innovation (e.g., Aghion et al., 2019; Chakravorty et al., 2022).

Our results show that the contribution of other firm-level characteristics to labor productivity growth is modest in Finnish exporting firms. Interestingly, we find that labor productivity growth is higher in firms that are belove the median sector-specific equity ratio. Especially from 1999 to 2007, labor productivity growth, as a response to trade shock, was higher in firms that were more financially constrained. During the financial crisis, labor productivity growth, as a response to trade shock, was higher in firms that were less financially constrained. This is in line with previous findings that indicate that firms which are more dependent on external banking finance grow significantly less during economic crises (e.g., Görg and Spaliara, 2014).

There are also interesting differences in the results regarding innovation (patents). Having patents is associated with labor productivity, but the direction of this relationship is dependent on economic cycles. For example, the relationship was negative in 2007-2011. This is potentially because firms already invested in the new capital, training, and new employees required to embody patents into new processes or products before the crisis. When the crisis hit in 2008, it had negative consequences in firm performance (e.g., lower access to finance, declining exports and sales). Deteriorating firm performance combined with high initial investment may have resulted in lower labor productivity. Further analysis is needed to examine the mechanisms of stagnated productivity growth as a response to trade shocks.

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5 Comparison of marginal products and average unit costs

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Abstract: In the competitive market of price-taking firms, the profit-maximizing firms demand labor and capital inputs such that their marginal products equal the corresponding marginal costs. This chapter compares empirically whether this first-order condition is satisfied in 16 selected industries in Finland. To account for heterogeneity of firms even in narrowly defined industries, the marginal products are locally estimated using the convex quantile regression, which does not require any prior assumptions about the functional form of the production function. Our empirical results indicate large departures from first-order condition. The ratio of marginal product and the average unit cost of labor systematically correlates with some observed firm characteristics, which may signal systematic misallocation of labor. For the capital input, such correlations cannot be found.

5.1 Introduction

Recent economic literature has identified misallocation of resources as a substantial source of productivity differences across countries (e.g., Restuccia & Rogerson, 2008; 2017, Hsieh & Klenow, 2009). However, the measured magnitude of misallocation depends on the estimation approach and context. Further, no dominant source of misallocation has been identified in the literature, rather, many factors seem to contribute a small part of the overall effect (Restuccia & Rogerson, 2017).

Empirical work on misallocation is typically based on the equilibrium condition of a monopolistic competition model where the marginal revenue products of capital and labor are equalized across heterogenous producers (e.g., Hsieh & Klenow, 2009). Recent studies recognize major challenges related to estimation and measurement (e.g., Haltiwanger et al., 2018). Blis et al. (2021) argue that differences in measured average products need not reflect differences in true marginal products. They show that introducing a correction for measurement error lowers potential gains from reallocation by 20% in India and by 60% in USA. Li & Wang (2021) extend Hsieh and Klenow (2009) by relaxing the assumption of constant markup. They show that under variable markup the estimated misallocation of China is considerably smaller than Hsieh and

Klenow (2009) suggest. Recently Hang (2022) considers the impact of capacity utilization, noting that the varying capacity utilization introduces bias in the measurement of misallocation.

These recent findings motivate us to approach misallocation from a more data-driven perspective, allowing for variable markups, varying capacity utilization, and heterogeneity of firms and their production functions. Empirically observed productivity differences between firms, which are both large and persistent even in narrowly defined industries (e.g., Syverson, 2011), can be largely due to heterogeneity of labor and capital inputs. We argue that it is important to take the heterogeneity explicitly into account in the estimation of production functions: a single production function may not capture well the marginal products of an industry consisting of a heterogenous group of firms that differ in terms of their technology and managerial efficiency.

To model heterogeneity explicitly, we resort to local estimation of the marginal products using the convex quantile regression (CQR) (Wang et al., 2014; Kuosmanen and Zhou, 2021). CQR is a fully nonparametric method that does not require any prior assumptions about the functional form of the production function. CQR builds directly on the monotonicity and concavity properties implied by the Weak Axiom of Profit Maximization (WAPM) by Varian (1984). In contrast to the deterministic test approach by Varian (1984), we estimate multiple quantiles to account for the productivity differences, and use the nearest quantiles to the firm to locally estimate the marginal products.

Applying CQR to the data of 16 selected industries in Finland, we empirically assess to what extent the first-order conditions of profit maximization are satisfied. Our empirical results indicate large departures from the optimality conditions. On the average, the estimated marginal products of labor exceed the average unit costs, suggesting that labor is under-utilized in most industries. In contrast, the estimated marginal products of capital tend to be lower than the corresponding unit cost of capital. Interestingly, the ratio of marginal product and the average unit cost of labor systematically correlates with some observed firm characteristics, which may signal systematic misallocation of labor. For the capital input, such correlations cannot be found.

The rest of this chapter is organized as follows. In Section 5.2 we introduce the first-order conditions from the theory of the firm. Section 5.3 presents the convex quantile regression approach to estimate the marginal products. Section 5.4 introduces the data and variables of the 16 selected industries. Section 5.5 compares the estimated marginal products and the average unit costs. In Section 5.6 we use linear regression analysis to examine if the ratio of marginal products and unit costs correlates with observable firm characteristics. Section 5.7 presents our concluding remarks.

5.2 Theory of the firm

Following Restuccia and Rogerson (2017), consider a profit maximizing firm under monopolistic competition that demands the optimal amounts of labor L and capital K solving the following unconstrained optimization problem

$$\max_{L,K} z_i f(L,K) - w_i L - r_i K, \qquad (5.1)$$

where f is a monotonic increasing and concave production function, z_i is firm-specific productivity term, and w_i, r_i are the prices of labor and capital faced by firm i. Without a loss of generality, we assimilate possible output-price differences to the productivity terms z_i.

The familiar first-order condition states that the marginal costs are set equal the marginal revenues, that is,

$$z_i f'_L(L,K) = w_i \qquad (5.2)$$

$$z_i f'_K(L,K) = r_i. \qquad (5.3)$$

where f'_L and f'_K denote the partial derivatives of the production function, and hence $z_i f'_L(L,K)$ [$z_i f'_K(L,K)$] is the marginal product of labor [capital] at the given level of input use (L,K). In other words, the profit maximizing firm increases its labor and capital inputs until the marginal increase in output equals the input price, which is the marginal cost of a price-taking firm. Note that heterogeneity of firms in terms of their productivity levels and the factor prices can render the first-order conditions different across firms. The firm-specific first-order conditions form a natural point of departure to examine empirically whether the observed allocation of labor and capital resources are allocatively efficient.

Consider possible violations of the first-order conditions (5.2)-(5.3). Suppose, for example, that we could observe the true marginal products and input prices at the firm level, and find that

$$z_i f'_L(L,K) > w_i,$$

$$z_i f'_K(L,K) < r_i.$$

This would imply that the firm is using too much capital input K, and too little labor input L, compared to the optimal profit-maximizing level. In other words, the firm should take measures to avoid overinvestment, and hire more workers until equations (5.2) and (5.3) are satisfied. The sign of the inequality indicates whether the firm is using too much, or too little of a specific resource. Note, however, the adjustment to the optimal allocation would typically require adjustments to both inputs: the marginal product of labor depends on the capital input, and vice versa.

In the real-world, the marginal products are not directly observable and must be estimated from the data. The main challenge in the estimation is the fact that firms are heterogenous, and so are their technologies and input resources. Even in a relatively narrowly defined industry, there are large productivity differences across firms, which may relate to the quality of workers (e.g., education and experience) and the vintage of capital, among other things.

To account for the heterogeneity, we take the following measures:

1) We only consider specific industries defined at the 2-5 digit level of NACE or TOL 2008 industry classification, which produce relatively simple and homogenous products, and include a reasonable number of firms.

2) We estimate the marginal products locally using convex quantile regression, to be explained in more detail in the next section.

3) We estimate the average unit costs of labor and capital at the firm-level, allowing the prices of labor and capital inputs differ across firms, potentially reflecting quality differences in these resources.

Despite these measures, some unobserved heterogeneity always remains: outputs of the firm can differ even in a relatively narrowly defined industry, and the wages tend to differ across workers even within the same firm. Further, the wage rate of the workers currently employed may differ from the potential new hires available in the job market. Indeed, a violation of the first-order condition (5.2) could be due to mismatch of skills: even if a firm would like to hire more employees with certain skills required for the job, no suitable workers might not be available in the job market. The capital inputs such as buildings, vehicles, machinery, as well ICT equipment such as computers and telephones are similarly heterogenous in terms of their marginal products and marginal costs. Therefore, we find it more meaningful to compare the industry averages instead of firm-specific deviations from the first-order conditions.

5.3 Convex quantile regression approach

The empirical estimation of the production function usually departs from the regression model

$$y_i = f(L_i,K_i) \cdot \exp(\varepsilon_i).$$

where y denotes the output (here value added) and ε is a composite error term that captures the latent productivity differences z_i across firms i (indicated by the subscripts). The productivity differences can arise due to differences in the technology, quality of outputs y, quality of inputs (e.g., education and experience of workers, or the vintage of capital), managerial efficiency, or heterogenous operating environment. The underlying sources of productivity differences are not of primary interest of this study, the main point is that we need to account for the productivity differences when estimating the marginal products. Analogous to the first-order conditions (5.2) and (5.3), the marginal products depend on ε because

$$\partial y_i \,/\, \partial L_i = f'_L(L_i,K_i) \cdot \exp(\varepsilon_i).$$

$$\partial y_i \,/\, \partial K_i = f'_K(L_i,K_i) \cdot \exp(\varepsilon_i).$$

Intuitively. the higher the productivity level (represented by ε), the higher the marginal products of labor and capital.

To take productivity differences and heterogeneity of firms explicitly into account, we resort to the conditional quantile production function Q_y (Dai et al., 2020) defined as

$$Q_y\,(\tau \mid L,K) = f(L,K) \cdot F^{-1}_{\varepsilon}(\tau).$$

where τ ($0 < \tau < 1$) is the order of quantile, and F^{-1} denotes the inverse of the cumulative distribution function of ε. By controlling the parameter τ, we can evaluate the potential output level obtained by $\tau \cdot 100\%$ of firms with the given resources L, K. We can also evaluate the marginal products at the relative performance level $\tau \cdot 100\%$ using

$$\partial Q_y\,(\tau \mid L_i,K_i) \,/\, \partial L_i\,.$$

$$\partial Q_y\,(\tau \mid L_i,K_i) \,/\, \partial K_i\,.$$

While a user is free to specify any arbitrary τ, for our purposes, it is logical to apply τ that closely resembles the actual level of performance. To this end. Kuosmanen and Zhou (2021) propose to estimate a grid of quantiles (e.g., ten different levels of τ = 0.05. 0.15. 0.25. … . 0.85. 0.95) to map the different performance levels. They then identify τ that yields best fit to the firm i, and use that specific τ for estimating the marginal products locally.

In this study we employ a similar approach. but with one minor deviation. Instead of identifying the nearest quantile τ, we apply the weighted average of all ten quantiles estimated, setting the weights based on the kernel function applied to the residuals e. Specifically, for a given firm i, we set the weights of quantiles τ using the Gaussian kernel function

$$w_{i,\tau} = \exp(-(e_{i,\tau}{}^2) / \Sigma_\tau\, e_{i,\tau}).$$

These weights assign the highest weight to the quantile nearest to the observation i, but in order to reduce overfitting, it also assigns some small positive weight to quantiles located in the neighborhood of observation i.

To estimate the quantiles empirically, we resort to a fully nonparametric approach that does not require any assumptions about the functional form of the production function or its smoothness, but imposes the monotonicity and concavity properties implied by WAPM (Varian, 1984). In practice, we need to solve the following linear programming problem for each quantile τ

$$\min \Sigma_i (1 - \tau)e_i^- + \Sigma_i \tau e_i^+ \qquad (5.4)$$

subject to

$$y_i = \alpha_i + \beta_{Li} L_i + \beta_{Ki} K_i + e_i^+ - e_i^- \qquad \text{for all } i = 1,\dots,N$$

$$\alpha_i + \beta_{Li} L_i + \beta_{Ki} K_i \le \alpha_h + \beta_{Lh} L_i + \beta_{Kh} K_i \qquad \text{for all } i,h = 1,\dots,N$$

$$\beta_{Li} \ge 0,\ \beta_{Ki} \ge 0 \qquad \text{for all } i = 1,\dots,N$$

$$e_i^+ \ge 0,\ e_i^- \ge 0 \qquad \text{for all } i = 1,\dots,N$$

In the objective function, parameter τ assigns asymmetric weight to the negative deviations e_i^- and the positive deviations e_i^+ from the quantile (note: the special case τ = 0.5 that assigns equal weight to positive and negative deviations is referred to as the median regression). The first constraint is a linearized regression equation. The second inequality constraints impose concavity of the production function. Our main interest is in the coefficients β_{Li} , β_{Ki}, which directly indicate the marginal products of labor and capital of firm i, evaluated using a given quantile τ. Recall that we estimate the model using a grid of ten alternative values of τ. and then take the weighted average of the coefficients β_{Li}. β_{Ki} corresponding to different levels of τ.

In practice, the constrained optimization problem (5.4) can be solved by linear programming. In this study we employ the Python package pyStoNED developed by Dai et al. (2021), which is freely available at GitHub,[5] and has been installed on the Statistics Finland server. We make use of the STATA-Python integration that enables us to process the firm data and run the pyStoNED code conveniently in STATA.

5.4 Data, variables and industries

Since the estimation of marginal products of labor and capital is computationally demanding, we focus on examining 16 industries in three years 2005, 2012 and 2018, which yields the total of 48 distinct samples. Similar to Chapter 2, we use of the Financial Statement Data Panel of Statistics Finland that contains firm-level accounting data covering exhaustively all enterprises in almost all industries. The output y is measured by the value added (thousand euros), the labor input L is measured by the number of employees (in the full-time equivalent units), and the capital input K is measured by the fixed assets (thousand euros). All nominal values are deflated to the constant prices of the year 2010 using the GDP deflator of Statistics Finland.

We compare the estimated marginal products with the average unit costs of labor and capital, which are estimated based on the functional distribution of the factors of production as follows. The average unit costs of capital are measured as the ratio of the revised operating margin (i.e., the operating margin minus other operating income) and the fixed assets. Note that the operating margin indicates the firm's gross accounting profit. On the other hand, the average unit cost of labor is measured as the difference of the value added and the revised operating margin, divided by the number of employees. Note that if we multiply the labor and capital inputs by their unit costs, and add together, the resulting sum is equal to the value added of the firm.

Following the selection criteria discussed above in Section 5.2, we analyze 16 industries defined at the 2-5 digit levels of the Finnish TOL 2008 industry classification. The selected industries are listed in Table 12 below. The first eight of the industries are from the manufacturing, the other eight industries represent other sectors of the economy.

Observations with missing values in the relevant variables, and observations with zero employees are excluded from all industries. To keep the sample size manageable in industries consisting of large numbers of small firms, we exclude firms with less than

[5] The pyStoNED package, https://github.com/ds2010/pyStoNED.

one employee in industries C26 and C16100, less than five employees in industries C10 and J62010, and less that ten employees in industries F41200 and H49410.

Table 12. Selected industries and their TOL codes.

Industry	TOL08
Manufacturing	**C**
- Manufacture of food products	C10
- Sawmilling and planing of wood	C16100
- Manufacture of paper and paper products	C17
- Manufacture of chemicals and chemical products	C20
- Manufacture of basic pharmaceutical products and pharmaceutical preparations	C21
- Manufacture of basic metals	C24
- Manufacture of computer. electronic and optical products	C26
- Manufacture of furniture	C31
Electricity, gas, steam and air conditioning supply	**D**
- Production of electricity with hydropower and wind power	D35111
- Combined heat and power production	D35113
Construction	**F**
- Construction of residential and non-residential buildings	F41200
Transportation and storage	**H**
- Freight transport by road	H49410
Accommodation and food service activities	**I**
- Hotels	I55101
Information and communication	**J**
- Computer programming activities	J62010
Human health and social work activities	**Q**
- Dental practice activities	Q86230
Arts, entertainment and recreation	**R**
- Activities of sport clubs	R93120

5.5 Comparison of estimated marginal products and average unit costs

As noted in Section 5.4, we consider 16 industries in three years, which yields 48 distinct cases in total. For the sake of brevity, we discuss three interesting industries in more detail in this section. The complete results of all 16 industries in all three years are presented in Appendix 2.

