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Richard Sellner, Nico Pintar, Norbert Ernst

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Richard Sellner, Nico Pintar and Norbert Ernst *

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Abstract

In this paper we provide firm-level evidence on the role of resource misallocation for total factor productivity development in Austria. We apply the indirect approach of measuring misallocation via the dispersion in marginal products within narrowly defined industries of Hsieh and Klenow (2009) to a firm-level dataset for the period 2008-2018. Our estimates suggest that capital misallocation increased during the recession in the late 2000s, but declined thereafter. This result contrasts with most of the literature on European countries that finds increasing capital misallocation over time, but is compatible with evidence for Austria's main benchmark country and most important trading partner Germany. In line with the literature we find that misallocation is higher in services and for capital. Our estimates suggest that if Austrian efficiency was raised to the US benchmark level, TFP could be raised by 50%. We further find evidence that firms with higher marginal capital/labor productivity build up more capital/labor and that financial constraints play a significant role, especially in the reallocation of capital in Austria.

Keywords: Factor Misallocation; Total Factor Productivity; Austria; Firm Level Data.

JEL Classification: C23; D22; D24; O47

*Oesterreichische Nationalbank (OeNB), Otto-Wagner-Platz 3, A-1090 Vienna; Richard Sellner: richard.sellner@oenb.at, Nico Pintar: nico.pintar@oenb.at, Nobert Ernst: norbert.ernst@oenb.at

Non Technical Summary

In the last decades productivity growth slowed down in most advanced economies including Austria. Besides global macroeconomic trends such as structural and demographic change, numerous factors have been suggested in a rich firm-level based literature to explain this slowdown. One of the most prominent factors emerging from this literature is that the misallocation of production factors increased over time, i.e. that market frictions prevented labor and capital to be utilized most productively. Empirical results point towards potentially huge total factor productivity (TFP) gains from improving allocative efficiency. Given a fully efficient resource allocation, TFP levels would have been raised by 57% in the Netherlands in 2017 (see Bun and de Winter, 2022) and 79% in Portugal in 2011 (see Dias et al., 2016).

While there is a vast international literature on the role of reallocation for past productivity growth and the potential gains from moving towards an optimal allocation, the empirical evidence for Austria is still scarce. Decompositions of past productivity growth using Austrian firm-level data found that reallocation contributed only marginally or negatively (see Hassine et al., 2021; Hölzl and Lang, 2011) or found very high positive contributions for certain industries (services and utilities) over the medium-term (see Peneder and Prettner, 2021). However, there is no empirical evidence on potential gains of a more efficient allocation on TFP for Austria yet.

Using the approach of Hsieh and Klenow (2009), we approximate misallocation via the dispersion in marginal revenue products of capital and labor within industries. Our work relates to OECD (2019) and Gorodnichenko et al. (2018) in that these studies provided similar measures of misallocation for Austria. We add to the literature by i) employing a novel and quality-proofed firm-level database maintained by the Austrian Central Bank (OeNB) for its in-house credit assessment, ii) providing first estimates on the gains from moving to a more efficient allocation and iii) providing estimates on the evolution of allocative efficiency controlling for financial constraints.

Our results suggest that, contrary to the US and Netherlands but similar to Germany, overall misallocation did not steadily increase over time. Hence, we do not find evidence that increasing misallocation dampened productivity growth in Austria in the period 2008-2018. In line with other international studies, misallocation is substantially higher in services compared to manufacturing, possibly due to higher regulation and less exposure to international competition. Moving the Austrian economy up to US allocative efficiency levels would increase TFP by up to 50%. Furthermore, we find that financial constraints (low cash holdings or high leverage) impeded capital reallocation. The higher misallocation in services and the dampening impact of financial constraints on reallocation that we find, are in line with policy recommendations for Austria regarding the reform of services regulation to increase competition while preserving high quality standards and to undertake measures to strengthen corporate equity levels.

1 Introduction

Austrian productivity growth and the total factor productivity (TFP) contribution to output growth lagged behind its peer countries in the last decade (Peneder and Prettner, 2021; Commission, 2022). Table 1 shows the average yearly TFP growth 1996-2019 for Austria, typical benchmark countries as well as the global technological frontier countries USA and Japan. With the exception of Denmark and Japan, all countries shown experienced a marked slowdown in TFP growth after the financial crisis when comparing the period prior to it. With an average growth of just 0.04% per year over the period 2011-2019, Austrian TFP developed weaker than most other benchmark countries.

Table 1: Average yearly TFP growth, in %

	1996-2007	2007-2011	2011-2019	1996-2019
Austria	1.13	-0.25	0.04	0.51
Germany	0.88	0.08	0.60	0.64
Netherlands	1.08	-0.32	-0.00	0.46
Belgium	0.37	-0.82	0.13	0.08
Denmark	0.18	-0.58	1.00	0.33
Finland	2.23	-0.90	0.24	0.99
Sweden	1.52	-0.30	0.34	0.79
USA	1.29	0.74	0.37	0.87
Japan	0.50	-0.12	0.76	0.48

Source: OECD Productivity Database.

The productivity development in Austria is strongly influenced by trends common to most advanced economies, such as structural and demographic change, which are essentially signs of a successful development (high productivity in the manufacturing sector and increasing life expectancy). Fenz et al. (2020) documented that the increasing share of the lesser productive service sector contributed to the slowdown of aggregate productivity growth in Austria. Regarding demographic change and productivity growth, the empirical evidence for Austria is scarce. While there seems to be no significant negative impact of an aging workforce on productivity in Austrian firms (see Mahlberg et al., 2013), population ageing is associated with a lower business dynamism which should slow down productivity growth (see OECD and of Public Finance, 2020, for regions in OECD countries). Another trend that is subject to extensive research is the rise in inequality. While Austria in general ranks among top performers regarding social welfare, its performance is weaker in areas such as the income share held by the poorest quintile and education/gender equality.[1] Though there is no empirical evidence for Austria, inequality is found to be detrimental to innovation (see Bell et al., 2018) and growth (see Cingano, 2014). Regarding technological capabilities, Austria ranks very high in terms of gross domestic R&D expenditures in percent of GDP (3.1% compared to 2.6% OECD and 2.1% EU-27 average in 2019)[2], but it still has to catch up to its benchmark countries in terms of innovation outcomes (see Commission et al., 2022a).

Benchmark studies of international organizations (OECD, 2021; Commission, 2022) often trace back the weak Austrian productivity growth to over-boarding regulation in services (especially for entry in professional services), a weakly developed market for equity and venture capital financing and shortcomings in selected areas of the digital transformation (foremost the coverage with fixed very high-capacity internet). As a result, technology diffusion and reallocation of resources is hindered as overall business dynamism remains at very low levels in Austria. Furthermore, resource misallocation is one of the most prominent factors[3] mentioned regarding the growth and productivity slowdown (see for instance Gordon, 2015; Cette et al., 2016; Gordon and Sayed, 2019) that many countries experienced in the past decades.

The losses in TFP growth due to declining allocative efficiency can be substantial. Calligaris et al. (2018), for instance, found that if resource misallocation in Italy had stayed at its 1995 level, TFP in 2013 would have been 18% higher. Dias et al. (2016) estimated that increasing misallocation in Portugal may have reduced annual TFP growth by 1.3 percentage points during 1996-2011. This paper thus aims at shedding some light on the role of misallocation for Austrian TFP growth. According to theory, an efficient allocation of resources is reached if firms adjust their factor inputs such as to equalize the marginal returns and marginal costs of the factors. Firms with marginal revenue products of capital (MRPK) or labor (MRPL) higher (lower) than their competitors would increase (decrease) their respective production inputs thereby reallocating production factors from less to more productive firms. However, in practice distortions may hinder the free reallocation of resources and consequentially productivity growth.

In this paper, we computed the dispersion of MRPK and MRPL as measures of misallocation (following Hsieh and Klenow, 2009) and derive the gap between the observed and 'efficient' TFP level for groups of industries in Austria covering the period 2008-2018 (based on a balanced sample including only continuing firms). Furthermore, we estimate the sensitivity of capital (labor) accumulation to MRPK (MRPL) and a series of financial constraint variables (based on the full sample of firms). To our knowledge, this is the first contribution to provide a comprehensive quan-

[1] See OECD (2020), Commission et al. (2022b) or Lafortune et al. (2022).

[2] See OECD (2014).

[3] At the firm level, the literature presents a variety of possible explanations for slow productivity growth, among which Boppart and Li (2021) cite the rise in market power which hinders knowledge diffusion (see for instance Loecker et al., 2020; Akcigit and Ates, 2021), reduced business dynamism due to slowing population growth (see Hopenhayn et al., 2022), declining research productivity (see Bloom et al., 2020), decline in long-term interest rates Liu et al. (2022) and declining allocative efficiency (see Baqaee and Farhi, 2020).

tification of factor misallocation for Austria. The work that is most closely tied to this paper is Gorodnichenko et al. (2018), who calculated MRPK and MRPL dispersion measures for the US and a variety of European countries, among others Austria, using the Orbis database. We depart from Gorodnichenko et al. (2018) in that we extend the analysis by computing the potential TFP gains from moving the Austrian economy up to US allocative efficiency levels and an econometric estimation on the sensitivity of factor accumulation to factor productivity. Furthermore, we use a newly created dataset which covers a more recent time period. A major advantage of this dataset is that the financial statements used in this dataset are highly granular and that the data quality is high since the reported data is checked by means of the dual-control-principle. Our results foremost contribute to the strand of literature on indirect measures of misallocation and the TFP gap (such as Hsieh and Klenow, 2009; Gamberoni et al., 2016; Gorodnichenko et al., 2018). Furthermore, we contribute to the literature on financial restrictions as a barrier to capital reallocation (e.g. Midrigan and Xu, 2014; Gopinath et al., 2017; González et al., 2021).

Our key results can be summarized as follows. For the total economy (manufacturing and market service industries), we find that capital misallocation, as measured by the dispersion in MRPK, increased during the great financial recession in the late 2000s but decreased thereafter, while labor misallocation steadily declined. Since overall resource misallocation in Austria stayed roughly the same between 2008 and 2018, our findings would not indicate that increasing resource inefficiency significantly dampened Austrian TFP growth during our sample period.

Leaving aside differences in the sample periods, our results are somewhat different from typical empirical findings of increasing capital misallocation in European countries (see Gamberoni et al. (2016) for Belgium, France, Italy and Spain, Bun and de Winter (2022) for the Netherlands, Calligaris et al. (2018) for Italy, Deutsche Bundesbank (2021) for various EU countries and Gorodnichenko et al. (2018) for the EU-28). Regarding Germany, however, Gamberoni et al. (2016) and Gopinath et al. (2017) found that allocation of capital has not worsened over time and since the Austrian and German economic framework conditions and industry structure are very similar, our results seem plausible to that end. The results for the overall economy mask the substantial heterogeneity between manufacturing and services. In line with the results of previous studies (see Dias et al., 2016; Bun and de Winter, 2022), we find misallocation of both capital and labor in market services is substantially higher than in manufacturing industries. The overall trends in the evolution over time, however, are similar.