Consider first the manufacture of basic metals (TOL code 24). Table 13 reports the averages of the estimated marginal products and unit costs in three years 2005, 2012, and 2018. For convenience, we also report the ratios of these two averages: recall that the ratio is equal to one in the competitive equilibrium of price-taking profit-maximizing firms, whereas the ratio less than one indicates under-utilization of the resource and the ratio greater than one points towards overuse of the resource. In the manufacture of basic metals, the ratios of the marginal products and unit costs are relatively close to one in 2005. The allocation of labor input remains relatively good in 2012, 2018, but the capital input appears more problematic in this industry: the estimated marginal products point towards over-capacity in 2012, which has changed to under-capacity in 2018.

Table 13. Manufacture of basic metals (24): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	41 361	42 368	43 336
Marginal product	46 033	45 576	40 069
Capital			
Unit costs	0.56	0.46	0.39
Marginal product	0.60	0.28	0.58
Unit costs / marginal product			
Labor	0.90	0.93	1.08
Capital	0.94	1.68	0.66
Number of firms	134	127	100

Next, consider the construction of residential and non-residential buildings (TOL code 41200), reported in Table 14. In this industry, the marginal product of labor is on average considerably lower than the unit cost in all three years considered. This points towards under-employment. In contrast, the marginal product of capital falls short of the average unit cost in all years, suggesting the capital intensity is higher than optimal in this industry. There are several possible explanations for this finding. Note that this industry has experienced major growth over the past decades, especially in the urban centers of Finland. As a result, there has been shortage of skilled workers in many firms, which can contribute to the excessive capital intensity. On the other hand, a large proportion of employees in this industry are foreign workers, whose bargaining power in the wage negotiations can be lower than that of native employees. Finally, the biggest construction firms tend to outsource a large proportion of manual labor to subcontractors, which can bias the functional distribution of the factor shares as the outsourced labor is treated as an intermediate input.

Table 14. Construction of residential and non-residential buildings (41200): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	37 698	40 503	39 658
Marginal product	60 051	60 048	59 510
Capital			
Unit costs	0.89	0.67	0.79
Marginal product	0.49	0.35	0.46
Unit costs / marginal product			
Labor	0.63	0.67	0.67
Capital	1.79	1.90	1.72
Number of firms	642	783	1883

Table 15. Computer programming activities (62010): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	53 593	56 025	53 328
Marginal product	73 699	75 902	74 706
Capital			
Unit costs	0.91	0.99	0.91
Marginal product	0.33	0.37	0.07
Unit costs / marginal product			
Labor	0.73	0.74	0.71
Capital	2.75	2.68	13.55
Number of firms	585	586	807

As a third example, consider the computed programming industry (TOL code 62010), reported in Table 15. Similar to the construction industry, the marginal product of labor is on average considerably lower than the unit cost in all three years considered, whereas the marginal product of capital is lower than the average unit cost in all years, suggesting the capital intensity is higher than optimal also in this industry. This industry has been the fastest growing export industry of Finland, and has also had shortage of skilled programmers.

Considering the other 13 industries (see Appendix 2 for details), we find that capital bias in the form of excessive capital intensity is rather common in the selected industries considered in this study. One possible explanation for the systematic capital bias might relate to the entrepreneurs' risk: while the employees are typically paid pre-agreed wages and salaries that do not depend on profitability, the return on equity includes compensation for the business risk, which may increase the unit cost of capital beyond the marginal product. On the other hand, the compensation of private entrepreneurs' labor is often paid in the form of dividends rather than salary for the sake of a lower marginal tax, which can cause bias especially in small enterprises. In the large firms, outsourcing of labor to subcontractors can also cause bias to the functional distribution of the factors of production.

5.6 Regression analysis

To shed further light on the apparent capital bias observed in the previous section, in this section we apply regression analysis to investigate whether observed characteristics of firms correlate with the deviations from the first-order conditions. As the dependent variable, we use the ratio of the average unit cost and the estimated marginal product. Observations for which the average unit cost of capital was negative were excluded from the regressions.

The independent variables include age of the company (in years), the number of employees as a proxy for the firm size, the equity/debt ratio, and a dummy for foreign ownership. We pool all three years to the same panel, and include dummy variables for the years 2012 and 2018, treating the year 2005 as the reference category. Finally, we include the dependent variable of the labor input to the regression model of the capital input, and vice versa. The results of the ordinary least squares regressions are reported in Tables 16-18 below.

Consider first the manufacture of basic metals (TOL code 24), reported in Table 16. The left-hand side of the table summarizes the regression results for the labor input, the right-hand side reports the similar results for the capital input. To control for the possible interactions between labor and capital inputs, the regression model for the labor unit cost / MP ratio includes the corresponding unit cost / MP ratio of the capital input, and vice versa. In Table 13, the variable “Unit cost / MP ratio” refers to the dependent variable of the other regression model.

Considering the labor input, we find that the firm age, the firm size, and the foreign ownership have significant positive association with the ratio of unit cost and the marginal product of labor,[6] suggesting that the older firms, larger firms, and foreign owned firms pay on average higher wages relative to the marginal product of labor. In contrast, the equity/debt ratio has significant negative association with the dependent variable, which suggests that more leveraged firms pay higher wages relative to the marginal product. Interestingly, no significant correlations can be found for the capital input.

[6] Statistical significance of the regression coefficients is commonly tested using the Student’s t-test, using the significance levels of 0.05 or 0.01. In Tables 13-15, the statistical significance can be directly read from the reported p-values, which indicate the highest significance level at which the null hypothesis can be rejected. In other words, coefficients with the p-value less than 0.05 are considered significant and those with the p-value of less than 0.01 are considered highly significant.

Table 16. Manufacture of basic metals (24): regression results

	Labor			Capital		
	Coef.	Std. Err.	P > t	Coef.	Std. Err.	P > t
Unit cost / MP ratio	0.000	0.000	0.346	-6.53E+18	6.49E+18	0.346
Firm age	0.206	0.071	0.004	-6.77E+18	4.54E+19	0.433
Nr. of employees	0.013	0.005	0.009	-1.04E+17	1.20E+18	0.931
Equity/Debt ratio	-0.095	0.016	0.000	3.38E+18	6.51E+18	0.389
Foreign ownership	43.122	6.432	0.000	-1.75E+20	1.96E+21	0.770
Year 2012	9.987	2.035	0.000	1.92E+21	1.47E+21	0.933
Year 2016	3.927	1.901	0.039	1.45E+20	1.57E+21	0.381
Constant	63.688	1.873	0.000	6.35E+20	1.31E+21	0.718

The results for the Construction of residential and non-residential buildings (TOL code 41200) are analogously reported in Table 17. The picture is very similar to that of the basic metals industry: the firm age, the firm size, and the foreign ownership have significant positive association with the ratio of unit cost and the marginal product of labor, whereas the equity/debt ratio has significant negative association with the dependent variable. Again, no significant correlations can be found for the capital input.

Table 17. Construction of residential and non-residential buildings (41200): regression results

	Labor			Capital		
	Coef.	Std. Err.	P > t	Coef.	Std. Err.	P > t
Unit cost / MP ratio	0.000	0.000	0.159	1.14E+13	8.09E+12	0.159
Firm age	0.161	0.056	0.004	-1.76E+13	2.06E+13	0.394
Nr. of employees	0.014	0.004	0.000	4.90E+10	1.37E+12	0.971
Equity/Debt ratio	-0.078	0.018	0.000	6.82E+12	6.79E+12	0.315
Foreign ownership	14.028	5.315	0.008	-4.53E+14	1.97E+15	0.818
Year 2012	5.181	1.558	0.001	-9.18E+13	5.79E+14	0.874
Year 2016	3.120	1.440	0.030	4.39E+14	5.35E+14	0.412
Constant	61.929	1.468	0.000	-6.71E+14	7.40E+14	0.365

Table 18. Computer programming activities (62010): regression results

	Labor			Capital		
	Coef.	Std. Err.	P > t	Coef.	Std. Err.	P > t
Unit cost / MP ratio	0.000	0.000	0.122	3.98E+08	2.58E+08	0.122
Firm age	0.123	0.125	0.326	-6.05E+08	1.23E+09	0.623
Nr. of employees	0.032	0.007	0.000	-1.83E+07	6.76E+07	0.787
Equity/Debt ratio	0.012	0.014	0.370	3.96E+07	1.35E+08	0.77
Foreign ownership	22.093	3.205	0.000	-1.87E+10	3.20E+10	0.56
Year 2012	-1.534	2.634	0.560	2.62E+09	2.59E+10	0.919
Year 2016	-6.401	2.500	0.011	3.05E+10	2.46E+10	0.216
Constant	66.369	2.317	0.000	-2.12E+10	2.85E+10	0.456

Finally, consider the Computer programming activities (TOL code 62010), reported in Table 18. Only the firm size and the foreign ownership have significant positive association with the ratio of unit cost and the marginal product of labor in this industry. There are no significant association with the capital input in this industry either.

5.7 Conclusions

In this chapter we have estimated the marginal products of labor and capital using the convex quantile regression. This approach enables us to estimate the partial derivatives of the production function locally without imposing any prior assumptions about the functional form. We restricted attention to 16 industries in three years, focusing on industries that produce relatively homogenous products and have a reasonably large sample size. For the sake of brevity, the previous sections discuss three specific industries in more detail, the remaining 13 industries are reported in Appendix 2.

The comparison of the estimated marginal products and the average unit costs points towards notable capital bias in most of the industries and years considered. The average unit costs of capital exceed the marginal product in most industries and years considered. Already more than two decades ago Pohjola (1996) sharply criticized the growth policy of Finland, which lead to inefficient utilization of capital. According to our findings, capital resources remain inefficiently used in many industries.

In contrast, the marginal product of labor typically exceeds that of the average unit cost, which suggest that it would be socially optimal for most firms to hire more employees. There are many possible explanations for this finding. One possible explanation concerns the mismatch of jobs and skills. Indeed, many firms and industries have complained about the shortage of skilled employees in the popular media. Another potential explanation relates to the taxation of labor and capital earnings of private entrepreneurs. A third possible explanation relates to the outsourcing of labor, which might cause bias in the measurement of the primary factors of production and the intermediate inputs. Finally, the mismatch of marginal products and unit costs can relate to lack of competition and local market power (cf., e.g., Böckerman and Maliranta, 2003). Further research is needed to shed further light on the relative importance of these and other possible explanations for the observed capital bias in these industries.

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6 Optimal resource allocation: A quantile approach

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Abstract: The question of optimal allocation of resources across sub-units has attracted considerable interest in the context of centralized decision-making systems such as bank branches or super-market chains. Drawing insight from these studies, in this chapter we examine how much the output and productivity of an industry could potentially increase if the resources were efficiently allocated between firms. We increase robustness to random noise and heteroscedasticity by resorting to local estimation of multiple production functions using the convex quantile regression. Our empirical results reveal large potential for productivity gains through better allocation, keeping the current technology and resources fixed.

6.1 Introduction

Optimal allocation of resources is a fundamentally important topic not only in economics, but also in the multidisciplinary field of operations research and management science. In the latter field, the focus is typically on centralized decision-making systems where the central management assigns resources to sub-units. Examples of such systems include

- Bank branches (Ray, 2016)
- Fire departments (Athanassopoulos, 1998)
- Harbours (Fang, 2016; Lozano et al., 2011; Wu et al., 2016)
- Supermarkets (Korhonen & Syrjänen, 2004; Liesiö et al., 2020)

In these studies, the frontier production function is estimated using the deterministic Data Envelopment Analysis (DEA) method. However, DEA is known to be sensitive to extreme observations and outliers. Furthermore, extrapolating the 100% efficient DEA frontier to units that operate at the low-level of efficiency (e.g., less than 10% efficiency) requires strong homoscedasticity assumptions that likely fail in the real world.

To address these estimation challenges, in this chapter we resort to local estimation of production functions using the convex quantile regression. This method enables us to estimate multiple production functions for different levels of efficiency. Following Kuosmanen and Zhou (2021), we employ 10 equidistant quantiles, which can be interpreted as production functions for the ten deciles of the performance distribution (i.e., ten groups representing the 0%-10%, 10%-20%,…, 90%-100% levels of efficiency).

Another notable difference to the previous resource allocation studies is that we examine potential gains of reallocation in decentralized industries consisting of independent firms that operate in a more or less competitive environment. In this context, optimal resource allocation has not attracted much attention because it is widely believed that market competition will lead to efficient allocation. Indeed, the first fundamental theorem of welfare economics states that a competitive equilibrium with a set of complete markets, complete information and perfect competition will be Pareto efficient. However, the markets in the real world tend to be incomplete in different ways. Indeed, there is plenty of empirical evidence of misallocation in the recent economic literature (e.g., Restuccia & Rogerson, 2008; 2017; Hsieh & Klenow, 2009). Therefore, it is worth to ask how far the current allocation of resources is from the optimal one? The purpose of this chapter is to shed new light on this fascinating question.

The rest of this chapter is organized as follows. Section 6.2 briefly introduces the quantile production functions (for a more detailed presentation, please refer to Section 5.3). Section 6.3 presents the resource allocation problem and some of its variants considered in this chapter. Section 6.4 illustrates how the optimal allocation looks like for three selected industries. Section 6.5 introduces productivity measures. Section 6.6 presents the main empirical results on how much the output and productivity could increase as a result of better allocation. Section 6.7 concludes.

6.2 Quantile production functions

The first step to model resource allocation is to empirically estimate the production functions of industries considered. To take the heterogeneity of firms and differences in their productive performance explicitly into account, we partition the sample of firms to 10 mutually exclusive groups based on their productive efficiency, representing the *ten deciles of the performance distribution* (i.e., 0%-10%, 10%-20%,…, 90%-100%). Note that each group includes n firms by construction, where $n = N/10$ and N is the total sample size.

We use quantiles to characterize the technology of each decile. The quantiles are indexed by $\tau = 0.05, 0.15, \ldots, 0.95$, that is, the quantiles are fitted in the middle of each decile of the performance distribution. One could use any arbitrary number of quantiles and performance groups, but ten deciles is commonly used in the previous studies (cf., e.g., Dai et al., 2020; Kuosmanen and Zhou, 2021). Compared to the usual approach of applying a single production function to all firms, the use of ten deciles enables us to better capture heterogeneity of firms.

For a more detailed presentation of the quantile production functions and their nonparametric estimation, we refer to Section 5.3 of this volume.

6.3 Resource allocation problems

Our objective is to allocate the total resources of the industry denoted by vector **X** to counterfactual production plans y^{τ}_i, $\mathbf{x}^{\tau}_i$ to maximize the total output (value added) of the industry under the following assumptions:

1) Each decile of firms operates using the corresponding quantile production function. The quantiles τ = 0.05, 0.15, 0.25, …, 0.95 have been estimated in Section 5.3.

2) The labor and capital resources can be reallocated between firms, however, the total labor and capital resources of the industry remain constant.

3) Reallocation does not influence firms' productive efficiency, in other words, firms can move along the quantile production functions, but not increase or decrease their efficiency.

In the baseline case, the optimal resource allocation is obtained by solving the following linear programming problem:

$\max_{\mathbf{x},\mathbf{y}} \Sigma_{\tau}\Sigma_i\, y^{\tau}_i$	(total output of the industry)
s.t.	
$y^{\tau}_i \leq \alpha^{\tau}_h + \mathbf{x}^{\tau}_i{}'\boldsymbol{\beta}^{\tau}_h$ for all h, i, τ	(technology constraint)
$\Sigma_{\tau}\Sigma_i\, \mathbf{x}^{\tau}_i = \mathbf{X}$	(resource constraints)
$\mathbf{x}^{\tau}_i \geq 0$	(resources cannot be negative)

We index the counterfactual pseudo-firms of each quantile by $i = 1,\ldots,n$. Note that these firms do not have any connection to the real firms other than that they operate using the same quantile production function. One does not need to have firm-specific data of resources, it suffices to know the total resources of the industry **X** and the estimated coefficients α^{τ}_h, $\boldsymbol{\beta}^{\tau}_h$ that characterize the ten quantile production functions.

BOX 1: ILLUSTRATIVE ANALOGY WITH HOCKEY COACHING

To gain intuition, let us briefly compare our industry allocation problem to the ice hockey coach's problem to allocate playing time between lineups

The normal duration of an ice hockey match is 60 minutes. A problem of the hockey coach is to allocate the given 60 minutes of playing time between four offensive lineups and 3-4 defense pairs. For simplicity, let us consider the four offensive lines and ignore the penalties that lead to short-handed or power play situations.