We further estimated that by raising the Austrian allocative efficiency to the US level, TFP could be boosted by roughly 50%. These figures should be interpreted with caution, since our US benchmark comparison value differs in period and industry composition covered. Furthermore, since the dispersion measure used as a proxy for misallocation may be inflated in the presence of capital adjustment costs, heterogeneity in mark-ups and measurement error, the comparison to the

US level assumes a similar degree of distortion for the US due to these factors.

Finally, we show that firms with higher MRPK (MRPL) tend to build up more capital (labor), thus improving allocation. The results further indicate that the sensitivity of the accumulation with respect to productivity remained roughly constant throughout the periods 2008-2011, 2012-2014 and 2015-2018. Our results also bring to light a significant role of financial frictions in the capital reallocation process. In particular, lower cash holdings present a higher impediment to investment for smaller and younger firms in manufacturing.

The remainder of the paper is structured as follows. Section 2 summarizes the empirical firm-level evidence on reallocation and its role for productivity growth in Austria. In section 3 we outline the indirect methodological approach following Hsieh and Klenow (2009); Gopinath et al. (2017) for the calculation of the dispersion in marginal revenue products and TFP gap measures and outline the econometric exercise similar to Decker et al. (2020); Bouche et al. (2021). A description of the data used and the results of our empirical analysis are presented in section 4. A final section concludes.

2 Literature overview on the role of reallocation for Austrian productivity growth

While there is a vast international empirical literature on misallocation and TFP development (see Restuccia and Rogerson, 2013, for a literature overview), only a few studies employing Austrian firm level data exist. This is in part due to the fact that Austria had until recently very restrictive data access regulations on firm level data and studies using available multicountry datasets such as Orbis often disregard Austria in their analysis. In the following, we summarize the key findings of the empirical literature that have either focused on Austria or covered Austria in a multi-country analysis.

A comprehensive overview of the productivity development in Austria based on micro-aggregated data from the MultiProd project was recently given in Peneder and Prettner (2021) covering the period 2008-2018. On aggregate, the contribution of TFP to growth in Austria is low[4] compared to neighboring (Germany, Italy and Switzerland) and peer countries (Belgium, Denmark, Finland, Netherlands and Sweden). TFP grew at a higher rate per year in non-financial market services (between 1.2 to 3.4%, depending on the method) than in manufacturing[5] (0.7 to 2.4%), though

[4]This result is in line with the result of OECD (2019) that Austrian labor productivity grew less between 2008-2014 compared to the benchmark country aggregate consisting of Australia, Austria, Belgium, Canada, Chile, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Japan, the Netherlands, Norway, Portugal, and Switzerland.

[5]OECD (2019) found that, especially within manufacturing industries, the weak growth - in their case labor productivity - can be attributed to the most productive firms, which grew at lower rates than the median and least-productive firms.

Peneder and Prettner (2021) note that since intangible capital is excluded in the estimation of TFP, growth in non-financial market services may be overestimated assuming that intangible capital is more important for firms in those industries and its contribution ends up in TFP growth. In line with the overall findings of Berlingieri et al. (2018) for 22 OECD countries (MultiProd), Peneder and Prettner (2021) find a productivity-size premium for Austrian firms in manufacturing but not in non-financial market service industries.

In a dynamic productivity decomposition (as in Melitz and Polanec, 2015), Peneder and Prettner (2021) decompose TFP growth into contributions from entering, exiting and continuing firms. They decomposed the contribution of continuing firms further into within firm growth and a reallocation effect capturing the changes in market shares between continuing firms. Peneder and Prettner (2021) results show considerable differences regarding industries and the time interval applied to the analysis. Measuring TFP growth over just one year, entries show the largest positive growth contribution, while for growth over a five year period the reallocation component dwarfs all other contributions. The latter result is strongly driven by non-financial market services and the energy sector. By contrast, the contribution of reallocation to growth is negative in manufacturing industries and only the within-firm component of continuing firms shows a substantial positive contribution to growth.

These results are partially in line with earlier findings from a similar decomposition of labor productivity in exporting and non-exporting manufacturing firms[6] over the period 2002-2007 (see Hölzl and Lang, 2011). Also in this study, the majority of labor productivity growth is attributed to the within-firm component of continuing firms, but reallocation contributed positively to labor productivity growth. The estimated contribution of firm entry and exit is very small. However, the growth contribution of entering firms may be underestimated due to their weaker pricing and mark-up power, which are not reflected in revenue-based productivity estimates (see Foster et al., 2008).

For the more recent periods of 2008-2012 and 2013-2017, using a similar methodology and data on non-financial sector SMEs from Orbis, Hassine et al. (2021) found a negative contribution of reallocation on TFP growth. Further decomposing the continuing firms into zombie (i.e. firms which cannot cover their interest expenses out of their operating income as defined in Beer et al. (2021)) and non-zombie firms revealed that only zombie firms drive the negative reallocation effect entirely.

The above mentioned studies applied Olley-Pakes-type dynamic decomposition methods (see Olley and Pakes, 1996) to demonstrate the role of reallocation by quantifying the contribution of changes in market shares of continuing firms to productivity growth. Another strand of literature aims at quantifying the potential TFP gains from increasing the efficiency of reallocation. A

[6]They used data from the Short-Term Survey of the Industry.

popular approach, the one taken by our paper following Hsieh and Klenow (2009), for doing so is to calculate measures of dispersion in marginal revenue products of capital (MRPK) and labor (MRPL) in narrowly defined industries as an indicator for misallocation. Differences in marginal products imply that a reallocation of resources from firms with low marginal products to firms with high marginal products would improve aggregate productivity. Furthermore, if dispersion increases over time, the losses in aggregate TFP caused by misallocation increase as well.To the best of our knowledge, only two previous studies have analyzed the dispersion in marginal products for Austria.

Using the MultiProd database, OECD (2019) found that the dispersion[7] in labor productivity in Austria decreased persistently throughout the period 2008-2014, wheres in the benchmark countries dispersion grew from 2008 to 2010 and declined thereafter. Dispersion of productivity in market services fell in the benchmark countries, while it picked up in Austria in the last two years of their sample. While the level of labor productivity dispersion in Austria was lower than in benchmark countries, the gap reduced due to the increase in dispersion in market-services.

Gorodnichenko et al. (2018) computed the dispersion of MRPK and MRPL for 28 EU countries using data from Orbis for the periods 1994-2014. In this sample, Austria is ranked 12th in terms of the lowest dispersion in MRPK (1.35) and 18th for MRPL (0.66). The respective countries with the lowest misallocation are Spain (0.91) and Germany (0.98) for capital and France (0.36) and Germany (0.46) for labor. It appears that the dispersion of the Austrian MRPK increases over time, indicating a decline in the reallocation efficiency of capital. Gorodnichenko et al. (2018) further applied regression analysis to decompose the cross-country differences of the dispersion measures into differences in firm-characteristics and the differential impact of how these characteristics are translated into marginal revenue product dispersion depending on the regulatory, institutional and policy environment of a specific country. This analysis revealed that the low dispersion of MRPK in Germany is mainly due to how the German firm characteristics are translated into dispersion and not the firm characteristics per se. A counter-factual scenario in which German effect coefficients, and thus German framework conditions, were applied to the universe of Austrian firms, resulted in a 25% decrease of MRPK dispersion in Austria.

3 Methodological Approach

In the empirical literature, misallocation of resources is either measured via a direct or indirect approach (Restuccia and Rogerson, 2013). The direct approach usually entails selecting a specific, empirically-measurable factor that is assumed to contribute to misallocation and assess its role on

[7]OECD (2019) defined dispersion as the gap in productivity between firms in 10th and 90th percentile of the productivity distribution.

allocation and TFP development within a model of heterogeneous firms. The indirect approach, by contrast, infers misallocation directly from the dispersion in marginal revenue products within narrowly defined industries, with more dispersion implying higher misallocation. An advantage of the indirect approach is that it requires just a few key variables at the firm level that are available in our balance and income sheet data.

3.1 Indirect approach to measuring resource misallocation

We follow the approach of Hsieh and Klenow (2009) and Gopinath et al. (2017). In this section, we summarize the key features and equations that facilitate the understanding of how factor market distortions lead to dispersion in marginal revenue products of production factors within industries and why such dispersion lowers aggregate TFP growth.[8]

Let us first consider an economy in which a representative firm produces a single final good in a perfectly competitive market. This single final good is produced using inputs from a continuum/set of industries denoted by s via Cobb-Douglas technology. Output of each industry s is itself a CES aggregate of the differentiated products produced by individual firms i with heterogeneous productivities. Firms face an iso-elastic demand and produce their variety of output y_{ist} at period t with a Cobb-Douglas production function $y_{ist} = A_{ist} k_{ist}^{\alpha_s} l_{ist}^{1-\alpha_s}$ using real capital k_{ist}, labor l_{ist} and their individual physical productivities A_{ist} with a sector-specific elasticity of output with respect to capital of α_s. Since we do not observe prices at the firm level, y_{ist} corresponds to nominal value-added ($p_{ist} y_{ist}$) divided by an industry-level value-added price index. Nominal value-added is defined as operating revenue minus materials. Throughout the paper, we proxy real capital with nominal tangible fixed assets, deflated using a sector-specific gross-capital formation price index. Real labor input is proxied with wage costs, deflated by a sector-specific value-added price index.[9]

Hsieh and Klenow (2009) extended this Melitz (2003)-type model of firms with heterogeneous productivities by introducing firm-specific distortions to output, and although there is no distortion to the factor labor, there is a distortion to profitability of capital relative to labor. These distortions enter the profit equation as wedges and are supposed to stand in for various market imperfections in a parsimonious way. Profits are given by:

[8]Restuccia and Rogerson (2017) mentioned three broad categories of factors that might distort the allocation of inputs: 1) statutory provisions, including features of the tax code and regulations that vary with e.g. size or age of firm or a tariff or labor regulation that applies to certain goods, 2) discretionary provisions made by the government or other entities such as banks including corruption, cronyism, subsidies, tax breaks, low interest rate loans granted to specific firms, unfair bidding practices for government contracts, preferential market access, or selective enforcement of taxes and regulations, and 3) market imperfections such as monopoly power, market frictions, and enforcement of property rights.

[9]Price indices are sourced from EUROSTAT (tables *NAMA_10_A64* and *NAMA_10_A64_P5*).

$$\pi_{ist} = (1-\tau^y_{ist}) p_{ist} y_{ist} - (1+\tau^k_{ist})(r_t + \delta_{st}) k_{ist} - w_{st} l_{ist}, \tag{1}$$

where w are wages, r the real interest rate, δ the depreciation rate and p_{ist} the output price of firm i that is a function of its output y_{ist}. Output distortions τ^y_{ist} are higher for firms that face restrictions on output and lower for firms that receive subsidies. Relative capital-labor distortions τ^k_{ist} are higher for firms with, for instance, restricted credit access and lower for firms with subsidized access to credit. Note that, while all firms within an industry s face the same wage and interest rate, distortions may vary by individual firm.

Hsieh and Klenow (2009) shows that profit maximization of firm i in sector s leads to the standard condition that firms set a fixed markup over marginal costs:

$$p_{ist} = \left(\frac{\sigma}{\sigma-1}\right)\left(\frac{r_t+\delta_{st}}{\alpha_s}\right)^{\alpha_s}\left(\frac{w_{st}}{1-\alpha_s}\right)^{1-\alpha_s}\frac{(1+\tau^k_{ist})^{\alpha_s}}{A_{ist}(1-\tau^y_{ist})}, \tag{2}$$

with σ being the elasticity of substitution between varieties which we set equal to 3 as in Hsieh and Klenow (2009); Gopinath et al. (2017).[10] All else equal, firms with higher physical productivity A_{ist} set a lower price, whereas firms with higher distortions set a higher price. From the first order conditions for the capital-labor ratio, labor demand and output we get:

$$\frac{k_{ist}}{l_{ist}} = \frac{\alpha_s}{1-\alpha_s}\frac{w}{(1+\tau^k_{ist})(r_t+\delta_{st})} \tag{3}$$

$$l_{ist} \propto \frac{A_{ist}^{\sigma-1}(1-\tau^y_{ist})^{\sigma}}{(1+\tau^k_{ist})^{\alpha_s(\sigma-1)}} \tag{4}$$

$$y_{ist} \propto \frac{A_{ist}^{\sigma-1}(1-\tau^y_{ist})^{\sigma}}{(1+\tau^k_{ist})^{\alpha_s\sigma}}. \tag{5}$$

The allocation of resources across firms does not solely depend on physical productivites but also on the two distortions. Higher output distortions lower output and labor input and higher capital distortions lower the capital labor-ratio, ceteris paribus. The respective marginal revenue productivities for capital and labor are given by (see Hsieh and Klenow, 2009):

[10] Hsieh and Klenow (2009) note that typically values between 3 and 10 are found in the trade and industrial organization literature. They also note that the results regarding the TFP gap are highly sensitive to the choice of this parameter and that $\sigma = 3$ is conservatively low. We implemented robustness checks setting σ to 5 and 9. The total economy TFP gap increases from around 65% ($\sigma = 3$) to 95% ($\sigma = 5$) and 125% ($\sigma = 9$). Note however, that the dispersion of MRPK and MRPL are unaffected by the choice of σ.

$$MRPK_{ist} := \left(\frac{\alpha_s}{\mu}\right)\left(\frac{p_{ist}y_{ist}}{k_{ist}}\right) = \left(\frac{1+\tau^k_{ist}}{1-\tau^y_{ist}}\right)(r_t + \delta_{st}) \tag{6}$$

$$MRPL_{ist} := \left(\frac{1-\alpha_s}{\mu}\right)\left(\frac{p_{ist}y_{ist}}{l_{ist}}\right) = \left(\frac{1}{1-\tau^y_{ist}}\right)w_{st}, \tag{7}$$

with MRPK being the marginal revenue product of capital, MRPL the marginal revenue product of labor and $\mu = \frac{\sigma}{\sigma-1}$. Note that the right hand side of equations 6 and 7 correspond to the marginal costs and rearranging would yield the standard condition that marginal revenue products equal marginal costs times markup (μ). Since all firms within an industry s face the same factor costs, firms which face distortions have higher (in case of disincentives) or lower (in case of subsidies) marginal costs and revenue products. The more variation in the distortions between firms within a narrowly-defined industry s exists, the higher the dispersion in marginal products of that industry. Equations 6 and 7 are central for the empirical analysis of this paper, as we will use them as approximations for misallocation.

To demonstrate how an increase in dispersion of these marginal revenue products may decrease the aggregate productivity growth of the economy, it is vital to distinguish between physical (A_{ist}) productivity and revenue-based total factor productivity ($TFPR_{ist}$), with the latter being defined as the product of the price and the physical productivity (see Foster et al., 2008). Hsieh and Klenow (2009) show that the revenue-based total factor productivity can be expressed as a geometric average of the marginal revenue products:

$$TFPR_{ist} := p_{ist}A_{ist} = \frac{p_{ist}y_{ist}}{k^{\alpha_s}_{ist}l^{1-\alpha_s}_{ist}} = \mu\left(\frac{MRPK_{ist}}{\alpha_s}\right)^{\alpha_s}\left(\frac{MRPL_{ist}}{1-\alpha_s}\right)^{1-\alpha_s} \tag{8}$$

Hsieh and Klenow (2009) argue that an increase in dispersion of marginal revenues and thus revenue TFP within industries s decreases aggregate physical productivity. Since the revenue productivity is also affected by changes in prices, it is the physical productivity that is relevant to policy makers concerned with issues like growth, efficiency and welfare. For a given level of A, firms with higher distortions face higher marginal costs (see equations 6 and 7), a higher TFPR (see equation 8), set higher prices (see equation 2), and as a result face lower demand for their products (see equation 5). If $TFPR$ and A are positively correlated, then firms with higher physical productivity A are smaller than optimal, leading to a smaller aggregate TFP. Note that this essentially implies that more productive firms tend to face higher distortions, which is a very strong assumption that is not further motivated and discussed in Hsieh and Klenow (2009) or subsequent papers applying their methodology (i.e. Gopinath et al. (2017)). Nevertheless, this assumptions holds in the data used in Hsieh and Klenow (2009) and in this study (see Section 4.3). One possible reason may be size-dependent or information asymmetry-related financial constraints. Start-up companies may be more innovative and productive, but may also be more financially constrained due to the lack of credit history, collateral and information asymmetries regarding the risk of their enterprise.

Input factors would be allocated optimally if all firms within a narrowly defined industry s faced the same distortions (i.e. $\tau^y_{ist} = \tau^y_{st}$ and $\tau^k_{ist} = \tau^k_{st}$) including the case of no distortions (i.e. $\tau^y_{ist} = \tau^k_{ist} = 0$ for all i within s). In this case, firms with higher physical productivity would increase their input factors until the returns to factors (MRPK and MRPL) were equalized across firms within industry s. Gopinath et al. (2017) show that the observed level of industry physical productivity TFP_{st} is given by:[11]

$$TFP_{st} = \frac{Y_{st}}{K_{st}^{\alpha_s} L_{st}^{1-\alpha_s}} = \frac{\overline{TFPR}_{st}}{P_{st}} = \left[\sum_{i=1} \left(A_{ist} \frac{\overline{TFPR}_{st}}{TFPR_{ist}} \right)^{\sigma-1} \right]^{\frac{1}{\sigma-1}}, \tag{9}$$

Equation 9 shows that equalizing the firm level revenue productivities $TFPR_{ist}$ with their respective average industry productivity $\overline{TFPR}_{st} = \frac{P_{st}Y_{st}}{K_{st}^{\alpha_s} L_{st}^{1-\alpha_s}}$ increases the physical productivity TFP_{st} of the industry. This follows from the (empirical) positive correlation between physical productivity and revenue productivity. If highly productive firms also face higher distortions, their contribution to aggregate TFP is weighted less, according to equation 9. The inverse holds true for less productive firms.

Given estimates of $TFPR_{ist}$, a counterfactual optimal efficiency level of physical productivity in the case of no dispersion can be constructed and related to the observed productivity level to get an estimate of the TFP gap due to distortions in resource allocation. Equalizing marginal revenue products and thus $TFPR$ across firms within industry s, the hypothetical efficient level of physical productivity TFP^e_{st} is given by $TFP^e_{st} = \left[\sum_{i=1} A_{ist}^{\sigma-1}\right]^{\frac{1}{\sigma-1}}$. Since we do not observe price levels p_{ist} at the firm level to retrieve the physical firm-level productivity directly, we follow Hsieh and Klenow (2009) and approximate A_{ist} by:

$$\tilde{A}_{ist} = \left(\frac{(P_{st}Y_{st})^{-\frac{1}{\sigma-1}}}{P_{st}} \right) \left(\frac{(p_{ist}y_{ist})^{\frac{\sigma}{\sigma-1}}}{k_{ist}^{\alpha_s} l_{ist}^{1-\alpha_s}} \right). \tag{10}$$

The indirect approach to measuring misallocation outlined above provides a useful framework since it only requires the balance sheet data and income statements. However, as Hsieh and Klenow (2009) and others noted (see Restuccia and Rogerson, 2017), this simplicity comes with some drawbacks. The main issue is that differences in marginal revenue products may be related to fac-

[11] The industry aggregates of output, capital, labor and the industry price index are given by $Y_{st} = \left[\sum_{i=1} y_{ist}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$, $K_{xt} = \sum_{i=1} k_{ist}$, $L_{st} = \sum_{i=1} l_{ist}$ and $P_{st} = \left[\sum_{i=1} p_{ist}^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$ respectively.

tors other than misallocation, which will lead to biased results. Asker et al. (2014) argued that in the presence of adjustment costs in investments (i.e. time needed to build a new plant) and transitory idiosyncratic TFP shocks, dispersion in marginal products arise naturally.[12] Peters (2020) argues that markups vary systematically across firms and thus represent a source of misallocation that is disregarded when one assumes a constant elasticity of substitution that is common to all firms. Convergence in market power of firms would thus reduce TFPR dispersion without increasing efficiency in any way (see Calligaris et al., 2018). Another obvious drawback of the approach is that some more or less arbitrary level of sectoral aggregation is given by the data. At this aggregation level firms are assumed to be similar in the sense that they produce using the same Cobb-Douglas production function and, thus, any deviation in capital-labor ratios turns up as misallocation. Another potential issue are measurement errors, such as omitted or double-counted revenue or inputs from different divisions within the firm, that can lead to a significant overestimation of the degree of misallocation (see Bils et al., 2021). Finally, the approach disregards misallocation at the extensive margin, i.e. via the selection channel. Yang (2021) demonstrates that selection can magnify the estimated aggregate TFP losses from distortions by over 40 percent.

3.2 Estimating the change in reallocation efficiency and the role of financial constraints

Next, we explore the effect of the marginal revenue productivities obtained from equations 6 and 7 on the accumulation of capital and labor. In theory, firms with a higher marginal revenue product of a production factor should accumulate more of that factor than a firm with a lower marginal revenue product. We test how the efficiency of the reallocation mechanism evolved over time, i.e. if and how this elasticity changes between sub-periods of our sample. We also take into account that more productive firms may not be able to accumulate factors when they are financially constrained, especially small and young firms[13]. Hence, in our analysis we include a series of variables that approximate financial frictions and control for age and size effects.

Following Decker et al. (2020) and Bouche et al. (2021) we estimate the responsiveness of capital and labor factor accumulation with respect to their marginal productivities using the following relationship:

$$g(f_{i,t}) = \beta\, prod_{i,t-1} + \sum_{p} \gamma_p D_p\, prod_{i,t-1} + \theta f_{i,t-1} + \sum_{k} \mu_k x_{i,k,t-1} + \delta_{s,t-1} + \varepsilon_{i,t-1}, \qquad (11)$$

[12] In a similar manner, Oberfield (2013) adjusted for the factor utilization by using measures of energy consumption. Hang (2022) showed that differences in utilization rates will introduce two sources of bias with opposing signs and the direction of the overall bias being dependent on the empirical application.