Coaches typically assign most playing time to their first and second offensive line that usually includes the best goal-scorers of the team. However, performance of a player quickly deteriorates due to fatigue as the playing time increases. Therefore, the third and fourth lines do also get a significant share of playing time. Often the third and fourth lines have a more defensive role in the team strategy.

Analogously, we can think of the 10 quantiles (or the corresponding deciles of the performance distribution) as lineups consisting of multiple firms (players). Different quantiles may adopt a more capital-intensive or more labor-intensive strategy, analogous to the offensive vs defensive roles of the hockey lineups. Our problem is to allocative the given aggregate labor and capital resources between the quantiles to maximize the output of the industry, similar to the coach's allocation of playing time between lineups to maximize the probability to win the game. Analogous to fatigue, the firm performance deteriorates as the decreasing returns to scale set in.

Note that the above baseline formulation does not allow for entry or exit of firms. Meaningful modelling of entry should somehow avoid the trivial solution where we just replicate the most productive firm N times. The possibility of exit can be modeled as follows. We first introduce a binary decision variable b_i that gets value of 1 if the firm is allocated resources, and 0 if the firm is forced to exit. In the case where exit is allowed, the resource allocation problem can be stated as the following mixed-integer linear programming problem

$\max_{\mathbf{x},\mathbf{y},\mathbf{b}} \Sigma_\tau \Sigma_i \, y^\tau_i$ (total output of the industry)

s.t.

$y^\tau_i \leq \alpha^\tau_h + \mathbf{x}^\tau_i{}' \boldsymbol{\beta}^\tau_h + (1 - b_i)M$ for all h, i, τ (technology constraint)

$y^\tau_i \leq b_i M$ ($b_i = 0$ relaxes technology constraint)

$\mathbf{x}^\tau_i \leq b_i M \mathbf{1}'$ ($b_i = 0$ relaxes technology constraint)

$\Sigma_\tau \Sigma_i \, \mathbf{x}^\tau_i \leq \mathbf{X}$ (resource constraints)

$\mathbf{x}^\tau_i \geq 0$ (resources cannot be negative)

$b_i \in \{0,1\}$ (firm i is active 1 or inactive 0)

The binary variable b_i makes the problem computationally harder, but modern integer programming solvers can handle resource allocation problems with thousands of pseudo-firms.

In the previous two formulations, resources can be reallocated between firms that operate at different quantiles. This can be a strong assumption if performance differences mainly arise from inherent quality differences in resources. Consider, for example, the vintage of capital or the education and skills of employees. To address this issue, we can easily impose additional restrictions that allow reallocation to take place only within pseudo-firms of a given quantile, but not move resources from one quantile to another. In this case, we rewrite the resource constraint of the previous formulations as

$$\Sigma_\tau \Sigma_i \mathbf{x}^\tau{}_i = \mathbf{X}^\tau \qquad \text{for all } \tau,$$

where $\mathbf{X}^\tau$ is a vector of total resources assigned to quantile τ in the observed allocation.

To summarize, we compute the optimal allocations using the following four alternative sets of constraints:

- Maximize output allowing reallocation only within deciles, no exit allowed.
- Maximize output allowing reallocation only within deciles, forced exit allowed.
- Maximize output allowing reallocation both between and within deciles, no exit allowed.
- Maximize output allowing reallocation both between and within deciles, exit allowed.

Note that the output of the optimized allocation will be higher if reallocation between deciles is possible or if the exit of firms is allowed because in such cases the constraints of the resource allocation problem are less restrictive.

6.4 How do the optimal allocations look like?

Consider the baseline allocation problem without exit possibility. The optimal solution provides information on how large proportion of resources to allocate to each decile of the performance distribution, but the allocation to firms within the group is completely immaterial because each firm of a given group is assumed to operate with the same technology. Typically all firms at the given deciles receive exactly the same resources in the optimal solution, except for leftover resources that cannot be equally divided. The following three tables illustrate the optimal solutions in the cases of the three industries considered already in Section 5.

Table 19 reports the optimal shares of labor, capital and output for the manufacture of basic metals (TOL 24) in the no-exit scenario of year 2005. In this industry, virtually all resources are concentrated to the most efficient deciles 1, 2, 3, and 5. All other quantiles only get the minimal resources (rounded to zero in Table 19) to keep up firms in operation. he largest share is allocated to quantile 3 that represents 70-80% of the performance distribution. Note further that the fifth quantile (50-60% of the performance distriInterestingly, not all resources are allocated to the most productive firms, in fact, tbution) operates more labor-intensively than other quantiles in the optimal solution.

Table 19. Manufacture of basic metals (24): the shares of labor, capital and output assigned to each decile in the optimal allocation for the year 2005 in the no-exit case.

Decile	Labor	Capital	Output
1 (90%-100% efficiency)	23	27	26
2 (80%-90% efficiency)	18	29	25
3 (70%-80% efficiency)	35	36	36
4	0	0	0
5 (50%-60% efficiency)	24	8	13
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0
10 (0%-10% efficiency)	0	0	0

Consider next the construction of residential and non-residential buildings reported in Table 20. In this industry all deciles receive at least 1-2 percent of labor resources in the optimal allocation, but the most resources are assigned to the most productive deciles 1-4. Interestingly, the most productive decile operates using a relatively labor-intensive technology in the optimal allocation, whereas the second decile of the productivity distribution takes a more capital-intensive approach.

Table 20. Construction of residential and non-residential buildings (41200): the shares of labor, capital and output assigned to each decile in the optimal allocation for the year 2005 in the no-exit case.

Decile	Labor	Capital	Output
1 (90%-100% efficiency)	41	7	52
2 (80%-90% efficiency)	19	73	24
3 (70%-80% efficiency)	4	1	2
4 (60%-70% efficiency)	24	15	19
5	2	1	1
6	2	0	1
7	1	0	0
8	2	0	1
9	2	2	1
10 (0%-10% efficiency)	2	1	1

Table 21. Computer programming activities (62010): the shares of labor, capital and output assigned to each decile in the optimal allocation for the year 2005 in the no-exit case.

Decile	Labor	Capital	Output
1 (90%-100% efficiency)	36	43	51
2 (80%-90% efficiency)	51	42	44
3 (70%-80% efficiency)	3	15	3
4	1	0	1
5	1	0	0
6	1	0	0
7	1	0	0
8	1	0	0
9	1	0	0
10 (0%-10% efficiency)	2	1	0

Finally, Table 21 presents the analogous results for the computer programming industry. All deciles receive at least one percent of labor resources in the optimal allocation, but the most resources are assigned to the most productive deciles 1-3. The most productive decile operates using a relatively capital-intensive technology in the optimal allocation, whereas the second decile is assigned more than half of the total labor resources.

In conclusion, these three examples illustrate that it is beneficial to concentrate more resources to the top deciles of the productivity distribution, however, it is not necessarily optimal to allocate all resources to the most productive firms. The returns to scale in production seem to drive this result. Our empirical estimation of quantile production function allows for variable returns to scale: there can be first increasing returns to scale that turn to decreasing returns to scale after the most productive scale size has been reached. Note that the returns to scale properties are not imposed but are estimated in a data-driven fashion: we only assume monotonicity and concavity of the quantile production functions.

The examples also illustrate that the optimal capital intensity can differ across different productivity levels. There can be room for more capital-intensive and more labor-intensive clusters of firms even within the same narrowly defined industry.

6.5 Productivity measures

Let the optimal solution to the allocation problem be Y^*. This represents the maximum output that the industry could produce with the given labor and capital resources, if optimally allocated across firms. If Y is the current level of output. then allocative efficiency of the industry can be measured as

Allocative efficiency = 100%(Y/Y^*)

The inverse of the allocative efficiency indicates the potential increase in output that could be achieved by improving allocative efficiency of the industry. Since labor productivity is simply the ratio Y/L, and since we assume that L does not change, the potential labor productivity increase through reallocation is also equal to

100%(Y^*/Y – 1) = 100%((Y^*/L)/(Y/L) – 1) = 100%([(Y^*/L) - (Y/L)] /(Y/L))

Since the capital input is also held at the constant level, the potential increase of total factor productivity is the same 100%(Y^*/Y – 1).

To put these productivity measures in perspective, we also compare the output of the current allocation (Y) and the optimal allocation (Y^*) with that of a random allocation.

The random allocations are computed using the same quantile production functions as those used in solving the optimal allocations by applying the following procedure:

- For each pseudo-firm *i*, draw two random numbers uniformly distributed between zero and one.
- Apply those two random draws as share-weights to compute the simulated firm-shares of the industry's total labor and capital resources, and assign resources to pseudo-firms according to their shares.
- Apply the quantile production functions to calculate the simulated outputs according to the randomly assigned resources.
- Sum over all pseudo-firms to get the total output of the industry.
- Repeat the simulation 1,000 times. Compute the average and median output of the random resource allocations.

6.6 How far is the current allocation from the optimum?

In this section we assess efficiency of the current allocation relative to the random allocations (average and median of the simulated random allocations) and the optimal allocations. The optimal allocations have been computed using the four alternative sets of constraints as explained in Section 6.3.

Table 22. Manufacture of basic metals (24): Value added (Million €, prices of 2010) in the current allocation, random allocations, and the four optimized allocations in 2005, 2012, and 2018. The columns % indicate the potential percentage increase relative to the current allocation.

	2005		2012		2018	
	M €	%	M €	%	M €	%
Current allocation	1 860		1 026		1 456	
Random allocation, average	1 924	3	945	-8	2 231	53
Random allocation, median	1 927	4	951	-7	2 251	55
Within decile reallocation, no exit	2 608	40	1 797	75	3 279	125
Within decile reallocation, exit allowed	2 612	40	1 800	75	3 288	126
Between deciles reallocation, no exit	3 815	105	2 537	147	3 815	162
Between deciles reallocation, exit allowed	3 822	105	2 544	148	3 828	163

Let us first consider in detail the three industries examined in Section 6.4. Table 22 compares the value added of the basic metals industry (24) in the current allocation, random allocations, and the four optimized allocations in years 2005, 2012, and 2018. We also report the potential percentage change of output through reallocation relative to the current allocation. We find that the basic metals industry achieved similar output as the random allocations in 2005 and 2012, but fell notably short of the random allocations in 2018. Optimizing the allocation by keeping the total resources of each decile fixed would already yield substantial increase in output, ranging from 40 percent in 2005 up to 125 percent in 2018. The potential benefit of reallocation further increases if we allow reallocation of capital and labor across quantiles.

Consider next the construction industry 41200 reported in Table 23, organized analogously to Table 22. This industry is also competitive with the random allocations in 2005 and 2012, but does not reach its potential in 2018. Optimizing the allocation by keeping the total resources of each decile fixed would yield relatively modest increase in output, ranging from zero to 11 percent in the no exit scenarios and from four to 22 percent when forced exit is allowed. If reallocation of capital and labor between quantiles is allowed, the potential benefits of reallocation increase considerably, ranging from 42 to 105 percent depending on the year and whether forced exit is allowed or not.

Table 23. Construction of residential and non-residential buildings (41200): Value added (Million €, prices of 2010) in the current allocation, random allocations, and the four optimized allocations in 2005, 2012, and 2018. The columns % indicate the potential percentage increase relative to the current allocation.

	2005		2012		2018	
	M €	%	M €	%	M €	%
Current allocation	1 465		1 939		4 380	
Random allocation, average	1 495	2	1 899	-2	5 147	18
Random allocation, median	1 495	2	1 900	-2	5 150	18
Within decile reallocation, no exit	1 565	7	1 939	0	4 870	11
Within decile reallocation, exit allowed	1 716	17	2 021	4	5 361	22
Between deciles reallocation, no exit	2 284	56	2 754	42	7 604	74
Between deciles reallocation, exit allowed	2 487	70	3 032	56	8 963	105

Our third example is the computer programming industry 62010 reported in Table 24. This industry is relatively competitive with the random allocations in all years. Optimizing the allocation within deciles would yield notable increase in output, ranging from four to 20 percent in the no exit scenarios and from ten to 29 percent when exit is allowed. When reallocation of capital and labor across quantiles is considered, the benefits of reallocation sharply increase, especially in year 2012.

Table 24. Computer programming activities (62010): Value added (Million €, prices of 2010) in the current allocation, random allocations, and the four optimized allocations in 2005, 2012, and 2018. The columns % indicate the potential percentage increase relative to the current allocation.

	2005		2012		2018	
	M €	%	M €	%	M €	%
Current allocation	1 564		1 849		2 426	
Random allocation, average	1 610	3	1 982	7	2 430	0
Random allocation, median	1 612	3	1 985	7	2 430	0
Within decile reallocation, no exit	1 820	16	2 228	20	2 511	4
Within decile reallocation, exit allowed	1 904	22	2 380	29	2 678	10
Between deciles reallocation, no exit	2 788	78	5 112	177	3 553	46
Between deciles reallocation, exit allowed	2 922	87	5 373	191	3 810	57

Having discussed the three examples in detail, we next turn to the all 16 selected industries. Let us first consider allocative efficiency of the current allocation relative to the optimal allocation in the case where reallocation is possible within the deciles, but reallocation between deciles is not allowed. Table 25 reports the estimated allocative efficiency as a percentage of the value added in the current allocation relative to the value added in the optimal allocation for the 16 selected industries in years 2005, 2012, and 2018, computed both with and without the exit possibility. Overall, the allocation turns out to be relatively inefficient in most manufacturing industries, except for the manufacture of computer, electronic and optical products (26) and the furniture industry (31). In the service industries the allocative efficiency is at higher level when we only consider reallocation within deciles, but not between deciles.

Consider next the scenario where resources can be reallocation both within and between deciles. Table 26 reports the estimated allocative efficiency as a percentage of the value added in the current allocation relative to the value added in the optimal allocation, analogous to Table 25. In these scenarios the allocative efficiency decreases further compared to the case where reallocation is only allowed within the deciles, as expected. The drop is notable in the service industries that performed relatively well in the previous scenario where resources were only reallocated within the deciles.

Table 25. Allocative efficiency of the 16 selected industries in 2005, 2012, and 2018, measured as percentage of the observed value added of the maximum value added in the optimal reallocation within deciles. The columns in italics refer to the optimal allocation when exit of firms is allowed.

	2005		2012		2018	
Industry	**No exit**	***Exit***	**No exit**	***Exit***	**No exit**	***Exit***
Manufacturing (C)						
Food products (10)	75.8	*74.6*	74.3	*72.8*	72.9	*71.7*
Sawmilling and planing of wood (16100)	77.1	*76.5*	64.4	*64.4*	75.4	*74.6*
Paper and paper products (17)	59.3	*59.2*	64.8	*64.7*	52.0	*52.0*
Chemicals and chemical products (20)	65.8	*65.7*	71.7	*71.6*	71.5	*71.4*
Basic pharmaceutical products (21)	70.5	*70.5*	60.6	*60.1*	64.4	*63.7*
Basic metals (24)	71.2	*71.3*	57.2	*57.0*	44.4	*44.2*
Computer, electronic and optical products (26)	92.6	*92.6*	59.8	*59.0*	49.0	*48.9*
Furniture (31)	89.6	*86.7*	96.8	*95.2*	91.1	*89.7*
Electricity, gas, steam, air conditioning (D)						
Hydropower and wind power (35111)	36.0	*35.9*	26.6	*26.6*	68.1	*68.0*
Combined heat and power (35113)	90.8	*90.0*	83.8	*82.3*	82.0	*81.4*
Construction (F)						
Residential and non-residential buildings (41200)	93.5	*85.4*	100	*95.9*	89.9	*81.7*
Transportation and storage (H)						
Freight transport by road (49410)	94.5	*94.1*	94.8	*94.6*	94.0	*93.7*
Accommodation and food services (I)						
Hotels (55101)	92.9	*90.5*	93.0	*90.9*	89.6	*86.7*
Information and communication (J)						
Computer programming activities (62010)	85.9	*82.1*	83.1	*77.7*	96.6	*90.6*
Human health and social work activities (Q)						
Dental practice activities (86230)	89.3	*88.9*	91.5	*89.7*	93.8	*92.7*
Arts. entertainment and recreation (R)						
Activities of sport clubs (93120)	86.5	*82.3*	70.6	*68.4*	77.6	*76.2*

Table 26. Allocative efficiency of the 16 selected industries in 2005, 2012, and 2018, measured as percentage of the observed value added of the maximum value added in the optimal reallocation both within and between deciles. The columns in italics refer to the optimal allocation when exit of firms is allowed.

	2005		2012		2018	
Industry	**No exit**	***Exit***	**No exit**	***Exit***	**No exit**	***Exit***
Manufacturing (C)						
Food products (10)	54.5	*52.9*	39.7	*39.2*	38.9	*38.4*
Sawmilling and planing of wood (16100)	61.9	*61.3*	53.1	*53.1*	57.8	*56.8*
Paper and paper products (17)	43.5	*43.4*	33.9	*33.8*	27.4	*27.4*
Chemicals and chemical products (20)	50.3	*50.1*	49.0	*48.9*	36.7	*36.6*
Basic pharmaceutical products (21)	52.2	*51.8*	34.3	*34.2*	32.3	*31.1*
Basic metals (24)	48.7	*48.7*	40.5	*40.3*	38.2	*38.0*
Computer, electronic and optical products (26)	85.7	*85.3*	28.0	*27.7*	41.5	*41.3*
Furniture (31)	46.3	*0.9*	69.1	*67.9*	44.4	*43.5*
Electricity, gas, steam, air conditioning (D)						
Hydropower and wind power (35111)	27.8	*27.8*	22.7	*22.7*	40.1	*40.0*
Combined heat and power (35113)	84.3	*83.2*	67.4	*65.7*	63.2	*62.8*
Construction (F)						
Residential and non-residential buildings (41200)	64.1	*58.9*	70.4	*63.9*	57.6	*48.9*
Transportation and storage (H)						
Freight transport by road (49410)	81.5	*77.0*	83.0	*21.8*	80.8	*77.5*
Accommodation and food services (I)						
Hotels (55101)	68.6	*66.6*	61.0	*59.3*	57.2	*55.1*
Information and communication (J)						
Computer programming activities (62010)	56.1	*53.5*	36.2	*34.4*	68.3	*63.7*
Human health and social work activities (Q)						
Dental practice activities (86230)	62.6	*1.5*	76.2	*73.9*	76.1	*74.9*
Arts. entertainment and recreation (R)						
Activities of sport clubs (93120)	52.1	*4.2*	55.6	*53.6*	55.6	*54.2*

It is interesting to note that the possibility of force exit has only marginal impact on the optimal allocation in most industries. This suggests that a large majority of the observed firms are viable in the optimal allocation, the biggest productivity gains could be achieved by better allocation of resources between existing firms. Only in the construction industry the forced exit of the least efficient firms would seem to yield notable productivity gains in all three years considered. There are very large but temporary gains also in the freight transport by road (in year 2012), dental practice activities (2005), and activities of sport clubs (2005).

While the deciles can differ in terms of quality of resources (e.g., vintage of capital, skills and education of employees), most likely at least some reallocation of resources between the deciles should be feasible. If we interpret the results of Table 25 as an upper bound and those of Table 26 as a lower bound for allocative efficiency, then the level of allocative efficiency appears to be in the ballpark range of 40 – 70 percent in most manufacturing industries and 60 – 90 percent in most service industries. In other words, there is enormous potential for productivity growth at the industry level through better allocation of resources, which does not require more resources, technical progress or any efficiency improvement at the firm level.

6.7 Conclusions

It is widely held that free market competition is the most efficient way to allocate resources. However, recent economic literature has found evidence of systematic misallocation of labor and capital in many countries (e.g., Foster et al. 2001, 2008; Hsieh & Klenow, 2009). In the spirit of the previous literature but using a more general estimation approach, we find large and persistent allocative inefficiencies in 16 relatively homogenous industries in Finland.

In most industries considered, the current allocation of resources is barely competitive with random allocations and a far cry from the optimal allocation. Many industries achieve only about a half of the potential output that could be produced with the same labor and capital resources, and by using the same technology at the constant level of productivity, if only the resources were more efficiently allocated across the observed firms.

Misallocation seems particularly severe in the manufacturing industries such as manufacture of paper and paper products. The decline of Finland’s ICT sector can explain the deteriorated allocation in the manufacture of computer, electronic and optical products. In the energy sector, the highly subsidized renewable energy production has much lower level of allocative efficiency than the conventional combined heat and power production. The highest levels of allocative efficiency are observed in service industries such as freight transport by road and dental practice activities, which include relatively large numbers of firms and a high degree of market competition.

The examination of the optimal allocations suggests that it would be more efficient to concentrate resources to the top deciles of the performance distribution to benefit from the economies of scale. However, it is not necessarily optimal to assign all resources or even the largest share of resources to the most productive firms. There can be viable niche firms that can combine a more capital-intensive or a more labor-intensive profile with a highly productive scale size.

It would be important to gain better understanding of how the government policy could help to stimulate and steer firms to achieve better allocation of resources to improve aggregate productivity. On one hand, misallocation can result from lack of competition in fragmented local markets, including the labor markets for employees with highly specific skills. On the other hand, competition policy might present obstacles for more efficient coordination between different firms in the innovation ecosystems and value chains. Based on the present study, one cannot conclude if more competition or more coordination would be needed. We leave this as an interesting challenge for further research.

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7 Allocation in the general equilibrium growth model

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Abstract: We study the allocative efficiency of innovative Finnish firms and their workers using a general equilibrium growth model. The innovation market is prone to misallocation due to underinvestment (as a result of technological externality), which may undermine economic growth and welfare. We study the optimality of allocative efficiency by first estimating a benchmark model economy. It reflects the actual economic conditions and the deep parameters that govern economic dynamics in the Finnish innovation markets. We then consider policies that push the economy towards optimality in different ways. We find that reaching optimal allocation necessitates addressing unmaterialized growth potential, not only supporting firms that currently have high productivity. We find that optimal policy drives out low-quality, low-productivity firms and gives room for high-quality firms that have growth potential that may have not yet been materialized. Policies that foster such creative destruction may have a significant effect on economic growth in the long run. Selective policies that are able to discriminate between high- and low-quality firms are the most efficient in achieving optimal allocation, but im-provements in allocation may be achieved even if such a distinction is hard to make.

7.1 Introduction

In chapter section, we study optimality of allocation in the Finnish economy with a general equilibrium growth model. We focus on innovative firms, as their market is both prone to misallocation and have major macroeconomic importance. These firms tend to conduct insufficient amount of R&D since they do not internalize the full value of their new innovations (e.g., Acemoglu, 2009). This is a fundamental cause of inefficiency and provide rationale for market interventions (see, Einiö et al. (2022) for recent literature review). Second, the market is inherently dynamic. The process by which innovative discoveries replace older technologies is at the heart of Schumpeter's notion of creative destruction and economic growth (e.g. Aghion et al. 2014).

In this research, we use the model proposed by Acemoglu et al. (2018) and its recent implementation for the Finnish economy, conducted by Einiö et al. (2022). [7] The model is an endogenous growth model in which firms make (optimal) decisions related to entering markets, scaling operations and exiting. The model is estimated with detailed, Finnish micro-level data. At the center of the model's focus is the allocation of the re-sources of the economy. The share of high-productivity and low-productivity firms in total output and how different policy measures affect this relationship are pivotal for the economic growth and welfare in the economy. While Einiö et al. (2022) studied the design of optimal policies in the model context, we further develop the analysis of al-locative efficiency.

In this model, future innovations builds on the current knowledge stock, implying that current innovations create a positive spillover to future innovators. As firms do not internalize the value of spillovers, the resulting underinvestment leads to too little employment of skilled workers in R&D and, on the other hand, too much employment in operations that merely sustain incumbent firms (Einiö et al., 2022).

We study the optimality of resource allocation by first estimating a benchmark model economy that reflects the actual economic conditions in Finland between the years 2000 and 2016. The estimation yields insights into the deep parameters that govern economic dynamics in the Finnish innovation makerts. We then consider policies that push the economy towards optimality in different ways. In a social planner's optimal allocation, the approach is extensive. The planner decides the optimal level of creative destruction and innovation. She or he knows the properties of individual firms (whether they are of low or high quality) and sets customized limitations and support for firms based on their perceived quality. Alternatively, we consider an optimal R&D subsidy, a policy that does not differentiate between firms based on their quality (as their quality may be unobservable) and rather, places similar policies on firms in the model based on observable characteristics.

Our analysis provides both meaningful counterfactuals and insights into the indirect effects of policies at the aggregate level as it builds on a careful characterization of individual firms' dynamic optimization, policy effects on their behavior, and market reactions. [8]

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[7] This research builds on and complements another Government's analysis, assessment and research activities' project "Yritystukien kokonaistaloudelliset vaikutukset" and its final report by Einiö et al. (2022).
[8] Innovation, production, and continuation decisions depend on the underlying efficiency of the firm in regard to innovation, its current productivity, and the overall characteris-tics of the markets. While firms expand their operations following successful innovation and capturing of new product markets, they exit due to exogenous destructive

7.2 The model

In this subsection, we briefly outline the model and highlight features that are important in our analysis. Box 2 provides technical details, while an exhaustive description of the model can be found in the work of Acemoglu et al. (2018).

Economic activity in the model builds on the use of skilled and unskilled labor provided by the representative households. There is a fixed quantity of both types. Skilled work is divided between performing R&D functions in order to provide new innovations and operating existing-technology product lines (with a product-line specific fixed cost). The unskilled workers are used to producing goods and services with the existing technology in active product lines.

There is competition for the technological leadership in each product line. Leadership is gained through successful innovation that leads to a labor productivity gain in a corresponding product. The firms in the model economy have different product lines to choose from, and their outputs are then combined into an aggregate final good.

The innovation can be conducted either by incumbent firms or through the market entry of new firms. That is, there are two different sets of firms: (i) a set of active firms, F, that own at least one product line, and (ii) a set of potential entrants of measure one that do not currently own any product line but invest in R&D for innovation.

The current technological leader has a monopoly of the corresponding product. The firm can own multiple product lines and can produce multiple intermediate goods simultaneously. However, there is monopolistic competition between intermediate products at the level of final consumption, as captured by a constant elasticity of the supply aggregator of the final product.

In the model, the exit of products and firms has the following three causes for the inactivity of some product lines (especially points i and iii):

(i) An exogenous destructive shock (given by the probability $\varphi > 0$) causes the firm to exit and shut down all its product lines.

(ii) (There will be creative destruction because of innovation by other firms. This replaces the leading-edge technology in a particular product line.

(iii) Firms voluntarily shut down some product lines because they are no longer profitable enough as regards the fixed cost of operation.

BOX 2: DETAILS OF THE ECONOMY AND FIRMS' OPTIMIZATION PROBLEM

Following the work of Acemoglu et al. (2018) and Einiö et al. (2022), let us use J_f to denote the set of active product lines wherein firm f has the leading-edge technology and chooses to produce the product, and n_f denotes the cardinality of this set.

After successful innovation, the production of the actual good requires unskilled labor in assembly and skilled workers in operation. In the model of Acemoglu et al. (2018), once firm *f* hires ϕ units of skilled labor for operation; this firm has access to a linear technology in product line *j* of the form $y_{f,j} = q_{f,j} l_{f,j}$, where $q_{f,j}$ is the leading-edge technology of firm *f* in intermediate good *j* (which means that firm *f* has the best technology for this intermediate good) and $l_{f,j}$ is the number of unskilled workers it employs for producing this good.

The product is used as a component of the aggregate consumption, $c_j(t) = y_j(t)$. The representative household has the following constant relative risk aversion (CRRA) preferences:

$$U_0 = \int_0^{\infty} \exp(-\rho t) \frac{C(t)^{1-\vartheta} - 1}{1-\vartheta} dt,$$

where ρ > 0 represents the discount factor and *C(t)* represents a consumption aggregate that can be described as:

$$C(t) = \left(\int_{\mathcal{N}(t)} c_j(t)^{\frac{\varepsilon-1}{\varepsilon}} dj \right)^{\frac{\varepsilon}{\varepsilon-1}},$$

where $c_j(t)$ is the consumption of product *j* at time *t*, $\mathcal{N}(t) \subset [0, 1]$ is the set of active product lines at time t, and ε > 1 is the elasticity of substitution between products.

The representative household has access to non-productive assets and maximizes its utility subject to the budget constraint that labor income equals consumption and net savings with the possibility for Ponzi schemes. We abstract from the open economy aspect of the optimal policy. That is, we assume that the policies have no effect on the current account and foreign (direct) investments. In that sense, our model misses some aspects of the Finnish economy.

Firms have different innovative capacities. Upon successful entry into the economy, each firm draws its type $\theta \in \{\theta^h, \theta^l\}$, which corresponds to one of two possible types: high (*h*) and low (*l*) productivity. We write:

$\Pr(\theta = \theta^h) = \alpha$ and $\Pr(\theta = \theta^l) = 1 - \alpha$,

where $\alpha \in (0.1)$ and $\theta^h > \theta^l > 0$. It is also assumed that high-type firms transition to low-type at the exogenous flow rate $v > 0$. This transition effect is complemented with another exogenous shock: each firm is subject to an exogenous destructive shock at the rate φ. If a firm is hit by this shock, its value becomes 0 and it exits the economy.

Successful innovations improve the productivity of a randomly chosen[9] product line by $\overline{\lambda q}$, where $\bar{\lambda}$ is the estimated average innovation step size that is estimated from the data and $\bar{q}$ is the average productivity of the current technology upon which the new innovation builds. This externality is the primary reason for economic growth in the model while it also creates a fundamental market failure in the economy.

Each entrant to the market has access to R&D technology $G(X^{entry}, \theta^{E})$; it specifies the number of skilled workers necessary for generating at an innovation rate of $x^{entry} > 0$. Thus, an entrant aiming at achieving an innovation rate of x^{entry} would need to hire the number of skilled workers following the equation:

$$h^{\text{entry}} = G\left(x^{\text{entry}}, \theta^{E}\right).$$

As explained in the work of Acemoglu et al. (2018), this implies that a potential entrant has access to the same R&D technology that an incumbent with the innovative capacity θ^{E} and a single active product would have.

The optimisation problem for entrants can be stated as:

$$\max_{x^{\text{entry}} \geq 0} \left\{x^{\text{entry}}\, \mathbb{E}V^{\text{entry}}\left(\hat{q} + \lambda\bar{\bar{q}}, \theta\right) - w^{s} G\left(x^{\text{entry}}, \theta^{E}\right)\right\}.$$ [10]

The equation implies that the entrant improves the productivity of a randomly chosen product line by $\overline{\lambda q}$, and at this point, the initial type of a firm, $\theta \in (\theta^{h}.\theta^{l})$, is also realized. The expected value of entry is $\mathbb{E}V^{entry}(.)$. Solving the equation determines the R&D intensity of an entrant. Given that there is a unit measure of potential entrants, x^{entry} is equal to the total entry flow rate.

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[9] It is assumed that firms do not know ex ante in which particular product line they will innovate. As a result, their expected return on R&D is the expected value across all product lines: $j \in (0.1)$. As a technical assumption, prices after entry are defined by Bertrand competition, implying that a more productive firm will be able to make sales and profits, and thus only this firm will pay a (small) cost $\epsilon > 0$ and enter the market. Hence, in equilibrium, the firm that has the leading-edge technology can charge the monopoly price independently of the productivity gap between itself and the next best technology.

[10] All the growing variables need to be normalised by $Q(t)$ in order to keep the stationary equilibrium values constant. We follow the work of Acemoglu et al. and denote the normalized value of a generic variable X using $\tilde{X}$.

Innovation by incumbents is approached as follows. Firm f of type θ_f hires h_f skilled workers for creating a new product, therefore adding one more product into its portfolio of products at the flow rate:

$$X_f = \theta_f^{\gamma} n_f^{\gamma} h_f^{1-\gamma},$$

where $\gamma \in (0,1)$ and n_f is the number of product lines that firm f owns in total.

The stationary equilibrium value function for a low-type firm can be written as:

$$\begin{aligned} &r\tilde{V}_l(\hat{Q}) \\ &= \max\Big\{0, \max_{x\geq 0}\Big[\textstyle\sum_{\hat{q}\in\hat{Q}}\Big[\tilde{\pi}(\hat{q}) - \tilde{w}^s\phi + \tau\big[\tilde{V}_l(\hat{Q}\setminus\{\hat{q}\}) - \tilde{V}_l(\hat{Q})\big] + \frac{\partial\tilde{V}_l(\hat{Q})}{\partial\hat{q}}\frac{\partial\hat{q}}{\partial w^u}\frac{\partial w^u}{\partial t}\Big], \\ &\qquad -n\tilde{w}^s G(x,\theta^l) + nx\big[\mathbb{E}\tilde{V}_l(\hat{Q}\cup\{\hat{q}+\lambda\bar{\hat{q}}\}) - \tilde{V}_l(\hat{Q})\big] + \varphi\big[0 - \tilde{V}_l(\hat{Q})\big]\Big]\Big\} \end{aligned}$$

where $\hat{Q} \cup \{\hat{q}_{j'}\}$ is the new portfolio of the firm after successful innovation in product line j' and $\hat{Q}\backslash\{\hat{q}_j\}$ denotes the loss of a product with technology $\hat{q}_j$ from firm f's portfolio $\hat{Q}$ that is caused by creative destruction. The symbol τ denotes the average creative destruction rate. This is endogenously determined in equilibrium.