[13] For the interplay between misallocation, factor dispersion and size-dependent financial constraints see e.g. Midrigan and Xu (2014); Gopinath et al. (2017); González et al. (2021); Gorodnichenko et al. (2018).

with $g(f_{i,t})$ referring to the growth rate (*100) of factor inputs (either capital or labor) from $t-1$ to t. We run regressions for capital and labor as dependent variable where we use real tangible fixed assets for capital (k) and real wage sum for labor input (l). Note that since the real wage sum is the product of the number of employees and the average real wage, an increase in this variable does not per se imply an accumulation in the sense of an increase in employment (as for instance in Bouche et al., 2021, who used employees) but can also reflect an increase in wages. As the number of employees is only poorly covered in our dataset, we cannot decompose this variable further. All explanatory variables enter lagged by one period. The main variable of interest is the log of the productivity indicator (*prod*) where we use the marginal revenue product of capital (MRPK) in the case of capital growth as the dependent variable and MRPL for labor growth. This productivity indicator is interacted with a period dummy (D) to allow for period-dependent effects of productivity on factor growth. We defined three time periods, the crisis period from 2008 to 2011, the recovery period 2012 to 2014 and the period leading up to the end of our sample, 2015 to 2018. A higher marginal revenue productivity should, all else equal, lead to a stronger accumulation of the respective factor, so we expect a positive sign on this parameter. To control for size and convergence effects, we include the (log) level of the production factor (f). A higher level of the respective factor should lead to a slower accumulation in terms of a growth rate, hence, we expect a negative sign on the respective coefficient. In a similar manner, we control for the age (x_k) of the firm, whereas we expect a less dynamic factor accumulation for more mature firms. The effect of financial constraints at the firm level is modeled via several proxy variables (x_k), explained in more detail below. Firms that are more financially constrained are expected to accumulate less capital, all else equal. Sectoral business cycles and trends are captured by industry-year dummies (δ). Finally ε refers to the idiosyncratic error term. Subscripts i refer to individual firms, t to years, p to periods and k to a specific control variable.

To estimate the (moderating) effects of financial constraints of firms on their ability to grow their factor inputs, we include the following control variables that have been used in the literature. Adapted from Levine and Warusawitharana (2021), we use the *leverage* (book debt to total assets), the ratio of cash holdings (*cash hold.*) to total assets and an estimate of the interest rate paid by the firm (interest paid to (non-accruals) debt over book debt, *int. rate*). As in Bonanno et al. (2020), we include an estimate of the ratio of *cashflow* to total assets.[14] For more information on the data-cleaning procedures of these financial variables, see Section A in the Appendix.

Since financial constraints may operate differently depending on size, age or industry of the firm, we ran additional robustness checks in which we interact financial constraints with size, age

[14] Since all these proxies for the financial situation of a firm are ratios, we multiply them by 100 so the estimated coefficients can be interpreted as semi-elasticities of a one percentage point increase of the ratio on percent of factor growth.

and industry dummies. We report the robustness checks for capital, as our results show stronger effects of financial constraints on the accumulation of that factor.

4 Empirical Analysis

4.1 Data Sources and Descriptive Statistics

For our empirical analysis we use a dataset similar to Beer et al. (2021) which we refer to for a more detailed description. The dataset, which was initially compiled for the purposes of the OeNBs inhouse credit assessment (ICAS), consists of annual financial statements (FS) of non-financial firms based in Austria for the period from 2008 until 2018. The FS for the ICAS are mainly drawn from three data sources. An essential part of the FS is taken from the Austrian public commercial register. However, the granularity of the FS varies substantially, as reporting requirements are much lighter for smaller firms. For this reason, the OeNB additionally collects more granular FS provided by banks who pledge loans as credit claims for the ICAS and from the firms themselves. All FS exhibit a detailed balance sheet and profit and loss statement to which we add respective firm characteristics such as NACE-sector and firm age. Before data-cleaning procedures are applied, we obtain a total dataset consisting of $76,927$ firm-years. Applying a number of plausibility checks and data-cleaning procedures (similar to Gopinath et al., 2017) reduces our sample to $62,309$ observations (see Section A).

However, the number of FS varies substantially between years. The complete set of FS for all years is only available for a subsample of firms as firms enter and leave the sample for a number of reasons. We do not have any further information regarding this issue, especially since banks and firms are not legally obliged to report FS to be included in the dataset. Thus, we cannot distinguish the reasons for firms dropping out of the sample. This might be – among other reasons – due to insolvencies, or because a bank no longer needs to pledge a certain loan to a firm as credit claim and therefore does not submit the respective FS.

We address this issue as follows. In the first part of our empirical analysis, we investigate how factor misallocation evolved over time within our sample period. To avoid having the results affected by sample composition effects, we only take into account those firms where a FS is available each year (permanent sample). According to the reporting requirements for the public commercial register only large firms have to report granular FS, it is likely that smaller (and less productive) firms are underrepresented. Thus, choosing the permanent sample might induce positive selection on firm size and productivity level. Nevertheless, this approach seems preferable since the observed change of factor misallocation, which we are interested in, is less likely to depend on sample composition effects.

In the second part of our empirical investigation we try to explain the growth of factor inputs (capital and labor) by their marginal productivities via linear regression. To increase the precision of the estimates, this analysis is applied to the full sample of firms[15] in our dataset. In order to attenuate the effects of sample composition on the estimation results, we include a set of firm-level controls and dummy variables (year-industry) to control for observed and unobserved heterogeneties. For specifics, please refer to Sections 3.2 and 4.4.

Given the indirect approach to measure misallocation we employ in this paper (see Section 3.1), it is necessary to subdivide our sample into firms which are assumed to have a similar production function. Following past literature using this approach, we use the NACE industry classifications for this division. We restrict our sample to NACE industries that are considered less distorted by subsidies and regulation, that contain more homogeneous firms and for which sufficient observations per year are available.

We, therefore, first exclude firms of the industries agriculture and mining since these firms benefit most from subsidies. In fact, the subsidies these sectors received on production accounted for 14% of their output according to the 2018 Austrian Input-Output Tables. Next, we drop all industries[16] for which our dataset does not contain a sufficient number of observations (less than 10 firms per industry and year) to compute the dispersion measures. Finally, we exclude firms in the industries energy, transport, construction and real estate since firms within those industries are too heterogeneous and this would result in a severe measurement bias of misallocation using the indirect approach. The lack of homogeneity is evident from the heterogeneity in markups (see section 4.2.1) which is significantly higher for these industries. High markup heterogeneity, in this context, implies that the marginal revenue dispersion is a poor proxy for misallocation. However, leaving those industries in our sample results in higher misallocation, but a similar development over time (increasing in the years after the great financial crisis and dropping afterwards).

After applying the data-cleaning procedures and subsequent filtering according to industry classification we retain a (full) sample of $42,476$ firms-years or financial statements (FS) that are associated with 17 industries. In the modeling exercise (results in Section 4.4), we further reduce the number of observations to a common sample over all independent variables. Moreover, because we analyze the effects of marginal productivities on the growth of factor inputs, we naturally also lose one year's observations, leaving us with $22,186$ firm-years that are used for estimation. The balanced panel (permanent sample) that we use for the analysis of the development of the misallo-

[15]Results based on the permanent sample are reported in Annex Section C.3. In general, we find that results based on the permanent sample are much less precisely estimated but robust in the sense that they do not contradict any results yielded from the analysis based on the full sample.

[16]The following eight industries are excluded: Water supply; sewerage; waste managment and remediation activities, financial and insurance activities, public administration and defence; compulsory social security, education, human health and social work activities arts, entertainment and recreation other services activities activities of households as employers.

cation of production factors in the Austrian economy consists of $4,200$ FS and 12 industries.

4.2 Factor Misallocation Development in Austria

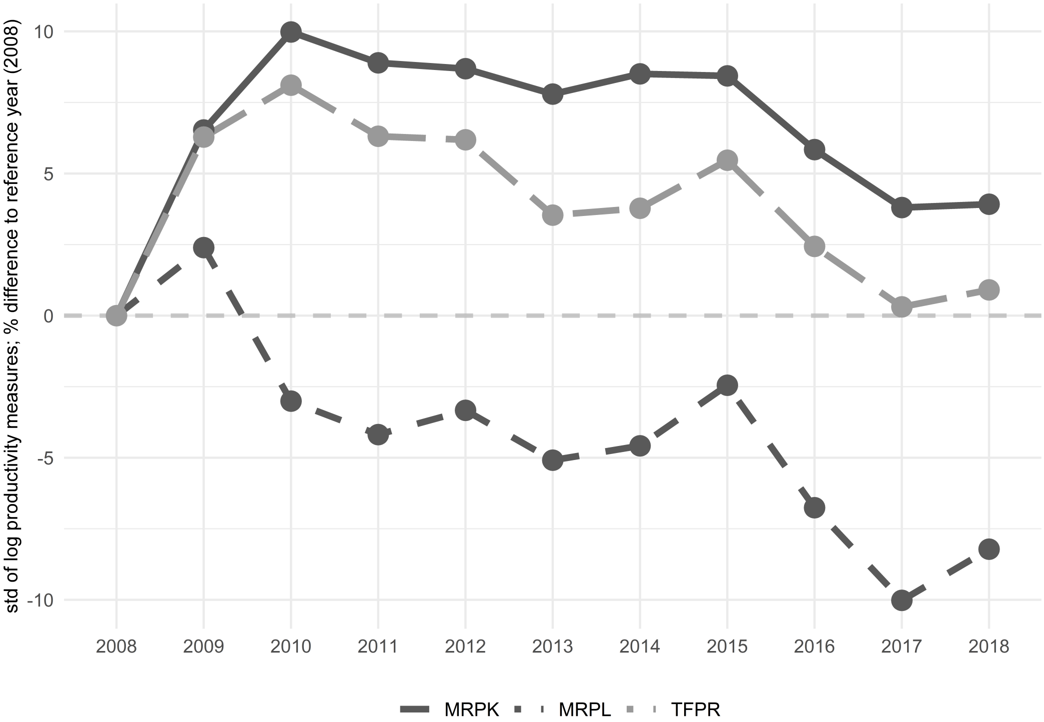
As outlined in Section 3, we proxy the misallocation of the production factors by their dispersion in marginal revenue products at the industry level. Following Gopinath et al. (2017), a.o., we employ weighted trends of within-industry misallocation to estimate the economy-wide level of misallocation. Specifically, we start by calculating the marginal revenue product of capital (MRPK) and labor (MRPL) via equations 6 and 7. Note, that while MRPK and MRPL are firm-specific, capital and labor shares (α_s) are industry-specific[17]. Industry estimates of the dispersion in marginal revenue products are calculated via the within-industry standard deviation of the log of MRPK and MRPL. These industry-level measures are then aggregated to get an estimate for the "total economy" [18] by calculating the average of the respective industry, weighted by a constant value-added share (average share of the sample period). In order to allow for different developments between the two given the results from the empirical literature we distinguish between *Manufacturing* and *Market-services* industries (see e.g. Bun and de Winter, 2022; Dias et al., 2016). Note that the within-industry dispersion of marginal revenue products is calculated at a more detailed NACE level and afterwards aggregated to these two macro sectors.