The value function in the equation above can be interpreted as follows. The left-hand side is the flow value of a low-type firm with a set of product lines given by $\hat{Q}$, given the discounting rate r. As is typical in these kinds of models, the right-hand side consists of the components that make up this flow value.

The first line (inside the summation) includes the instantaneous operating profits, with the fixed costs of operation subtracted, plus the change in firm value in the case when any of its products is replaced by another firm through creative destruction at the rate τ, plus the change in firm value. The latter is based on the increase in the economy-wide wage and accounts for the fact that, as the wage rate increases, the relative productivity of each of the products that the firm operates declines. Then, the first term in the second line depicts the R&D expenditure cost for firm f. The next term expresses the change in firm value when a low-type firm is successful with its R&D investment, materialising at the rate x. The last term captures the change in value when the firm exits due to an exogenous destructive shock, which the economy confronts at the rate φ.

Following the same logic as in the value function equation above, the value function of a high-type firm can be written as:

$$\begin{aligned} &r\tilde{V}_h(\hat{Q}) \\ &= \max\Big\{0, \max_{x\geq 0}\Big[\textstyle\sum_{\hat{q}\in\hat{Q}}\Big[\tilde{\pi}(\hat{q}) - \tilde{w}^s\phi + \tau\big[\tilde{V}_h(\hat{Q}\setminus\{\hat{q}\}) - \tilde{V}_h(\hat{Q})\big] + \frac{\partial\tilde{V}_h(\hat{Q})}{\partial\hat{q}}\frac{\partial\hat{q}}{\partial w^u}\frac{\partial w^u}{\partial t}\Big] \\ &\qquad\qquad -n\tilde{w}^s G(x,\theta^h) + nx\big[\mathbb{E}\tilde{V}_h(\hat{Q}\cup\{\hat{q}+\lambda\bar{\hat{q}}\}) - \tilde{V}_h(\hat{Q})\big] \\ &\qquad\qquad\qquad +\varphi\big[0 - \tilde{V}_h(\hat{Q})\big] + \nu\big[\tilde{V}_l(\hat{Q}) - \tilde{V}_h(\hat{Q})\big]\Big]\Big\}. \end{aligned}$$

7.3 Estimation

Our analysis builds on the estimation of the model created by Einiö et al. (2022). Next, we briefly describe the methodology.

7.3.1 Data

The dataset builds on the Business Register compiled by Statistics Finland (SF). It covers all enterprises and corporations with value-added tax liability or paid employees, except for very small companies with low labour input, turnover, and total assets.[11] It also employs the linked employer–employee data (i.e., the FLEED data), and information on R&D expenditure is drawn from the annual R&D Survey (RDS) of SF.

Our analysis includes the year 2000 through to the year 2016 for which the key variables are available. We follow Acemoglu et al. (2018) and focus on operative manufacturing firms that are continuously innovative. A firm is defined to be *continuously innovative* in year t if it is observed to be innovative in that year and in year $t-5$ or $t+5$. We only leave out firms that employ one person, that is, we use the baseline dataset found in Einiö et al. (2022).

We define a firm to be *innovative* in year t if it has positive R&D expenditure or a positive patent count in any year within a five-year window (that is, from $t-2$ to $t+2$). We define a firm to be *operative* if it has positive Business Register turnover, positive Business Register employment, or positive FLEED employment (for operative status, we examine both whether the firm has any employees in the last week of the year and whether the longest job spell of a worker is associated with the firm). A firm is defined as having *exited* in its last operative year (we restrict the analysis window so that the operative status is observed one year after its end).

We define *highly educated individuals* as those who have university/college degrees and *non-production workers* as those who are managers, professionals, assistant professionals, or technicians. The FLEED is also used to calculate the size of the workforce in managerial occupations or with a university/college degree in the fields of science, technology, engineering, and mathematics (STEM).

[11] Thesample frame excludes enterprises that (1) have been active for less than half a year; (2) have full-time equivalent employment below half worker years; (3) have a balance sheet of less than 170 000 euros; and (4) have turnover below an annually specified limit (for example, below 11 016 euros in 2014).

7.3.2 Simulated method of moments

We estimate the model with information on the underlying key characteristics of the economy. In particular, the procedure yields estimates of a set of underlying parameters for the model that are key factors in determining the dynamics of the model.

For each underlying parameter vector candidate, the model is solved computationally as a fixed point of a vector of six aggregate equilibrium variables: the equilibrium skilled wage rate, the average innovation step size in relative productivity terms, the shares of product lines operated by high- and low-type firms, and the expected franchise values of upgraded product lines—that is, a vector $(\tilde{w}^s, \Phi^h, \Phi^l, \bar{\hat{q}}, E[\Upsilon^h(\hat{q} + \lambda\bar{\hat{q}}), E[\Upsilon^l(\hat{q} + \lambda\bar{\hat{q}}))$. It turns out that the vector describes the equilibrium innovation decisions (the cost of innovation and its expected returns). In practice, the solution is obtained iteratively by using an initial conjecture vector and then updating the vector until the conjecture is verified following the work of Acemoglu et al. (2018). This procedure yields us a fixed point and also generates the stationary equilibrium distributions of relative productivities.

Similar to the work of Acemoglu et al. (2018), we take as a given some key underlying parameters. As standard choices in the literature and similar to the work of Acemoglu et al. (2018), we choose the discount rate of ρ = 2% and the inverse of the intertemporal elasticity of substitution as ϑ = 2. The intertemporal substitution elasticity is the same as that used for Finland by, for example, Gorodnichenko et al. (2012). The discount factor, circa 97% at an annual rate, also corresponds well with the Finnish case as, typically, the discount factor in the Finnish quarterly models is 0.99. Similarly, we pick a standard value for the elasticity of substitution between different products to be 2.9. Following micro-econometric innovation literature, we choose the elasticity of successful innovation with respect to R&D γ to be 0.5 (Blundell, Griffith, and Windmeijer, 2002; Hall and Ziedonis, 2001). Finally, we set the ratio of highly skilled workers to the total number of workers in the workforce in the economy to be 20.9%, which is the ratio of the number of workers who are in managerial occupations or hold a higher-education STEM degree to the number of workers in the economy, calculated from the linked employer–employee data that covers the whole working-age population.[12]

The remaining eight parameters are estimated with the simulated method of moments (SMM). We compute the model-implied moments from the model and compare them

[12] We aggregate employment to firm level by employing the company code of the employer for the primary job spell of a worker in the last week of a year.

with the data-generated moments to minimize the differences between model moments and the data moments. Our minimization problem is

$$min \sum_{i=1}^{18} \frac{|model(i)-data(i)|}{\frac{1}{2}|model(i)|+\frac{1}{2}|data(i)|}.$$

The SMM searches repeatedly across sets of parameter values (*i*) in the model until the model's moments are as close as possible to the empirical moments. In particular, 18 moments are measured from the model and compared with the empirical counterparts.

The moments are listed in Table 27. They describe firm entry (measured through employment shares), exit rates, size transition rates, employment and sales growth rates, and innovation intensities. These moments are selected because of their economic importance for the mechanisms of the model. In our estimations, we assign an equal weight for each variable, whereas Acemoglu et al. (2018) overweighted the aggregate growth rate of the economy.

The estimated moments can be found in Table 27. Moreover, the table also includes the baseline US estimates reported by Acemoglu et al. (2018). Overall, we find that the model fits the Finnish data relatively well, although the average deviation of the parameters is moderately larger than in the US data. This can be observed from the total score that measures the average percentual deviation of the model moments from the empirical moments.

As discussed by Einiö et al. (2022), this is partly because the estimation interval may not fully reflect stationary, long-term equilibrium. Rather, the moments reflect transitionary dynamics that our model is not equipped to incorporate. For example, the rate of transition from a large firm to a small firm has been somewhat higher than the rate of transition from a small firm to a large firm. On the other hand, this also reflects sample choices. Einiö et al. (2022) considers several alternative specifications and finds that the impact of policies on economic outcomes are somewhat dependent on them, but yield qualitatively similar results.

Let us describe some details of the estimated moments. First, young and small firms tend to grow faster and engage in more R&D activities than their older counterparts. However, they also have a higher exit rate from the market, implying that there are large risks involved in their operations. There are some deviations from the empirical moments. Our benchmark model moderately underestimates the exit rates in the empirical moment, which may result in exaggerating the importance of policies that build on fostering higher creative destruction rates. On the other hand, the R&D efforts of young and small firms are underestimated, which probably leads to a bias in the opposite direction. The fixed costs of operations relative to R&D are consistently estimated to be higher than in the data, taking the model closer to the work of Acemoglu et al. (2018). In this respect, it seems that finding a balance with other data moments necessitates a higher cost of operations in the model. Einiö et al. (2022) notes that finding an empirical counterpart for the moment is not quite straight forward, and our estimated moment falls in the range of possible values. Therefore, the discrepancy between the empirical and the model moment is not a great concern.

Table 27. Data and model matched moments

	Model baseline		Acemoglu et al. (2018)	
	Fin. model	Fin. data	US, model	US data
Transition from large to small	**0.028**	0.08	**0.021**	0.010
Transition from small to large	**0.033**	0.0081	**0.038**	0.014
Probability of being small (conditional on entry)	**0.871**	0.8628	**0.848**	0.753
Five-year entrant share	**0.226**	0.1704	**0.336**	0.393
Aggregate growth	**0.016**	0.0162	**0.023**	0.022
Firm exit (small-young)	**0.076**	0.1074	**0.097**	0.107
Firm exit (small-old)	**0.071**	0.092	**0.092**	0.077
Firm exit (large-old)	**0.016**	0.0531	**0.036**	0.036
R&D to sales (small-young)	**0.094**	0.1502	**0.086**	0.064
R&D to sales (small-old)	**0.057**	0.0571	**0.066**	0.059
R&D to sales (large-old)	**0.052**	0.0297	**0.059**	0.037
Sales Growth (small-young)	**0.077**	0.0892	**0.101**	0.107
Sales Growth (small-old)	**0.012**	0.01	**0.040**	0.024
Sales Growth (large-old)	**-0.027**	-0.0172	**-0.005**	-0.003
Employment growth (small-young)	**0.073**	0.0539	**0.101**	0.106
Employment growth (small-old)	**0.013**	-0.0003	**0.040**	0.035
Employment growth (large-old)	**-0.026**	-0.0277	**-0.005**	-0.005
Fixed cost - R&D labor ratio	**4.509**	3.3104	**4.175**	5.035
Total score	**0.532**		**0.290**	

7.3.3 Estimated parameters

We collect the estimated parameters in Table 28. Overall, the estimated model parameters indicate that there is a significant amount of dynamics in the productivity distribution. Similar to the work of Acemoglu et al. (2018), entrants have a large chance of being a high-type firm, that is, the probability of being a high-type entrant, α, is high. Incumbent firms are much more likely to be a high-type firms when young (rather than later in their life cycle). This is indicated by a high transition rate from high-type to low-type firms, ν. Moreover, high-type firms are, indeed, more innovative than low-type firms, which is indicated by the higher innovative capacity of high-type firms, $\theta_l < \theta_h$.

The average innovation step size, λ, is moderately smaller in the estimation based on the Finnish data when compared with the estimation of Acemoglu et al. (2018) for the US. Thus, the technological advances and their economic benefits are somewhat smaller than in the US. The fixed costs, $\phi,$ are estimated to be smaller in Finland, which may be partly due to the sample also including very small firms (Einiö et al., 2022). This, on the other hand, increases incentives for innovation. The exogenous destruction rate, $\psi,$ is somewhat smaller than in the US-data based model.

As Einiö et al. (2022) showed, the results are somewhat sensitive to the underlying dataset. When considering the estimated model in more detail, Einiö et al. (2022) found that the average innovation step size is larger when more emphasis is put on larger firms. The destruction rates are fairly similar, but the transition rates from high-types to low types is considerably smaller in the samples that emphasize larger firms. Consistently, the fixed costs are estimated to be larger in the samples that put more weight on larger firms.

Table 28. Underlying parameters of the model

Parameter	Parameter description	Model baseline	Acemoglu et al. (2018)	
λ	Innovation step size	0.115	0.132	Estimated
ψ	Exogenous destruction rate	0.015	0.037	Estimated
ν	Transition rate from high-type to low-type	0.273	0.206	Estimated
α	Probability of being high-type entrant	0.989	0.926	Estimated
ϕ	Fixed cost of operation	0.259	0.216	Estimated
θ_l	Innovative capacity of low-type firms	0.742	1.391	Estimated
θ_h	Innovative capacity of high-type firms	1.154	1.751	Estimated
θ_e	Innovative capacity of entrants	0.010	0.024	Estimated
ϵ	Constant elasticity of substitution	2.900	2.900	Fixed
ρ	Discount rate	0.020	0.020	Fixed
γ	Innovation elasticity	0.500	0.500	Fixed
σ	Inverse of the intertemporal elasticity of substitution	2	2	Fixed
L_s	Share of high-skilled workers	0.209	0.166	Fixed

7.4 Optimal allocation with different policies

7.4.1 Defining the counterfactuals

We construct two types of counterfactuals that we then compare with the results of our benchmark model that represents the average, actual features of the estimation period.

We first introduce a social planner that decides the optimal levels of creative destruction and innovation. The social planner knows the properties of individual firms (that is, it knows whether they are of low or high quality) and sets customized limitations and support for firms based on their perceived quality. Similar to the work of Acemoglu et al. (2018), the social planner cannot directly make production decisions or set prices and only allows control of the entry, exit, and R&D margins of different firms. This simplification abstracts us from the analysis of monopoly distortions per se, but allows simple quantification of the optimal policy. In the optimal scenario, the social planner chooses the same-per-product R&D for all high- and low-type firms. Then, we can represent the problem of the planner as choosing both type-specific R&D intensities and the threshold levels of surviving-firm productivities in order to maximize the representative household welfare, subject to the skilled labor market-clearing condition.

However, it may be unrealistic to assume that such information regarding the quality of the firms is available. Whereas the economic outcomes of individual firms are perceivable, the role of chance and other unobservable factors may conceal a firm’s underlying type. The social planner can observe the types of individual firms, while in practice, tax designs or support-granting agencies are limited in making such a distinction. Therefore, it is also useful to assess optimal support rates for policies that uniformly affect low- and high-type firms. We experiment with an optimal, indiscriminatory R&D subsidy, similar to all incumbent firms.

7.4.2 Productivity distribution in the benchmark

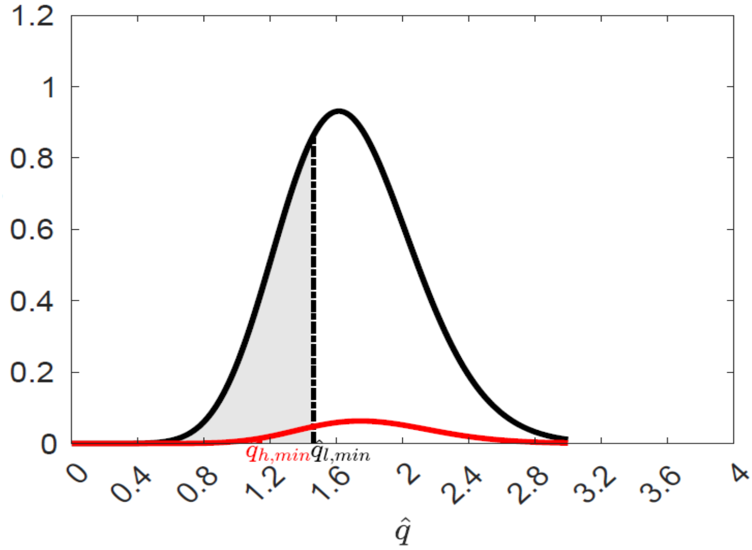
We first analyze our benchmark economy. We characterize the productivity distribution in the model and compare it with its empirical counterpart. In Figure 3, we describe productivity in terms of $\hat{q}$, which is the ratio $\frac{q}{w_L}$, where q is the productivity of a low-skilled worker in a specific production line, while the corresponding wage rate is

w_L.[13] The minimum survival productivities are denoted as $\hat{q}_{h,min}$ and $\hat{q}_{l,min}$, for high- and low-type firms, respectively. When productivity is below the survival threshold, the firm—knowing its innovation type—makes a decision to sieze the product line.