The development of misallocation for the total economy is shown in Figure 1. Capital misallocation (MRPK) increased during the great financial recession, leveled off between 2010 and 2015 and decreased afterwards to around 4% above its initial level in 2018. Contrary, labor misallocation (MRPL) almost steadily declines over the sample period, ending around 7.5% below its 2008 value at the end of the sample. The Austrian misallocation developments are only partly in line with previous findings for other European countries. Gorodnichenko et al. (2018) found that in most EU-28 countries misallocation of both capital and labor was trending up between 1996 and 2014, though to a much smaller extent for labor than for capital. Similar results are found for Belgium, France, Italy, Spain and Portugal (see Gamberoni et al., 2016; Gopinath et al., 2017, with evidence for the periods 2002-2012 and 1999-2012 respectively), the Netherlands (see Bun and de Winter, 2022, for 2001-2017) and 11 euro area countries (see Deutsche Bundesbank, 2021, for 2001-2015). However, capital misallocation fell from 2006 to 2012 onward in Germany and

[17] These industry-level elasticities of capital and labor inputs are calculated in the following way. First, firm-specific labor shares are given by taking the ratio of wage costs to value-added. Given the constant returns to scale Cobb-Douglas production of firms (see 3.1), the capital share (α) is defined as 1 minus the labor share. Next, we calculate industry-specific yearly averages that are weighted with the sales of the firm to account for the heterogeneity in firm-sizes within industries. To make sure that changes in MRPK and MRPL are not driven by changes in capital and labor shares over time, we use the average shares of the total sample period ("divisia-index", see e.g. Stehrer et al., 2019).

[18] Note that total economy here refers to an aggregate of all industries for which enough observations were left after the data cleaning process and that were not excluded for other reasons. See Appendix A for detailed information.

Figure 1: Development of factor misallocation, total economy



Note: Factor misallocation is proxied by the within-industry standard deviation of log productivity measures, aggregated to the total economy via constant value-added industry shares. The underlying data is the permanent sample, see Section 4.1. Development over time is depicted as percentage difference to the initial year (2008) value.

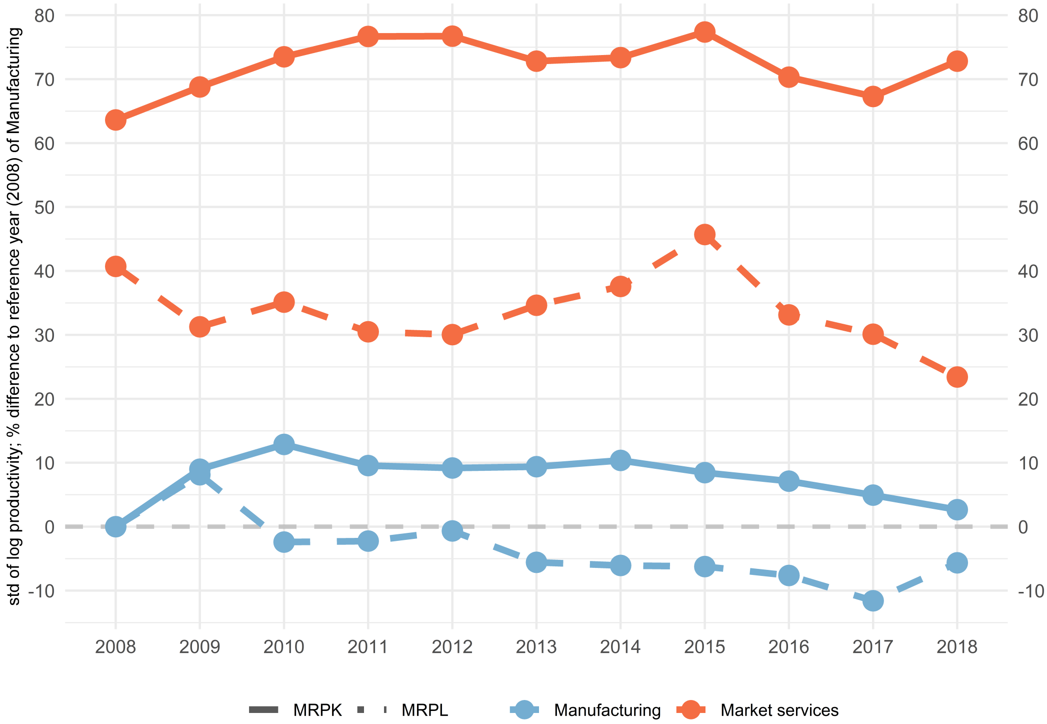
stayed roughly constant in Norway (see Gamberoni et al., 2016; Gopinath et al., 2017). The developments of Austria's capital misallocation seem more similar to German and Norwegian evidence. Given the similarities in economic structure, institutions and the intensive cultural and economic ties between Austria and Germany, a similar development seems plausible. However, the decline in labor misallocation in Austria stands out from the rest of the literature.

The light grey line in Figure 1 shows development of the dispersion in revenue-based total factor productivity, a measure of the total resource misallocation of the economy. Since it is a weighted geometric average of the two factor productivities (see equation 8) it lies between the dispersion of MRPK and MRPL. Overall, this particular measure of resource inefficiency reverted back to its initial level. This development also contrasts with comparable findings for the Netherlands (see Bun and de Winter, 2022) and Italy (see Calligaris et al., 2018, for period 1993-2013) that find an overall increase in total factor misallocation.

Figure 2 depicts the development in factor misallocation for manufacturing and market service industries, whereas all measures are normalized[19] to the initial (2008) dispersion in manufacturing.

[19]Note that differences in the dispersion levels between capital and labor cannot be readily interpreted, while the

Figure 2: Development of factor misallocation, industry aggregates



Note: Factor misallocation is proxied by the within-industry standard deviation of log productivity measures, aggregated to macro-sectors via constant value-added industry shares. The underlying data is the permanent sample, see Section 4.1. Development over time is depicted – for both *Manufacturing* and *Market services* – as percentage difference to the initial year (2008) value of *Manufacturing*. The solid lines represent the values for MRPK and the dashed line for MRPL, while the line colour indicates the sector.

A few key features are clearly visible. First, misallocation is significantly higher in services industries. This result is in line with Dias et al. (2016); Bun and de Winter (2022), and may be driven by less competitive pressure, lower international trade-ability, higher location-dependence and a higher degree of regulation in services (see for instance Duarte and Restuccia, 2010). Moreover, misallocation might be overestimated in the service sector due to additional variation stemming from the less detailed industry classifications of the market-services industries (see Table 6). Second, over the whole sample period, capital misallocation in market-services grew by around 10 percentage points while it reverted back to initial levels in manufacturing. Gamberoni et al. (2016) found that misallocation increased in both sectors, but particularly severe in services industries. Bun and de Winter (2022) found a similar upward trend for capital misallocation in both manufacturing and services for the Netherlands.

dispersion of a particular production factor of different industries can be compared.

4.2.1 The role of markup heterogeneity for capital misallocation in Austria

As outlined in the end of Section 3.1, the indirect approach to measuring misallocation employed in this study may lead to upward biased measures of misallocation due to other reasons not related to misallocation, for instance markup heterogeneity (see Peters, 2020), are picked up as revenue product dispersion. To estimate the share of capital misallocation driven by heterogeneity in markups, we follow the approach of David and Venkateswaran (2019) which is based on the methodology of De Loecker and Warzynski (2012). De Loecker and Warzynski (2012) extend the production function by the variable production factor materials input m_{ist}. When prices equal marginal costs (i.e. perfect competition), the elasticity of a variable production factor is equal to its expenditure share. Under imperfect competition a markup drives a wedge between the input's revenue share and its output elasticity. David and Venkateswaran (2019) further assume that while the choice of capital and labor is subject to distortions, the choice of materials input is undistorted except for the markup. The optimality condition implied by cost minimization is then given by:

$$\frac{p_{ist}}{MC_{ist}} = \frac{p_{ist}y_{ist}^{OR}}{p_{ist}^{m}m_{ist}}\theta_s \Rightarrow \theta_s\frac{MC_{ist}}{p_{ist}} = \frac{p_{ist}^{m}m_{ist}}{p_{ist}y_{ist}^{OR}}, \tag{12}$$

with θ_s being the output elasticity of materials input, $p_{ist}y_{ist}^{OR}$ being gross output (approximated by operating revenue), $p_{ist}^{m}m_{ist}$ being intermediate material input used and MC_{ist} referring to marginal costs. From equation 12 it follows that firms set the material share of gross output ($p_{ist}^{m}m_{ist}/p_{ist}y_{ist}^{OR}$) equal to the inverse of the mark-up, scaled by the elasticity of material input (θ_s). Given equation 12, we see that the within-industry dispersion of the logged material share maps one-to-one to the dispersion in the logged markups. Note that θ_s has no bearing on the dispersion, as it does not vary within industry. Following David and Venkateswaran (2019), we retrieve an estimate of how much of the variance in (logged) MRPK is explained by the variance in mark-ups (i.e. the (logged) share of materials) in our sample.

The shares of variation in MRPK explained by variation in mark-ups are depicted in Figures 4 (total economy) and 5 (for manufacturing and market-services) in Annex C.[20] Variation in markups explains between 13% and 21% of the variation in MRPK for the total economy, with an increasing trend over the sample period. This increasing trend is due to the decrease in MRPK dispersion after 2010 and the upward trends of dispersion in markups. Our results are somewhat below the values found in Bun and de Winter (2022) of 25% for the Netherlands and comparable to the ones for the United States found in David and Venkateswaran (2019) of 14%. We are thus confident, that our estimates of misallocation do not reflect mark-up heterogeneities to a large

[20]Analogous to the trends depicted throughout this text, these figures refer to within-industry measures that are aggregated to the total economy or macro-sectors using constant value-added shares of the respective industries.

extent.

Distinguishing manufacturing and market-services firms reveals more heterogeneous trends (see Figure 5), with manufacturing firms showing a higher variability in mark-ups relative to the total variation in MRPK. However, note that the variation in markups of manufacturing firms is much lower than the respective variation for service industries (see Figure 7).

4.3 TFP Gap Development

The indirect approach to measure misallocation allows to easily construct a counterfactual TFP level in the case of optimal factor allocation between firms within an industry. The industry-level measures of real TFP and real 'efficient' total factor productivity (TFP^e) are given by equations 9 and 10 in Section 3. Similar to the previous section (4.2), we aggregate the industry-level dispersion measures to the total economy and macro-sectors using weighted averages that take into account the value-added shares of industries (following Gopinath et al., 2017).

Note that the estimate for the "efficient" TFP is always above the actual observed TFP level - in other words there is potential to increase productivity if misallocation is reduced - because we observe a positive correlation between the firm TFPR and the estimate of physical productivity we employ in this study (z). Table 2 reports the empirical correlation coefficients for the total economy and macro-sector disaggregations. The correlation is moderately positive, more or less constant over time and somewhat higher in the market services sector over the whole sample period, suggesting a higher potential to increase efficiency in this sector compared to manufacturing. These results are somewhat in line with Dias et al. (2016), albeit they find a larger difference between manufacturing and service sectors.

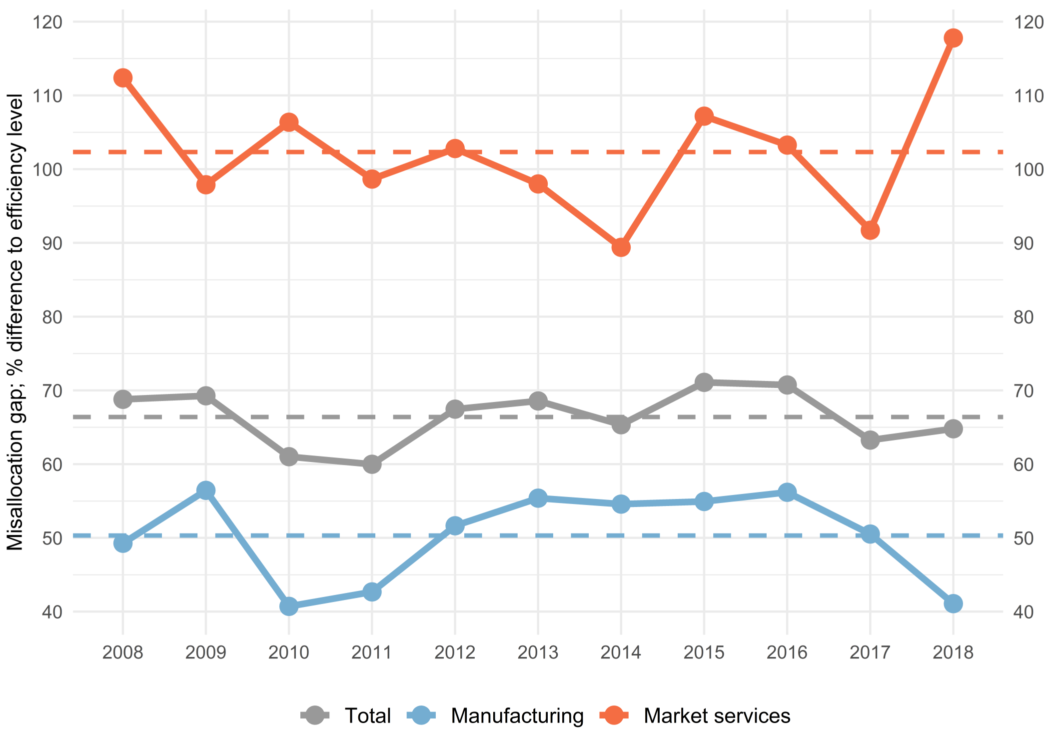
Table 2: Empirical correlation between revenue and physical productivity

	Average over time	2008	2013	2018
Total	0.65	0.69	0.62	0.63
Manufacturing	0.64	0.71	0.61	0.61
Market services	0.67	0.63	0.64	0.68

Note: Correlation coefficients refer to the bivariate Pearson correlation coefficient between TFPR and A (see equations 8, 10) and are based on the permanent sample, see Section 4.1. These correlation coefficients are calculated at the industry level and subsequently aggregated to the total economy and macro-sectors using constant industry value-added shares.

The TFP gap depicted in Figure 3 is calculated as $\lambda = \log(TFP^e) - \log(TFP)$. On average the gap amounts to roughly 66% for the total economy. The gap fluctuates between 60 and 71%, starting at 69% in 2008 and ending up at 65% in 2018. Our estimates fall between results reported in the related literature that reported TFP gaps for the total economy. To the best of our knowledge, we could not find any literature reporting TFP gaps due to misallocation for Germany, the typical Austrian benchmark country. The economies most resembling Austrian economic development for which empirical estimates are available are the Netherlands and the US. Bun and de Winter (2022) find that the Netherland's TFP of the total economy could be increased by 43% in 2001 which increases to around 57% in 2017. Consistent with the assumption that the United States economy represents a relatively undistorted market, David and Venkateswaran (2019) yield a small misallocation gap of about 12% for large publicly traded US firms for the period 1998-2009. In contrast, an empirical study of the Portuguese economy established that TFP could be between 48% and 79% higher in 1996 and 2011, if allocation were fully efficient (Dias et al., 2016).

Figure 3: Development of TFP gap, total economy and industry aggregates



Note: The misallocation gap is proxied by the difference of the logged "efficient" TFP and logged observed TFP at the industry level which is subsequently aggregated to the total economy or two macro-sectors via constant value-added shares. Figures are based on the permanent sample, see Section 4.1.

Figure 3 also shows the respective gaps for manufacturing and market-services industries. Again, disaggregating the total economy offers interesting insights. First, there seems to be a much higher potential to increase productivity in market-services industries than in manufacturing, which is due to the higher extent of misallocation in the former. On average over our sample period, service industries could about double their productivity, if factor allocation was efficient. Manufacturing firms are much closer to the efficient TFP level with an average of about 50% increase by the full elimination of misallocation within industries. As the misallocation gap fluctuates around the period average for both macro-sectors, we do not observe a clear trend for either *Market services* or *Manufacturing*.

Relating the misallocation gap of market-services firms to the existing literature sets the relatively high figures into perspective. Dias et al. (2016) report a hypothetical increase of 92% for service industries in Portugal in 2011. For the manufacturing sector, we also observe a considerably lower amount of misallocation in the related literature. For example, Dias et al. (2016) find a gap of about 54% for Portuguese firms in 2011 and Gopinath et al. (2017) report 28% for Spanish firms in 2012. Bellone et al. (2013) look at French firms and find a misallocation gap of 31% in 2005. Hsieh and Klenow (2009) show a potential TFP gain from a perfect allocation of production factors for US firms that amounted to 43% in 1997.

Note that the estimates of the potential gains from efficient reallocation tend to be upward biased, since the underlying measures of dispersion also capture heterogeneities in mark-ups, in firm production functions, measurement errors and the impacts of adjustments costs (see Restuccia and Rogerson, 2017). Thus, in the empirical literature, the gains relative to a more efficient benchmark country, such as the US, are often used as a more reasonable benchmark.

We follow this approach and calculate the gains in Austrian aggregate TFP when moving to the US efficiency using the most recent estimates of the misallocation gap of the US which are comparable to our sample of the total economy as well as the manufacturing sector. However, such a comparison should be interpreted with caution. First, we were limited to studies that closely follow the methodology of Hsieh and Klenow (2009) which reduced the choice to comparable work that also focused on the United States. Second, estimates of the misallocation gap are highly dependent on the specific sample, i.e. the composition of industries and firms within those industries. As David and Venkateswaran (2019) only cover very large publicly traded companies, we might assume that this benchmark is unattainable for the Austrian economy.

Adapted from Hsieh and Klenow (2009), we calculate the gains as:

$$\Delta logTFP_{AT}^{eUS} = \left[\left[\left(log\left(\frac{TFP_{AT}^{e}}{TFP_{AT}} \right) + 1 \right) / \left(log\left(\frac{TFP_{US}^{e}}{TFP_{US}} \right) + 1 \right) \right] - 1 \right] * 100. \tag{13}$$

We find that there is ample room for improvement for the Austrian economy when comparing to estimates of the US efficiency that relate to the period 1998-2009 (David and Venkateswaran, 2019). Specifically, the Austrian TFP level may be increased by 49%, relative to the arguably less distorted US market economy.[21] To put this number into perspective, consider the following thought experiment. Assuming a one per cent productivity growth per year (i.e. the average TFP growth in Austria prior to the great financial recession, see Table 1), it would take about forty years to reach the same level of productivity that could be achieved by meeting the US efficiency level.

In contrast, when comparing only the manufacturing sector of the Austrian and US economy, we do not see a huge potential of increasing allocative efficiency. Comparing the Austrian manufacturing industries to the admittedly somewhat dated estimates from the US (1997, Hsieh and Klenow, 2009), we only find a 5%[22] increase if the US efficiency level were to be applied to Austria.

4.4 Reallocation over time and the role of financial constraints

Lastly, we analyze the responsiveness of capital and labor accumulation with respect to their marginal productivities. Our research interest here is threefold. First, we test if there is a functioning reallocation mechanism of capital and labor at play in our sample. This would be the case if we find a positive relationship between the factor productivity and the accumulation rate of that factor. Second, we test if this relationship changed over time, i.e. if the reallocation mechanism improved or deteriorated. Third, we analyze the effects of financial constraints on reallocation. Note that the following results need to be interpreted with caution and not as causal effects since the marginal revenue products and our financial constraints variables are likely endogenous to factor accumulation.

A summary of the results of equation 11 is given in Table 3 for capital accumulation (growth rate of real tangible assets) as the dependent variable. All coefficients have the expected sign and most of them are statistically significant at conventional levels. A one percent higher marginal revenue product of capital is associated with a 1 to 1.3 percentage point higher growth rate of capital in the following year, for the base period 2008-2011. The differential effects for the periods 2012-2014 and 2015-2018 are not precisely estimated at conventional levels, thus suggesting a rather constant positive allocation effect over the whole sample period. Older and larger (higher stock of capital) firms show a weaker rate of capital accumulation. The role of financial constraints in the accumulation of capital is shown for each of our proxies separately in columns (1) to (4) and for all measures included at once in column (5). Lower leverage and lower implied interest rate on debt payments or higher cash holdings and cash flow are related to a larger capital accumulation. The parameters on all proxies retain their sign and except for the implied interest rate also their

[21] Following equation 13, we set the ratio of (log of) efficient TFP and actual TFP of Austria (taking the mean over time of our sample) (1.66) in relation to the US (1.12).

[22] Similar to the case of the total economy (see footnote 21), we compare the ratio of efficient to observed TFP of Austria with the US.

Table 3: Dependent variable is the growth rate of real tangible assets, full sample

	(1)	(2)	(3)	(4)	(5)
log MRPK	1.246***	1.039***	1.157***	1.165***	1.044***
	(0.326)	(0.327)	(0.327)	(0.327)	(0.327)
log MRPK:Period 2	-0.416	-0.380	-0.365	-0.478	-0.445
	(0.440)	(0.440)	(0.440)	(0.440)	(0.439)
log MRPK:Period 3	0.836	0.829	0.879	0.750	0.771
	(0.491)	(0.491)	(0.491)	(0.491)	(0.490)
log capital	-1.674***	-1.419***	-1.562***	-1.592***	-1.618***
	(0.186)	(0.186)	(0.186)	(0.186)	(0.187)
age	-0.048***	-0.043**	-0.045***	-0.043**	-0.046***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
leverage	-0.074***				-0.062***
	(0.009)				(0.010)
cash hold.		0.194***			0.138***
		(0.024)			(0.025)
int. rate			-0.389***		-0.281*
			(0.116)		(0.117)
cashflow				0.086***	0.061***
				(0.014)	(0.014)
time-industry FE:	yes	yes	yes	yes	yes
Num.Obs.	22186	22186	22186	22186	22186
R2 Adj.	0.020	0.020	0.018	0.019	0.023

Note: Results reported refer to the baseline specification introduced in Section 3.2. Standard errors are given in parentheses. Observations are derived from the full sample and limited to a common sample over all five models where all independent variables are available for each firm. ***, **, and * indicate significant at the 0.5%, 1%, and 5% level, respectively.

precision. Furthermore, the absolute size of the coefficients is largely retained, indicating that the variables capture different aspects of financial constraints to some extend.