As the Figure shows, the relative productivity of the continuing product line must exceed 1 (i.e., the value of the output must exceed the direct production costs [the unskilled labor costs]). However, as there are also fixed operation and R&D costs arising from the use of highly skilled labor, the survival productivities are strictly above 1. The product line's revenue has to cover all of its costs.

Before going into the details of the productivity distribution, it is worthwhile to compare it with the actual data. The model distribution is not matched with the data during the original estimation, and therefore, it shows important evidence of the ability of the model to match the data.

Figure 3. Productivity distribution of the product lines in the model. Frequencies are normalized so that the number of product lines with median productivity = 1.

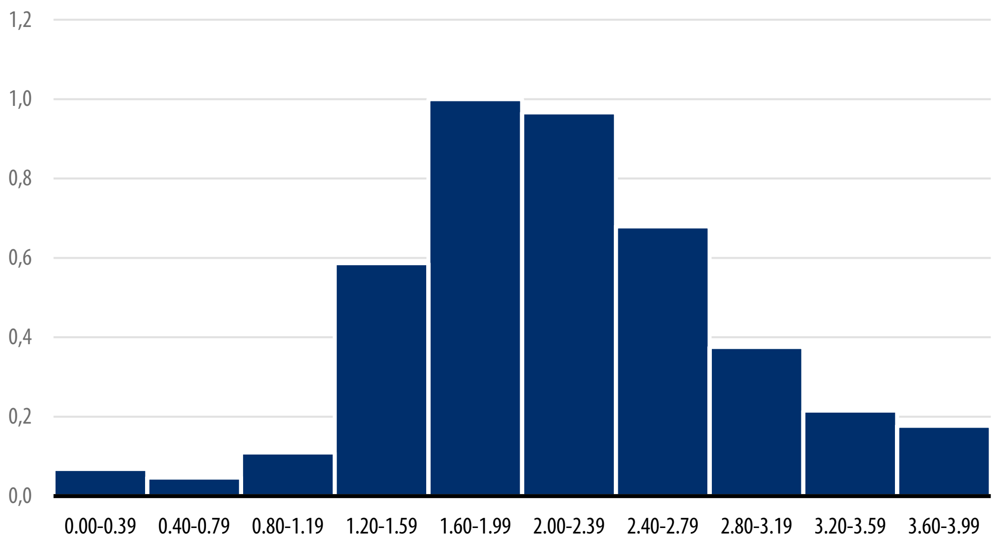


Note: The red line denotes the productivity of product lines that are operated by high-type firms and the black line shows the corresponding productivity for low-type firms. The grey area indicates inactive product lines for which productivity falls below the threshold productivities.

[13] As our economy is growing, the ratio is needed in order to charactize a stationary productivity distribution.

In Figure 4, we calculate the productivity distribution of individual firms from the actual data. While we do not have data on the productivity of individual product lines, and thus this comparison is tentative, we find that, overall, the match to the model's distribution is rather good. The median markup of labor productivity over the wage rate is of similar magnitude. Data, however, has somewhat more weight in the tails of the distribution, indicating that there may be, on one hand, more incentives to continue unprofitable firms, and on the other hand, individual firms may show productivity performance that exceeds our forecasts.[14]

Figure 4. Productivity distribution of the Finnish firms. Frequencies are normalized so that the median = 1.



Note: The firm-level average labor productivity per low-skilled wage rate ($\hat{q}$) during the time period 2000–2016.

Further analysis of the model distribution yields interesting insights into the underlying productivity distributions of the production lines operated by low- and high-type firms. First, it is notable that the higher probability of successful innovation by high-type firms allows them to continue operating at a lower level of relative productivity due to the higher probability of successful future innovation. That is, $\hat{q}_{h,min} < \hat{q}_{l,min}$. The higher expected value of their life-time production due to the prospects of future successes allows them to continue, even at a low current level of productivity.

[14] Note that for illustrative purposes, we only show the empirical productivity distribution that corresponds with the model's productivity interval. However, a small share of the data observations are above and below the chosen interval.

A closer look on the underlying key features in Table 29 underlines the dynamic nature of the productivity distribution. They show that for the high-type firms, the average innovation rate is 0.387**,** indicating that roughly two fifths of the innovation efforts lead to a breakthrough at an annual rate. The corresponding rate is halved in case of low types, 0.194, and it is only 0.003 for entrants (however, with a large pool of potential entrants). Overall, the innovation efforts lead into an average creative destruction rate of 0.142, indicating that the operator changes due to successful innovation in 14.2% of product lines, at an annual rate.

However, despite the superiority of the innovative capabilities of the high-type firms, their share of the active product lines remains relatively low. Only 5.8% of the product lines are operated by high-type firms, while 59.9% are operated by the low types (while the rest of the production lines are inactive). This is an indication of the strong pattern of negative selection in the model. Entrants have a large chance of being a high-type firm and incumbent firms are much more likely to be a high-type firm when young, rather than later in their life cycle. Many of the active product lines are operated by older firms that may have transitioned to low types. Overall, only a small share of the skilled workers, 18.6%, are engaged in R&D, while a large part of the skilled workforce is devoted to supporting existing technologies.

Albeit weakened by the low share of high-type firms, the dynamism shows up as a continuous increase in the productivity of the economy. The aggregate economic growth rate, 1.63%, is close to the actual, aggregate growth rate of the innovative firms during the estimation period.

Table 29. Key features of the model in different specifications

		Innovation rate (x)			The share of product lines operated (phi)		Threshold survival productivity for	
		Entry	low type	high type	low type	high type	low type	high type
Benchmark	**Fin**	**0.003**	**0.194**	**0.387**	**0.599**	**0.058**	**1.461**	**1.138**
	US	0.005	0.259	0.381	0.550	0.063	1.473	1.303
Social planner	**Fin**	**0.004**	**0.191**	**0.462**	**0.249**	**0.294**	**1.885**	**0.379**
	US	0.006	0.254	0.453	0.056	0.447	2.404	0.278
Optimal sub-sidy	**Fin**	**0.002**	**0.227**	**0.467**	**0.491**	**0.105**	**1.602**	**1.310**
	US	0.004	0.307	0.465	0.477	0.087	1.601	1.428

		R&D to skilled labor	Creative destruction rate (tau)	Aggregate growth rate	welfare, bm = 1
Benchmark	**Fin**	**0.186**	**0.142**	**1.63 %**	**1**
	US	0.199	0.172	2.26 %	1
Social planner	**Fin**	**0.327**	**0.188**	**2.16 %**	**1.037**
	US	0.342	0.223	2.94 %	1.045
Optimal sub-sidy	**Fin**	**0.261**	**0.163**	**1.88 %**	**1.015**
	US	0.264	0.191	2.51 %	1.012

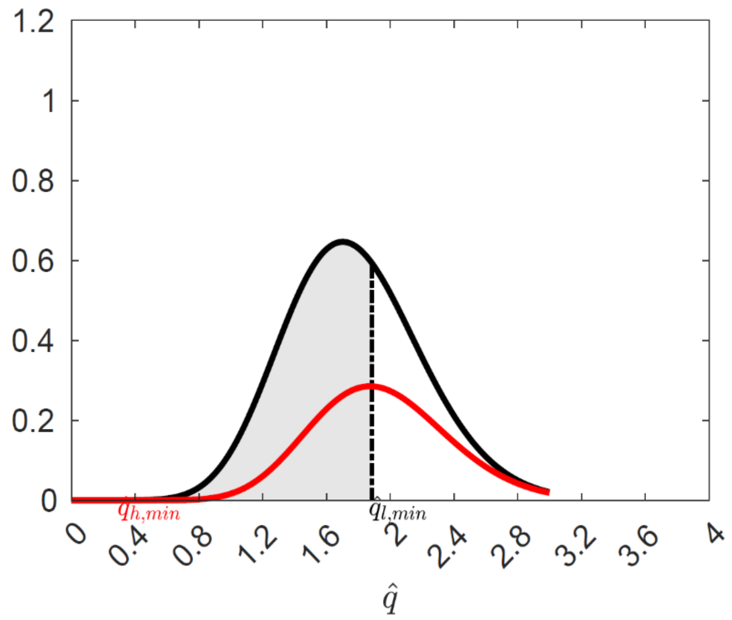
7.4.3 Comparisons to optimal allocation

We next turn to analyzing the optimality of the benchmark economy allocation by subjecting the model to counterfactuals that represent transfers to optimality through different policy options.

The social planner

We begin by analyzing the social planner optimum. The social planner knows the types of individual firms and sets customized limitations to continuation (it sets optimal sur-vival thresholds for both types) and support for firms based on their perceived quality (with optimal innovation rates for both types). Altogether, there are thus four optimized characteristics of the policy.

Figure 5. Productivity distribution of the product lines in the model, social planner solution. Frequencies are normalized so that the number of product lines with median productivity = 1.



Note: The red line denotes the productivity of product lines that are operated by high-type firms and the black line shows the corresponding productivity for low-type firms. The grey area indicates inactive product lines for which productivity falls below the threshold productivities.

The counterfactual productivity distribution is shown in Figure 5. A few substantial differences to the benchmark are notable.

The optimal policy drives out low-type, low productivity firms. The threshold productivity, $\hat{q}_{l,min}$, is considerably higher than in the benchmark. That is, product lines that have mediocre productivity and are operated by low-type firms are forcefully driven out of the market and remain inactive. Above all, this policy frees highly skilled workers from the support of existing product lines to R&D. Table 29 shows that the share of highly skilled workers engaged in R&D increases from 18.6% to 32.7%. An increased share, 45.7%, of the product lines remain inactive, as the table shows.

Meanwhile, the policy gives room for the entry of high-quality firms that have growth potential, but not necessarily high current productivity. The threshold productivity, $\hat{q}_{h,min}$, is below 1, indicating that, in principle, all product lines that are operated by high-type firms are allowed to survive by the policy. In practice, however, the existing product lines are for the most part profitable. Overall, the share of product lines operated by high-type firms increases from 5.8% to 29.4%.

Pushed by the policies that subsidize high-type innovation activities, the innovation rate of the high types increases from 38.7% to 46.2%. Also, the innovation rate of the entrants increases, whereas in the case of low-types, there is little change in the rate. Overall, the result of the policy is a strengthening of competition in the economy. The creative destruction rate rises to 18.8%.

When compared to the US, the gains from the optimal policy are of similar magnitude. We find that the consumption-equivalent welfare gain is 3.7% relative to the baseline economy.[15] In the US model, the corresponding gain is 4.5%. The economic growth rate increases in Finland from 1.63% to 2.16%, whereas it increases in the US from 2.26% to 2.94%.

It is worth noting that our counterfactual describes a long-term shift in the steady state of the economy. Thus, the (rather dramatic) change in the economy happens over time. While it shows the potential of creative destruction in fostering economic growth and welfare, we acknowledge that there may be some short-run inertia in the economy that our model does not capture.

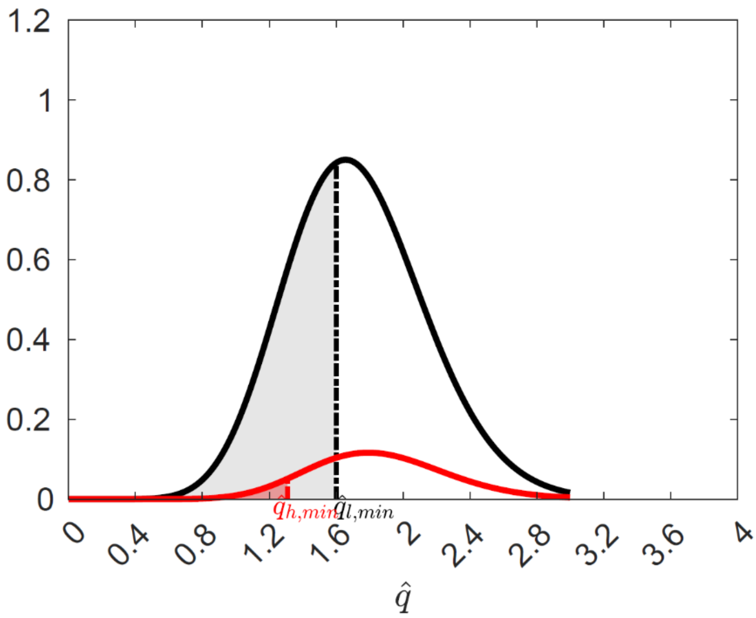
An optimal R&D subsidy

[15] When comparing welfare in the two economies with different policies, say with Subsidy Policies 1 and 2, and the resulting growth rates g(1) and g(2) with the initial consumption levels C0(1) and C0(2), consumption-equivalent changes in welfare need to be computed. This is done by calculating the fraction of initial consumption that will ensure the same discounted utility with the new growth rate as that given by the initial allocation.

It may be unrealistic to assume that information regarding the underlying type of the firms is available. Whereas the economic outcomes of individual firms are perceivable, the role of chance and other unobservable factors may conceal their underlying type. It is fair to ask whether the optimum can be achieved with feasible policies. Therefore, we also consider policies that do not differentiate between firms based on their quality but rather place similar policies on firms based on observable characteristics. In particular, we consider an optimal incumbent R&D subsidy.

We find in the work of Einiö et al. (2022) that the subsidy rate would be 41.66%, amounting to 3.9% of the innovative economy production. This alone would result in a 1.46% increase in welfare, while the economic growth rate would increase moderately, from 1.63% to 1.88%. The increase in subsidy is moderately higher than in the US, where the optimal increase would account for 3.62% of the innovative economy production.

Figure 6. Productivity distribution of the product lines in the model, optimal incumbent R&D subsidy. Frequencies are normalized so that the number of product lines with median productivity = 1.



Note: The red line denotes the productivity of product lines that are operated by high-type firms and the black line shows the corresponding productivity for low-type firms. The grey area indicates inactive product lines for which productivity falls below the threshold productivities.

Let us discuss the details of this policy from the distributional perspective. In Figure 6, we again show the distributions of product lines operated by low- and high-type firms.

When the incumbent R&D subsidy is increased, that leads to further creative destruction. The policy puts pressure on the profitability of the weaker firms and drives them out of the market. Above all, the effect arises through an increase in the skilled wage rate.

The survival productivity threshold increases for both types of firm. Overall, the share of active product lines falls by 6.1 pps according to Table 29. However, the decline concentrates on the low-type firms (a 10.8 pps decline), while the share of product lines operated by the high-type firms increases by 4.7 pps.

The policy leads to an increase in the innovation rates of both the low- and high-type incumbents while the share of skilled workers engaged in R&D rises from 18.6% to 26.1%. The innovation rate for the low types is 0.227 and for the high-types it is 0.467 (vs. 0.194 and 0.387 in the benchmark, respectively). The incumbent subsidy, however, decreases the innovation rate of the entrant firms, a feature that marginally decreases the effect of the policy (see Einiö et al., 2022, for details).

While both innovation and growth rates increase as a result of the policy, the overall effect remains smaller than in the case of the social planner policy. The policy increases the creative destruction rate by 0.021, which is only half of the 0.044 increase in the social planner optimum.

This highlights the finding of Einiö et al. (2022) and Acemoglu et al. (2018) that R&D support targeted uniformly to all companies, irrespective of their innovation capacity, is an effective policy, but not the most efficient. The uniform subsidies work through indirect impact routes, while they also mean that low-R&D-productivity companies receive subsidies and remain in business, binding the R&D worker resources to innovative activities that have a lower likelihood to succeed.

7.5 Conclusions

In this section, we studied the optimality of the allocation of Finnish innovative firms and their workers. Markets for innovation are notoriously prone to suboptimal behavior. They face well-known market failures that arise, above all, from the fact that firms do not internalize the full value of their innovations and thus may conduct an insufficient amount of R&D from a societal perspective.

We find that the model fits relatively well with the firm-level productivity distribution of the Finnish economy. The characterization of both individual firms' dynamic optimization problem and the aggregate market dynamics allows us to make inferences on the underlying, unobserved characteristics of the distribution. We find that the higher probability of the successful innovation of high-type firms allows them to continue operating at a lower level of productivity due to the higher probability of successful future innovation. The higher expected value of their life-time production due to the prospects of future successes allows them to continue, even at a low current level of productivity.