In an additional specification, we interacted the financial constraints variables with size, age and industry dummies. The results are summarized in Table 28 in Annex C.2. A differential role for financial constraints is only found for cash holdings. Its positive impact on capital accumulation declines with age and size and is also less prominent for market-services compared to manufacturing industries. In other words, the sensitivity of capital accumulation with respect to cash holdings is higher for small and young manufacturing firms.

Table 4 shows the result for the growth rate of the real wage sum as dependent variable. As for capital, we obtain a correctly signed and precisely estimated effect of the marginal revenue productivity of labor. A 1 percent increase in MRPL corresponds to an around 2.8 percentage points increase in the real wage sum in the base period (2008-2011). The differential effects for

Table 4: Dependent variable is the growth rate of real wage sum, full sample

	(1)	(2)	(3)	(4)	(5)
log MRPL	2.829***	2.845***	2.883***	2.903***	2.920***
	(0.469)	(0.469)	(0.468)	(0.470)	(0.470)
log MRPL:Period 2	1.133	1.143	1.171	1.144	1.176
	(0.739)	(0.739)	(0.738)	(0.739)	(0.738)
log MRPL:Period 3	0.722	0.739	0.746	0.719	0.735
	(0.782)	(0.782)	(0.781)	(0.782)	(0.781)
log wage	-1.207***	-1.190***	-1.227***	-1.193***	-1.223***
	(0.107)	(0.106)	(0.106)	(0.106)	(0.107)
age	-0.047***	-0.046***	-0.047***	-0.046***	-0.047***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
leverage	-0.006				-0.005
	(0.005)				(0.005)
cash hold.		0.016			0.009
		(0.014)			(0.014)
int. rate			-0.465***		-0.463***
			(0.067)		(0.067)
cashflow				-0.009	-0.013
				(0.008)	(0.008)
time-industry FE:	yes	yes	yes	yes	yes
Num.Obs.	22186	22186	22186	22186	22186
R2 Adj.	0.077	0.077	0.079	0.077	0.079

Note: Results reported refer to the baseline specification introduced in Section 3.2. Standard errors are given in parentheses. Observations are derived from the full sample and limited to a common sample over all five models where all independent variables are available for each firm. ***, **, and * indicate significant at the 0.5%, 1%, and 5% level, respectively.

the periods 2012-2014 and 2015-2018 are less precisely estimated but point towards an increase in sensitivity at the end of our sample. While size (log wage) and age variables are correctly signed, only for the interest rate we find a statistically significant negative effect.

5 Conclusion

Resource misallocation is often mentioned as a major factor impeding TFP growth. Empirical estimates from the literature suggest that the potential gains from reducing inefficiencies in the allocation of capital and labor can be substantial. Using a dataset covering financial statements of Austrian firms, we quantified the development of capital and labor misallocation for the years 2008-2018 using the indirect approach of Hsieh and Klenow (2009). Unlike many other advanced economies, resource misallocation in Austria did not steadily increase throughout the sample period. Capital misallocation increased during the great financial recession, remained roughly stable between 2010 and 2015 and then fell back to levels roughly 4% above 2008. In manufacturing industries, capital misallocation even reverted back to almost its initial level in 2018. In this respect, the Austrian economy compares well with existing evidence for Germany (see Gamberoni et al., 2016; Gopinath et al., 2017), finding a decrease in capital misallocation from 2006 onward. With labor misallocation steadily declining over the sample period, the overall resource misallocation in Austria roughly stayed the same between 2008 and 2018. These findings do not indicate that increasing resource inefficiency significantly dampened Austrian TFP growth during our sample period.

Nevertheless, increasing the efficiency of resource allocation may yield a substantial boost to TFP. We estimated that moving the Austrian economy up to the US efficiency level would increase TFP by up to 50%. In line with evidence for other countries, our results show that misallocation is particularly high in market services. Compared to manufacturing these industries are likely to be less exposed to domestic and international competitive pressure probably due to a higher degree of regulation (see e.g. Duarte and Restuccia, 2010; Dias et al., 2016; Bun and de Winter, 2022). Adapting regulations to increase competition while preserving high quality standards and consumer safety presents a recurring OECD recommendation for boosting productivity growth in Austria (see for instance OECD, 2021).

Since the dispersion in Austrian resource misallocation is largely attributed to capital (in line with the results from other studies), fostering the reallocation of capital among Austrian firms presents an untapped source for TFP improvements. Our econometric results suggest that financial constraints, such as a higher leverage-ratio or lower cash holdings, can act as impeding forces in the process of reallocation of capital. Previous studies found that while the average equity-ratio of non-financial firms in Austria improved since 2005 (see Breyer et al., 2021), the corporate leverage-ratio in 2019 was still elevated compared to peer countries in both manufacturing and services (see OECD, 2021). We also find some evidence (though not causal) pointing to a stronger impediment for small and young firms in manufacturing, which is in line with the higher leverage sensitivity of smaller firms found in OECD (2021).

From a survey among relevant stakeholders and experts, Breyer et al. (2021) summarize as three main impediments to raising equity capital: difficulties of business start-ups in raising adequate financing in growth stages, tax discrimination between debt and equity, and a lack of financial knowledge. To strengthen corporate equity levels, common suggestions of the interviewed stakeholders and experts include creating tax incentives, strengthening intermediation support for equity finance and building public-private partnerships (see Breyer et al., 2021).

However, the results of this paper should be interpreted with caution, since the indirect approach to measuring misallocation and their implied efficiency potentials come with some caveats. Several other factors, such as heterogeneities in mark-ups, in-firm production functions, measurement errors and the impacts of adjustments costs (see Restuccia and Rogerson, 2017) could also increase the dispersion in marginal revenue products which makes our measures of misallocation potentially upward biased. Additional variation may also be introduced via the less detailed industry classification levels used for calculating dispersion in market-services industries, which is one of the drawbacks of the dataset used in our analysis. The comparison with the US efficiency benchmark were restricted to studies sharing a similar methodology, which cover different sample periods and industry compositions. Furthermore, it needs to be assumed that the aforementioned sources of dispersion unrelated to misallocation are roughly comparable in size in the Austrian and US estimates of the efficient TFP level.

Moreover, our dataset is limited to a relatively short time span covering a period that was shaped by the great financial recession, the subsequent euro area slump and a very expansionary monetary policy throughout. As the dataset is strongly unbalanced, without information on reasons behind firms dropping out or entering the sample, we restricted the analysis on the development of the misallocation gap to a sample covering firms that are observed each year. While this should aid in interpreting time trends of our constructed measures, it may also introduce positive selection towards larger and more productive firms. Given the very scant empirical literature for Austria on this topic, further research is needed on the role of misallocation for TFP development in Austria, potentially utilizing a longer and more balanced firm-level dataset.

Though the period of our analysis precedes the COVID pandemic, a short discussion regarding the impact of the support subsidies to the corporate sector on reallocation may be insightful. Between 2020 and 2022 the cumulative COVID fiscal support measures to the corporate sector (including payments of the short-term work scheme) amounted to EUR 24 bn or 5.4% of terms of 2022 GDP (see Budgetdienst, 2023, for an overview of COVID support payments). These huge payments could hinder reallocation if they are biased towards lower productive firms or prevent the least productive ones from exiting. While there is evidence that the COVID support measures were poorly targeted from a fiscal perspective, and that they lowered overall insolvencies substantially (see Elsinger et al., 2022), there is no empirical evidence for Austria so far that the measures were targeted towards firms with especially low productivity either by design or de facto. The bulk of the support payments (45% according to the Austrian Central Banks estimates) were received by the two industries most heavily affected by the pandemic containment measures: retail/wholesale trade (G) and accommodation and food service activities (I). Historically (1995-2017) the productivity growth of these two industries was on par (1.3% p.a. for G) or below (0.3% p.a. for I) the total economy productivity growth (see Fenz et al., 2020). If history is any indication for future productivity development, the support measures could have prevented resources from being reallocated from these industries to more productive uses. However, the pandemic also spurred innovation in the retail trade sector (online shopping) supporting future productivity growth. The increased labor shortages in hotels/restaurants following the pandemic would not indicate that the Corona subsidies preserved employment in this industry. It therefore seems unlikely, that the Corona subsidies had a sizable negative net impact on productivity by hindering resource reallocation.

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Appendix

A Data Cleaning Procedures and Industry classification

As mentioned in Section 4.1, we apply a number of data-cleaning procedures. Here we closely follow Gopinath et al. (2017) in setting certain restrictions on the data. Our main variables of interest for the estimation of measures of productivity are tangible fixed assets (capital), wage costs (labor) and value-added. Before applying the procedures (below), our sample covers $76,927$ firm-level financial statements (FS) of the years 2008 to 2018 (see Section 4.1). As a first basic cleaning routine, we remove all observations with missings, negative or zero values of the labor, capital and value-added variable. Applying this removes $13,174$ firm-year observations. Further, we exclude firm-year observations where the ratio between capital and labor takes extreme values. We do this by excluding observations above the 99.9 and below the 0.01 percentile. This removes 128 financial statements. Finally, we also exclude observations where the ratio between labor and value-added exceeds 1[23] or falls below the 0.1 percentile. Applying this procedure excludes another $1,316$ observations, which leaves $62,309$ firm-years before any industry-related restrictions are applied.

To prepare the data to model the effects of financial constraints on reallocation efficiency (see Section 3.2), we apply the following data-cleaning procedures. Note that we do not remove firm-year observations from the dataset completely if they fail to pass the checks below but rather only set the corresponding observations of the variable to a missing value (NA). This keeps firm-year observations in the dataset for calculations where the specific financial constraint variable is not needed (e.g. the development of the misallocation gap, a.o.). We restrict *leverage* to non-negative, non-zero values. Conceptually, negative values of leverage cannot be interpreted and we cannot distinguish zero-entries from missing values. Moreover, values above the 99.9 percentile are also removed, to reduce positive outliers. Setting these restrictions introduces only 63 missing values in the variable *leverage*. Similarly, we restrict cash holdings to total assets (*cash hold.*) to non-zero positive values below 100, which introduces $2,788$ missing values (mainly due to zero values). For the interest rate (*int. rate*) variable we set the same restrictions as with *leverage*, which sets $4,650$ interest rate values to missing (most due to zero entries). Finally, we restrict the ratio of *cashflow* to total assets to non-zero values above the 0.1 and below the 99.9 percentile. Note that this variable is allowed to be negative. This creates $6,288$ missing values where most of them are again because of original values that were zero.

For robustness checks which we present in Section C of the appendix, we also need to set some limits on the variable of material costs. Similar to the data-cleaning steps related to financial

[23]The 99 percentile very closely coincides with the value 1.

constraint variables, we do not remove observations if they fail to fall within the restrictions but rather set them as missing values. In general, this applies to observations with negative and zero values of material cost. Furthermore, we exclude positive outliers of material cost where the ratio of materials and tangible fixed assets (capital) exceeds the 99.9 percentile. Doing so introduces $1,215$ missing values (most due to zero entries).

To distinguish industries, we employ an industry classification that is based on a combination of level 1 and 2 of the NACE (Rev. 2) codes, also used in the KLEMS database (Stehrer et al., 2019). As already stated in 4.1, we limit our analysis to non-agricultural, non-financial firms. Moreover, we exclude non-market services industries, such as health and education and network industries such as energy and transport. Lastly, we exclude real estate activities as this sector has experienced a tumultuous time after the great financial recession. Moreover, this sector warrants an exclusion also due the fact that it lacks data on wage costs in more than 50% of cases in our dataset. Since labor (wage cost) is necessary to estimate productivity measures, this signals that the real estate industry seems not to fit our empirical methodology.