Thus, our results show how inefficiency is an inherently dynamic concept in these markets. Reaching optimal allocation necessitates addressing unmaterialized growth potential, not only supporting firms that currently have high productivity. We find that the optimal policy drives out low-quality, low-productivity firms and gives room for high-quality firms that have growth potential that may have not yet have materialized. Policies that drive such creative destruction may have a significant effect on economic growth in the long run.

How feasible is the optimal allocation? It may be unrealistic to assume that information regarding the underlying type of the firms can be used to steer reallocation with policies. However, we find that improvements in allocation may be achieved even if the policy is not built on full knowledge of firm quality. Both discriminatory policies (such as directed subsidies that favor high-quality firms) and indiscriminatory policies (such as incumbent R&D subsidies) may have positive effects on the allocation. The latter effect arises through the indirect effects of the policies on creative destruction, especially through the tightening of the market for skilled labor.

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8 Policy implications: Boosting transformational entrepreneurship and switching of jobs and industries

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Abstract: This section summarizes the main lessons from the previous chapters and discusses their policy implications. We found that the current allocation of labor and capital is far from optimal, and that the allocation has deteriorated over time. We also found that misallocation of labor correlates with some firm characteristics, but no such correlations can be found for the capital input. We also found evidence about capital bias in most of the 16 industries considered. This chapter discusses the underlying source of the deteriorating allocation, and suggests ways to reverse the trend. The sharp increase in the number of microfirms over the past two decades suggests that the current policy may support subsistence entrepreneurship at the cost of transformational entrepreneurship. We also discuss possibility to improve the allocation through voluntary job switching and industry switching of firms.

8.1 Introduction

This report is one of the first attempts to examine misallocation of labor and capital in the Finland's business sector. The purpose of this section is to synthesize the main empirical findings of this study, discuss their policy implications, and suggest practical policy measures. We begin with a short summary of the key empirical results.

1) The current allocation is far from the social optimum (see Chapter 6). In almost all of the 16 industries considered, the output could increase substantially if only the resources were more efficiently allocated between the firms. In many industries, we find that the current allocation does not yield significantly greater output than a purely random allocation across firms would do.

2) Worse yet, resource allocation has deteriorated over time. The deteriorating Olley-Pakes allocation component was identified as the main culprit for the stagnation of labor productivity (see Chapter 2). In other words, the allocation deteriorates because employees do not switch from low-productivity firms to high-productivity firms.

3) Misallocation of labor systematically correlates with such firm characteristics as the firm age, size, equity-debt ratio, foreign ownership (Chapter 5) and changes in the patterns of international trade (Chapter 4). For the capital allocation, no significant correlations could be found. This points toward the sluggish labor market as a possible bottleneck that may deter mobility of employees to more productive jobs.

4) There is wide-spread capital bias in the business sector (Chapter 5). More specifically, the marginal product of labor exceeds the average unit cost of labor in a majority of firms across different industries in manufacturing and service sectors (Chapter 5). This suggests that firms do not employ as many workers as profit maximization would imply. In contrast, the marginal product of capital typically falls short of the average unit cost, which would suggest that firms tend to over-invest in capital. Such a systematic capital bias is inefficient from the societal point of view, but it may be rational for the individual entrepreneurs. Possible explanations for the capital bias may include the shortage of skilled employees and the matching problems in the labor market, distortionary effects of labor market regulations, as well as more favorable taxation of capital returns compared to wage income. However, identifying the underlying causes of the observed capital bias fall beyond the scope of the present study.

The purpose of this concluding chapter is to examine these findings in more detail to identify possible bottlenecks that may inhibit the improvement of allocation. Based on the further analysis, the policy implications and practical policy measures will be discussed.

8.2 Deteriorating allocation over time

In Chapter 2 we found that the structural change through entry and exit of firms has positive contribution to growth. Similar to previous studies, we find that the entering firms have on average considerably higher level of labor productivity than the continuing or the exiting firms. However, the key culprit of the productivity stagnation is that the highly productive startups do not hire more employees to grow. We next examine in more detail the possible sources of such misallocation.

Figures 7 and 8 plot the development of the number of firms by size class (firms with less than one employee, firms with less than 10 employees, firms with less than 100 employees, and all firms, respectively) and the number of employees in those size classes in the business sector of Finland in years 2000 – 2018. These figures have been constructed using the register data of firms in Statistics Finland as discussed in Chapter 2 of this report, excluding industries where data is considered unreliable as well as all non-profit associations, societies, public sector, religious organization and suchlike enterprises. Note further that these statistics do not include the so-called “light entrepreneurs” who do not have an official firm but invoice customers through an invoicing service.

Figure 7. Number of firms by size class

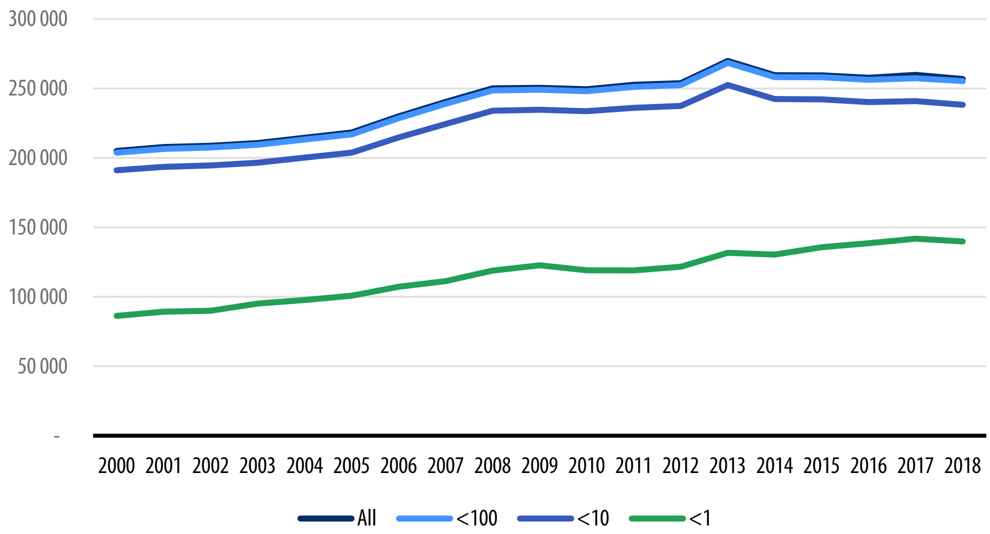
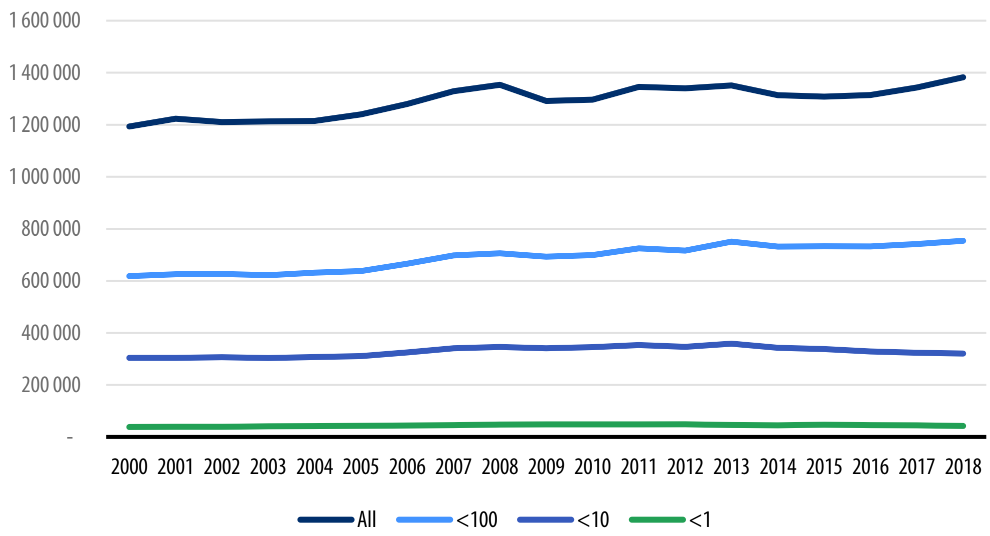


Figure 7 highlights the entrepreneurship and rapid growth of the microfirms over the past two decades. The group of firms with less than one employee consist of owner-operated enterprises that do not have any full-time workers. The number of such microfirms has increased rapidly since year 2000, and in 2018 more than half of all firms had less than one worker.

While the number of microfirms with less than one full-time employee has grown rapidly, their employment share remains small, as shown by Figure 8. Only about 3 percent of all employees in the business sector work in these smallest microfirms, excluding the owners who do not pay wage for their own work. If one assumes that each firm has one full-time entrepreneur in addition to the paid employees, then the employment share of microfirms with less than one employee increases to 11-12 percent during the end of this period. While the true employment share of microfirms remains somewhat uncertain, operating these 150 thousand microfirms obviously takes a considerable share of the human and capital resources and the entrepreneurial effort of

Finland’s business sector. It is important to stress that this is the class of firms that had the highest average labor productivity in most years and also the greatest growth potential in the future.

Figure 8. Number of employees by firm size class



The largest firms with more than 100 full-time workers employed approximately half of all workers in the business sector at the beginning of this century, and the employment share of the largest firms has decreased only marginally over the years. The large firms remain the most important employer. However, the largest increase in the employment share has taken place in the size class of firms with 10-100 employees.

These developments in the number of firms and the employment shares help to understand the deteriorating allocation found in Chapter 2. In particular, we found that the average labor productivity of new entrants was very high compared to that of continuing firms, especially during the latest sub-period of 2013 – 2018. These high-productivity startups are typically very small, employing less than 10 persons. However, the employment share of the startups remains very low, as Figure 8 also helps to illustrate. To summarize, the deteriorating allocation is due to the fact that the high-productivity startups do not grow as fast as it would be desirable to enhance productivity growth.

Why high-productivity startups do not grow? There are many plausible explanations that could be considered, however, more systematic examination of these explanations falls beyond the scope of this project. The following is a non-exhaustive list of possible reasons. First, hiring the first full-time employee is a major step for a microfirm, which also involves additional administration costs. Second, hiring a worker to a microfirm involves considerable risks both for the employer and the employee. Third, the owner-operated firms often rely heavily on the expertise, skills and professional networks of the owners, and many of the owners' tasks may be difficult to outsource to paid employees. Fourth, while labor productivity is a relevant measure for the economic wellbeing, market competition does not necessarily reward firms with high labor productivity; the notion on total factor productivity that also takes the capital input into account is more closely aligned with firms' competitiveness. Finally, it is important to recognize the possibility that a large majority of small firms may have no intention to grow larger.

Schoar (2010) argues that it is crucially important to differentiate between two very distinct sets of entrepreneurs, referred to as "subsistence" and "transformational" entrepreneurs. The subsistence entrepreneurs are mainly interested in self-employment, and this type of entrepreneurship is often characterized by low human capital and a strong motivation to support family. In contrast, transformational entrepreneurship is characterized by higher human capital and higher willingness to take risks. Schoar cites empirical evidence suggesting that people engaging in these two types of entrepreneurship are not only very distinct in nature, even more importantly, only a negligible fraction of them transition from subsistence to transformational entrepreneurship. In other words, it is rate that a subsistence entrepreneur matures to a transformational entrepreneur over time.

The distinction of subsistence to transformational entrepreneurship is important from the policy perspective. Based on empirical evidence from numerous prior studies, Schoar (2010) argues that "*entry regulations and labor market constraints adversely affect the growth of transformational entrepreneurs. Many of these regulations are initially intended to protect small businesses and help them maintain their position relative to the largest firms in the economy. But over time these regulations often prevent effective competition by new entrants and curtail the growth of the firms that have the most potential in the economy.*"

In Finland, Maliranta et al. (2018) have identified a rather similar disparity between the "self-employer" and "entrepreneurial" startups, which appear to closely match with Schoar's notions of "subsistence" and "transformational" entrepreneurs. Maliranta et al. (2018) show that the growth-seeking entrepreneurial startups have both a higher survival rates and the higher growth rates than the self-employer startups. They also find that the productivity of an entrepreneur's former employer company and the productivity and survival rate of his/her new company have a strong positive correlation.

Subsistence entrepreneurship is obviously preferable to unemployment from the societal point of view. However, it is the transformational entrepreneurship that drives productivity growth. From the policy perspective, it would be important to recognize these two fundamentally different types of entrepreneurs to design better policies and incentives to support the growth of high-productivity startups. While policies to support new and/or small firms may be helpful for subsistence entrepreneurs, there can be tradeoffs and unintended adverse effects on the growth-seeking transformational entrepreneurs (e.g., Schoar, 2010). Therefore, our recommendation is to carefully review the role of government policies and incentives as possible drivers of the sharp growth in the number of microfirms depicted in Figure 7, drawing a distinction between the subsistence and transformational entrepreneurs.[16]

8.3 Job switching

In Chapter 2 of this report we found that the main culprit for the labor productivity stagnation in the Finnish business sector has been the deteriorating Olley-Pakes allocation component. This does not mean that employees have massively downshifted from high-productivity jobs to low-productivity jobs. Rather, this finding suggests that employees do not switch from low-productivity firms to high-productivity firms as much as it would be desirable to enhance productivity growth. While the labor market reforms already attract considerable attention and debate in Finland, there has been relatively little attention on the productivity impacts of voluntary job switching, or perhaps more precisely, insufficient frequency of job switching.[17] Therefore, this subsection focuses particularly on this issue.

According to the job search models, employees continuously compare their current position with openings available on the job market, and will switch jobs if they find a better match with higher wages, despite possible search costs (e.g., Jovanovic, 1979). Clearly, a better match between employer and employee can increase both labor productivity and the earnings of employee, which should be highly correlated in the competitive labor markets. However, the impact on earnings critically depends on whether the job switching is voluntary or involuntary (see, e.g., Riekhoff, 2022, and references therein). Empirical evidence suggests that voluntary job switching is likely to result in higher earnings, however, involuntary job changes due to layoff, dismissal

[16] In a similar vein, Maliranta et al. (2018) suggest that "*Startup policy should be designed from the point of view of growth-oriented businesses not yet founded*."
[17] One notable exception is Professor Alf Rehn, who has discussed the advantages of job switching in his column: https://duunitori.fi/tyoelama/alf-rehn-kolumni-vaihtamalla-paranee.

or the ending of a temporary contract are more likely associated with lower wage growth or wage losses.

In addition, the timing and frequency of job switching also influences earnings. Empirical evidence suggests that job changes in the early career are more beneficial than in the later career (e.g., Sloane & Theodossiou, 1993). In the early career, job switching is seen as a normal process of professional growth and it gives a positive signal to employers (e.g., Topel & Ward, 1992; Oreopoulos et al., 2012). However, too frequent switching can be a negative signal for potential employers. Since the employer cannot directly observe the true labor productivity of a potential employee, the employment history may have disproportionate signaling effects on earnings.

The recent empirical study by Riekhoff (2022) has made use of longitudinal register data of earnings and employment from the Finnish Centre for Pensions, covering cohorts born between 1940 and 1980 for the years 1963–2019 (more than 5 thousand individuals and 72 thousand observations). According to this study, the marginal effect of job switching was positive and statistically significant in all age cohorts, both for men and women. Moreover, those with higher education almost always benefitted from job mobility, especially among men. Although job switching is positively related to earnings, staying in the same job offers its own advantages, especially for women and those approaching the end of their working career. Riekhoff (2022) concludes that the labor-market and family policies are needed to support careers to be either stable or dynamic at the right moment of the career.

From the perspective of productivity dynamics, the Finnish labor market seems to be sluggish. According to the employee survey by Statistics Finland (quoted by the YLE news),[18] the average job tenure in Finland was 10 years in 2013, compared to just 4 years in the USA. Further, more than 40 percent of respondents had served only one employer. Unfortunately, more recent employee surveys apparently did not include the questions about the length of job tenure so the latest information appears to be from year 2013.

In Chapter 4 we also found evidence that suggests firms do not employ as many workers as profit maximization would imply, but rather tend to over-invest in capital. Such a systematic capital bias may relate to the shortage of skilled employees, but also signal matching problems in the labor market. Form the policy perspective, the essential question is what kind of labor market reforms or policy interventions could help to create more jobs but also increase beneficial job switching?

[18] https://yle.fi/uutiset/3-8154206

On one hand, the strong labor unions and collective bargaining keep the wage rates relatively equal across employees within the same profession, irrespective of the individual productivity differences. Relatively uniform and rigid wages can reduce the financial incentives of employees to switch jobs to more demanding positions with higher productivity because the additional effort is not compensated by higher wage. The rigid wages and high job security may also discourage firms to actively compete for high-productivity employees with higher wages and salaries.

On the other hand, the relatively high job security and unemployment benefits can help to reduce the employees' risks associated with the job switching. For example, reducing the unemployment benefits might have an adverse effect of discouraging job switching that always involves some risks for the employees. Moreover, labor mobility also depends on many other factors such as the housing market and the social networks (e.g., Maczulskij and Böckerman, 2019). Further research-based evidence would be needed to understand the underlying reasons for the sluggish job switching in order to design more effective policy measures. The main contribution of this study has been to present empirical evidence that points towards the sluggish labor mobility and voluntary job switching as critical bottlenecks that may hamper reallocation of workforce to more productive use in other firms and/or industries.

8.4 Capital allocation

In Chapter 5 we found evidence about systematic over-investment in capital in most of the 16 industries considered. This capital bias could reflect the frictions and regulations in the labor market, which incentivize firms to substitute labor by capital inputs to an extent that is inefficient from the societal point of view. In Chapter 5 we also found that misallocation of labor systematically correlates with the firm characteristics such as the firm age, size, the debt-to-equity ratio, and the foreign ownership. In contrast, no significant correlations could be found for the capital allocation between firms. This sub-section briefly discusses the possibilities to reallocate capital inputs.

In economic theory, the physical capital is conventionally viewed as a fixed input in the short run. Indeed, it is difficult if not impossible to convert specialized machinery for another use, perhaps in another industry (consider, e.g., a paper machine). However, general purpose capital inputs tend to be easier adapted for different uses. For example, vehicles such as passenger cars, trucks, and tractors can be purchased and sold in secondary markets, and can be adapted for use in multiple different industries. While buildings are originally designed for some specific use, they can be converted for different use (consider, e.g., renovation of former industrial buildings to offices of loft apartments).

In the modern digital economy, the ICT capital such as computers, servers, smart phones and general purpose software tools can be quite easily and quickly purchased and sold, or taken for alternative use, possibly in a completely different industry. The increasing storage of data in the cloud servers reduces the time and cost of installation of the ICT capital. Furthermore, the intermediate inputs of the digital economy are omnipresent in virtually all other industries, which increases the flexibility of the ICT capital not only in the ICT industries, but across the economy as a whole.

By these arguments, we suggest that the capital inputs of the 21st century tend to be more “variable” in their nature than the industrial capital in the 19th and 20th centuries. Of course, there remain industries where the capital input can be meaningfully taken as a fixed input in the short run, but this seems no longer a typical situation across all industries.

Mobility of the capital inputs also affects the agility of firms to switch industry. While conventionally the market entry is associated with startups and the exit with bankruptcy, in fact, the entering firm can be an existing firm (consider, e.g., the smartphone called iPhone introduced by the computer manufacturer Apple). Analogously, the exiting firm may continue to operate in another industry (e.g., Nokia Corporation continues to operate in the mobile networks, among other industries, after its exit from the mobile phone market).

The recent study by Kuosmanen et al. (2022) found that industry switching of firms in Finland is more common than previously thought. Table 30 presents the number of inter- and intra-industry switches during three sub-periods of 2000-2018 based on that report. We note that thousands of firms switch industry every year. Frequency of industry switching increased during 2006-2012, that is, the years of the financial crisis and the subsequent Euro debt crisis. Interestingly, a majority of switches occur between two-digit industries and are hence referred to as “intra-industry” switches. The less radical switches between 5-digit industries within the same 2-digit industry are referred to as “inter-industry” switches. The number of industry switches during three time periods 2000–2005, 2006–2012, and 2013–2018 is presented in Table 30 below.

In this report, the results of Chapter 2 also indicate that industry switching can have notable productivity impacts. We would hypothesize that voluntary switches where firms respond to new growth opportunities tend to be productivity enhancing, directly analogous to voluntary switching of jobs by employees (cf., e.g., Riekhoff, 2022). In contrast, involuntary or forced industry switching where firms are moving from a more competitive industry to a less competitive one in order to survive will likely result as productivity decrease at the aggregate level.

Table 30. Frequency of industry switching in Finland's business sector.

	2000–2005	2006–2012	2013–2018
Number of firms	306 509	389 126	392 017
Number of industry switches	28 381	42 927	11 748
of which inter-industry switches (2-digit)	19 770	26 383	9 475
of which intra-industry switches (5-digit)	8 611	16 544	2 273

Source: Kuosmanen et al. (2022)

One documented example of such "switching to survive" has been noted by Kuosmanen and Kuosmanen (2021) who discuss the switching of Finnish farms from pastoral farming to crop farming. Since the subsidies of pastoral farming are based on the headcount of animals, the pastoral farming sector of Finland has consolidated over time to include a smaller number of farms with larger head counts. As a result of the consolidation, many smaller and less competitive farms have switched from pastoral farming to crop farming. In the crop farming, the subsidies have been decoupled from the output and are paid based on the land area under cultivation. By applying a structural change decomposition similar to the one used in Chapter 2 of this report, Kuosmanen and Kuosmanen (2021) show that the switching of farms from a more productive pastoral farming to less productive crop farming had a negative effect on productivity of the agricultural sector as a whole. This example illustrates that intra-industry switching induced by government policy can also have negative effects on the aggregate productivity of the industry.

The Schumpeterian notion of creative destruction highlights the important role of the entry and exit of firms in the dynamic evolution of the economy. In contrast, industry switching of continuing firms can be a smoother way to reallocate management skill as well as labor and capital resources from less productive industries or deteriorating markets towards high-productivity industries with greater growth potential. To encourage productivity enhancing industry switching in the government regulation, we would recommend the possible barriers of market entry to be considered more broadly in the government regulation, not only from the perspective of startups or foreign firms, but also recognizing the possibility of industry switching by existing domestic firms.

8.5 Policy recommendations

We conclude the report by summarizing the practical policy recommendations brought forward in the previous sub-sections:

1) We recommend a critical review of the role of government policies and incentives affecting startups and small firms in order to reverse the negative trend in resource allocation. In particular, drawing a distinction between the subsistence and transformational entrepreneurs would be important to support the growth of dynamic high-productivity startups.

2) Policies to increase competition and voluntary mobility in the labor market are recommended to improve reallocation of workforce. We find that allocation of labor has deteriorated due to insufficient labor mobility from low productivity to high productivity firms.

3) We recommend the barriers of market entry to be considered more broadly in the government regulation, not only from the perspective of startups or foreign firms, but also recognizing the needs of transformational entrepreneurs and potential industry switchers. The growth opportunities of the transformational enterprises are critically important for the productivity growth, while industry switching can provide a smoother way to reallocate management, labor, and capital resources to more productive uses than the Schumpeterian creative destruction.

Since this is a scientific project, we state the policy recommendations deliberately at a rather general level, abstracting from specific policy instruments that have not been studied in this project. Indeed, the incentives of startups and small firms, labor mobility and the barriers of market entry depend on a large and diverse set of policy instruments in such areas as the tax policy, employment policy, and the competition and innovation policy, which have not been systematically studied in the present project. Further, improving the allocation of labor resources also critically depends on the labor unions and the employer associations as in Finland the collective labor market agreements apply to all employees, not only the union members. While the results of the present project point towards the labor market frictions and regulations as potential sources of misallocation, our results do not pinpoint any specific market reforms or policy interventions to improve the matters.

We stress that further research would be needed to assess effectiveness of existing policy measures and design more efficient instruments to enhance productivity. However, systematic evaluation of causal effects of specific policy instruments falls beyond the scope of the present project. Despite these limitations, we believe that the results of this report have shed new light on the allocation of labor and capital resources in Finland’s business sector. This report highlights the great potential for productivity growth through more efficient allocation of resources in Finland’s business sector.

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Appendix 1: Productivity levels and group shares in manufacturing, construction, information and communication, and service industries

This appendix presents the average levels of labor productivity in the four industries considered in Chapter 2 to support the interpretation of the components of productivity change presented and discussed in Section 2.5. The following tables have been organized analougs to Table 1 in Section 2.4.

Table A1.1 Manufacturing: Average levels of labor productivity (1000 € per worker, in 2010 prices) and the shares of firms in groups of surviving firms, switching firms and entering and exit-ing firms (in percentage).

Period	Levels				Group Shares			
	Same industry	Industry switch	Exit	Entry	Same industry	Industry switch	Exit	Entry
2000	47.6	48.0	41.7		65.5	6.4	28.2	
2005	53.9	55.9		47.8	68.8	6.9		24.4
2006	55.4	59.0	49.1		52.7	14.5	32.8	
2012	51.5	51.8		45.7	56.6	14.2		29.2
2013	58.3	43.3	41.8		67.9	2.7	29.4	
2018	62.3	51.8		61.3	77.5	3.0		19.5

The number of firms in the considered years: 23,615 (2000); 22,480 (2005); 22,355 (2006); 20,813 (2012); 20,4430 (2013); and 17,904 (2018).

Table A1.2 Construction industry: Average levels of labor productivity (1000 € per worker, in 2010 prices) and the shares of firms in groups of surviving firms, switching firms and entering and exit-ing firms (in percentage).

Period	Levels				Shares			
	Same industry	Industry switch	Exit	Entry	Same industry	Industry switch	Exit	Entry
2000	50.0	48.9	51.2		68.5	2.7	28.8	
2005	54.6	56.1		56.9	58.2	3.0		38.1
2006	57.1	115.5	59.7		59.2	4.3	36.5	
2012	54.9	74.3		58.8	49.9	5.2		44.8
2013	55.3	48.0	59.1		63.9	1.6	34.5	
2018	64.1	49.7		127.7	72.4	2.2		25.4

The number of firms in the considered years: 27,667 (2000); 32,185 (2005); 34,374 (2006); 40,753 (2012); 40,850 (2013); and 36,054 (2018).

Table A1.3 Information and communication: Average levels of labor productivity (1000 € per worker, in 2010 prices) and the shares of firms in groups of surviving firms, switching firms and entering and exit-ing firms (in percentage).

Period	Levels				Shares			
	Same industry	Industry switch	Exit	Entry	Same industry	Industry switch	Exit	Entry
2000	50.6	29.8	46.3		54.7	7.1	38.1	
2005	54.7	59.8		48.1	46.8	5.3		47.8
2006	54.7	60.4	51.5		42.0	18.2	39.9	
2012	53.9	61.8		52.0	34.5	14.3		51.2
2013	54.4	54.9	46.3		60.1	2.9	37.0	
2018	56.4	78.8		164.9	58.9	3.2		37.9

The number of firms in the considered years: 5,825 (2000); 6,810 (2005); 7,243 (2006); 8,816 (2012); 8,958 (2013); and 9,146 (2018).

Table A1.4 Service industries: Average levels of labor productivity (1000 € per worker, in 2010 prices) and the shares of firms in groups of surviving firms, switching firms and entering and exit-ing firms (in percentage).

Period	Levels				Shares			
	Same industry	Industry switch	Exit	Entry	Same industry	Industry switch	Exit	Entry
2000	40.6	41.6	39.0		66.4	3.4	30.1	
2005	46.2	47.9		42.1	57.6	3.1		39.3
2006	49.0	46.4	45.9		53.0	10.7	36.3	
2012	48.6	42.7		45.7	44.9	7.7		47.5
2013	45.8	35.3	38.4		62.4	2.3	35.3	
2018	47.1	47.6		129.2	70.0	2.6		27.4

The number of firms in the considered years: 61,527 (2000); 70,003 (2005); 75,161 (2006); 88,779 (2012); 89,547 (2013); and 79,902 (2018).

Appendix 2: Estimated marginal products and average unit costs

This appendix presents the estimated marginal products and average unit costs for the remaining 13 industries, similar to Tables 10-12 in Section 5.5.

Table A2.1 Manufacture of chemicals and chemical products (20): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	40 527	48 614	49 317
Marginal product	63 795	65 413	52 271
Capital			
Unit costs	0.46	0.39	0.42
Marginal product	0.28	0.24	0.28
Unit costs / marginal product			
Labor	0.64	0.74	0.94
Capital	1.61	1.61	1.51
Number of firms	224	220	201

Table A2.2 Production of electricity with hydropower and wind power (35111): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	37 568	35 315	23 860
Marginal product	108 314	168 819	159 229
Capital			
Unit costs	0.09	0.08	0.10
Marginal product	0.08	0.07	0.06
Unit costs / marginal product			
Labor	0.35	0.21	0.15
Capital	1.12	1.17	1.78
Number of firms	32	44	68

Table A2.3 Combined heat and power production (35113): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	43 374	52 457	52 523
Marginal product	124 155	81 485	113 892
Capital			
Unit costs	0.11	0.09	0.10
Marginal product	0.12	0.09	0.09
Unit costs / marginal product			
Labor	0.35	0.64	0.46
Capital	0.91	1.07	1.10
Number of firms	30	37	42

Table A2.4 Dental practice activities (86230): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	25 608	34 230	38 362
Marginal product	51 389	60 686	58 384
Capital			
Unit costs	1.89	1.54	0.81
Marginal product	0.23	0.38	0.18
Unit costs / marginal product			
Labor	0.50	0.56	0.66
Capital	8.06	4.08	4.48
Number of firms	835	905	850

Table A2.5 Hotels (55101): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	28 825	30 070	28 725
Marginal product	41 291	38 280	38 382
Capital			
Unit costs	0.18	0.10	0.15
Marginal product	0.13	0.09	0.21
Unit costs / marginal product			
Labor	0.70	0.79	0.75
Capital	1.40	1.20	0.73
Number of firms	447	384	413

Table A2.6 Freight transport by road (49410): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	38 635	41 958	40 895
Marginal product	42 791	47 641	42 541
Capital			
Unit costs	0.30	0.32	0.32
Marginal product	0.29	0.30	0.35
Unit costs / marginal product			
Labor	0.90	0.88	0.96
Capital	1.02	1.06	0.91
Number of firms	606	687	763

Table A2.7 Manufacture of furniture (31): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	21 204	27 752	29 120
Marginal product	40 442	40 856	59 681
Capital			
Unit costs	0.82	0.52	0.69
Marginal product	0.24	0.11	0.42
Unit costs / marginal product			
Labor	0.52	0.68	0.49
Capital	3.43	4.76	1.63
Number of firms	1063	810	627

Table A2.8 Manufacture of basic pharmaceutical products and pharmaceutical preparations (21): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	41 281	47 723	52 513
Marginal product	50 128	57 073	86 358
Capital			
Unit costs	0.37	0.58	1.16
Marginal product	0.86	1.53	1.00
Unit costs / marginal product			
Labor	0.82	0.84	0.61
Capital	0.42	0.38	1.16
Number of firms	28	23	23

Table A2.9 Activities of sport clubs (93120): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	13 100	18 936	23 448
Marginal product	40 195	33 102	30 249
Capital			
Unit costs	0.60	0.31	0.22
Marginal product	0.19	1.24	0.52
Unit costs / marginal product			
Labor	0.33	0.57	0.78
Capital	3.12	0.25	0.42
Number of firms	846	69	84

Table A2.10 Manufacture of paper and paper products (17): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	42 092	45 239	45 149
Marginal product	51 135	49 305	46 009
Capital			
Unit costs	0.34	0.28	0.35
Marginal product	0.21	0.35	0.48
Unit costs / marginal product			
Labor	0.82	0.92	0.98
Capital	1.62	0.80	0.73
Number of firms	174	152	141

Table A2.11 Sawmilling and planing of wood (16100): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	34 469	38 107	35 009
Marginal product	44 477	47 037	52 590
Capital			
Unit costs	0.23	0.21	0.31
Marginal product	0.13	0.17	0.28
Unit costs / marginal product			
Labor	0.77	0.81	0.67
Capital	1.82	1.21	1.09
Number of firms	340	260	240

Table A2.12 Manufacture of computer, electronic and optical products (26): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	41 711	48 785	47 251
Marginal product	47 412	59 957	62 398
Capital			
Unit costs	0.63	0.57	0.59
Marginal product	0.83	0.27	0.14
Unit costs / marginal product			
Labor	0.88	0.81	0.76
Capital	0.76	2.12	4.28
Number of firms	333	290	315

Table A2.13 Manufacture of food products (10): estimated marginal products and unit costs, and their ratios in 2005, 2012, and 2018

	2005	2012	2018
Labor (€ / worker)			
Unit costs	34 378	38 052	37 087
Marginal product	44 680	46 490	43 026
Capital			
Unit costs	0.28	0.28	0.28
Marginal product	0.23	0.27	0.30
Unit costs / marginal product			
Labor	0.77	0.82	0.86
Capital	1.25	1.03	0.92
Number of firms	494	482	482

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