In order to get meaningful estimates of the dispersion (of productivity measures) within industries, we further set a minimum number of 10 firms per industry that must be met each year in order for the industry to be included in the analysis. After setting these restrictions, our full and permanent samples distinguish 17 and 12 industries, respectively (see Tables 5 and 6). In total, the full sample now covers $42,476$ firm-year observations and the permanent sample reduces to $4,200$ FS.

In Table 7, we list industries we exclude from the analysis. Note that only five industries were excluded because they fell below the minimum number of firms per year, when creating a balanced panel from the full dataset.

Table 5: Industry classification used, full sample

Industry	Descr.	Macro industry
C10-C12	Food products, beverages and tobacco	Manufacturing
C13-C15	Textiles, wearing apparel, leather and related products	Manufacturing
C16-C18	Wood and paper products; printing and reproduction of recorded media	Manufacturing
C20	Chemicals and chemical products	Manufacturing
C22_C23	Rubber and plastics products, and other non-metallic mineral products	Manufacturing
C24_C25	Basic metals and fabricated metal products, except machinery and equipment	Manufacturing
C26	Computer, electronic and optical products	Manufacturing
C27	Electrical equipment	Manufacturing
C28	Machinery and equipment n.e.c.	Manufacturing
C29_C30	Transport equipment	Manufacturing
C31-C33	Other manufacturing; repair and installation of machinery and equipment	Manufacturing
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles	Market services
G46	Wholesale trade, except of motor vehicles and motorcycles	Market services
G47	Retail trade, except of motor vehicles and motorcycles	Market services
I	Accommodation and food service activities	Market services
J62_J63	IT and other information services	Market services
M_N	Professional, scientific, technical, administrative and support service activities	Market services

Note: Industry classifications are based on aggregations used in the EU KLEMS database (Stehrer et al., 2019) which derive from NACE (Rev. 2) industry codes.

Table 6: Industry classification used, permanent sample

Industry	Descr.	Macro industry
C10-C12	Food products, beverages and tobacco	Manufacturing
C16-C18	Wood and paper products; printing and reproduction of recorded media	Manufacturing
C20	Chemicals and chemical products	Manufacturing
C22_C23	Rubber and plastics products, and other non-metallic mineral products	Manufacturing
C24_C25	Basic metals and fabricated metal products, except machinery and equipment	Manufacturing
C28	Machinery and equipment n.e.c.	Manufacturing
C31-C33	Other manufacturing; repair and installation of machinery and equipment	Manufacturing
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles	Market services
G46	Wholesale trade, except of motor vehicles and motorcycles	Market services
G47	Retail trade, except of motor vehicles and motorcycles	Market services
I	Accommodation and food service activities	Market services
M_N	Professional, scientific, technical, administrative and support service activities	Market services

Note: Industry classifications are based on aggregations used in the EU KLEMS database (Stehrer et al., 2019) which derive from NACE (Rev. 2) industry codes.

Table 7: Industry classifications excluded, full and permanent samples

Industry	perm.	full	Descr.
A	x	x	Agriculture, forestry and fishing
B	x	x	Mining and quarrying
C13-C15	x		Textiles, wearing apparel, leather and related products
C19	x	x	Coke and refined petroleum products
C21	x	x	Basic pharmaceutical products and pharmaceutical preparations
C26	x		Computer, electronic and optical products
C27	x		Electrical equipment
C29_C30	x		Transport equipment
D	x	x	Electricity, gas, steam and air conditioning supply
E	x	x	Water supply; sewerage; waste management and remediation activities
F	x	x	Construction
H49	x	x	Land transport and transport via pipelines
H50	x	x	Water transport
H51	x	x	Air transport
H52	x	x	Warehousing and support activities for transportation
H53	x	x	Postal and courier activities
J58-J60	x	x	Publishing, audio-visual and broadcasting activities
J61	x	x	Telecommunications
J62_J63	x		IT and other information services
K	x	x	Financial and insurance activities
L	x	x	Real estate activities
O	x	x	Public administration and defence; compulsory social security
P	x	x	Education
Q	x	x	Health and social work
R	x	x	Arts, entertainment and recreation
S	x	x	Other service activities
T	x	x	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use

Note: Industry classifications are based on aggregations used in the EU KLEMS database (Stehrer et al., 2019) which derive from NACE (Rev. 2) industry codes. This comparison shows industry codes which were excluded in the process of data-cleaning for the full and permanent sample, respectively.

B Firm Level Data Descriptive Statistics

B.1 Summary statistics, variables of interest, full sample

Table 8: Value-added (nominal), full sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	14	1,540.75	4,458.5	17,690.74	14,054.50	1,637,559	3,882
2009	24	1,425.25	4,205.5	16,432.46	12,920.00	1,664,051	4,042
2010	25	1,547.25	4,275.0	16,229.64	12,601.50	1,704,123	4,682
2011	14	1,703.00	5,022.5	19,308.93	15,308.75	1,763,990	4,958
2012	25	1,742.75	5,417.0	22,446.36	17,450.75	1,994,805	4,788
2013	2	1,753.50	5,833.0	24,476.59	19,129.50	1,947,876	4,203
2014	22	1,562.25	5,313.0	24,323.63	19,201.00	2,032,637	3,738
2015	18	1,440.00	4,710.0	23,990.87	18,219.00	2,553,694	3,601
2016	16	1,429.00	4,285.0	23,492.53	16,643.50	1,660,151	3,307
2017	32	1,444.75	4,453.0	25,659.44	18,847.50	1,757,931	2,812
2018	32	1,614.00	5,217.0	28,435.32	22,065.50	1,846,417	2,463

Note: Data is based on the full sample, see Section 4.1. "no. obs." refers to the total number of observations (firms) in the respective year. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 9: Capital (real), full sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	1.00	232.75	1,219.22	8,179.51	4,977.48	1,479,859	3,882
2009	1.00	224.09	1,218.21	7,828.64	5,081.81	1,594,783	4,042
2010	1.00	208.00	1,207.50	7,198.99	4,769.00	1,601,458	4,682
2011	0.98	276.94	1,452.38	8,787.85	5,600.23	1,719,281	4,958
2012	0.95	329.95	1,713.64	10,561.56	6,617.89	1,399,231	4,788
2013	0.93	368.98	1,971.56	11,983.27	7,456.09	1,390,434	4,203
2014	0.92	435.37	2,093.61	12,520.97	7,970.83	1,449,856	3,738
2015	0.91	402.38	2,000.88	12,091.43	7,826.17	1,475,454	3,601
2016	0.90	451.13	1,951.03	12,610.27	7,397.33	1,525,678	3,307
2017	0.89	472.95	2,174.59	13,919.77	8,218.07	1,551,058	2,812
2018	0.87	676.41	2,669.83	15,240.76	9,636.59	1,594,004	2,463

Note: Data is based on the full sample, see Section 4.1. "no. obs." refers to the total number of observations (firms) in the respective year. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 10: Wage costs (real), full sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	0.99	641.54	2,031.06	7,421.58	6,583.01	705,687.8	3,882
2009	1.92	604.90	1,863.66	6,743.51	5,858.81	736,072.6	4,042
2010	1.00	640.00	1,910.50	6,749.80	5,596.50	745,110.0	4,682
2011	1.97	705.89	2,144.67	8,008.41	6,666.56	767,752.5	4,958
2012	0.96	700.24	2,350.26	9,363.74	7,863.64	726,208.6	4,788
2013	0.96	728.00	2,567.42	10,260.77	8,695.26	751,581.9	4,203
2014	0.92	664.10	2,314.63	10,198.95	8,749.35	738,714.5	3,738
2015	0.91	576.19	2,001.41	9,860.38	7,977.46	695,196.7	3,601
2016	0.89	541.20	1,815.78	9,837.53	7,600.35	704,249.8	3,307
2017	3.52	555.75	1,913.45	10,878.64	8,422.59	648,814.4	2,812
2018	1.74	605.08	2,175.13	11,804.44	9,737.54	569,933.5	2,463

Note: Data is based on the full sample, see Section 4.1. ”no. obs.” refers to the total number of observations (firms) in the respective year. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 11: MRPK, full sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	0.00	0.57	1.38	12.75	5.04	3,480.05	3,882
2009	0.01	0.52	1.30	11.10	4.95	3,973.65	4,042
2010	0.00	0.53	1.39	13.80	5.63	3,402.02	4,682
2011	0.00	0.52	1.34	12.85	5.21	3,824.40	4,958
2012	0.01	0.49	1.22	11.24	4.59	1,861.37	4,788
2013	0.00	0.48	1.16	10.24	4.14	2,507.97	4,203
2014	0.01	0.45	1.01	8.54	3.23	1,713.50	3,738
2015	0.01	0.44	1.00	6.61	2.89	872.62	3,601
2016	0.00	0.41	0.94	5.42	2.73	1,164.06	3,307
2017	0.00	0.42	0.89	4.57	2.66	789.65	2,812
2018	0.01	0.39	0.84	5.23	2.28	770.41	2,463

Note: Data is based on the full sample, see Section 4.1. ”no. obs.” refers to the total number of observations (firms) in the respective year. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 12: MRPL, full sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	0.23	0.47	0.59	0.84	0.78	21.05	3,882
2009	0.22	0.48	0.60	0.86	0.80	22.86	4,042
2010	0.23	0.48	0.60	0.87	0.80	24.80	4,682
2011	0.24	0.49	0.61	0.85	0.81	26.19	4,958
2012	0.25	0.49	0.61	0.82	0.80	28.94	4,788
2013	0.23	0.48	0.60	0.81	0.80	25.68	4,203
2014	0.24	0.49	0.61	0.83	0.82	25.51	3,738
2015	0.25	0.51	0.63	0.83	0.84	24.83	3,601
2016	0.26	0.52	0.65	0.91	0.87	31.05	3,307
2017	0.30	0.52	0.65	0.87	0.86	25.13	2,812
2018	0.30	0.53	0.66	0.91	0.91	29.28	2,463

Note: Data is based on the full sample, see Section 4.1. ”no. obs.” refers to the total number of observations (firms) in the respective year. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 13: Age, full sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.	NA’s rel.
2008	0	7	16	19.35	28	108	3,882	0.01
2009	0	8	16	20.02	28	109	4,042	0.01
2010	0	9	17	20.45	28	110	4,682	0.01
2011	0	9	17	20.89	28	111	4,958	0.04
2012	0	9	17	21.37	29	112	4,788	0.08
2013	0	9	18	21.75	29	113	4,203	0.08
2014	0	10	18	21.76	28	114	3,738	0.09
2015	0	10	17	21.10	28	112	3,601	0.10
2016	0	10	17	20.85	27	114	3,307	0.10
2017	0	10	17	20.84	28	115	2,812	0.12
2018	0	11	18	21.68	29	118	2,463	0.12

Note: Data is based on the full sample, see Section 4.1. ”no. obs.” refers to the total number of observations (firms) in the respective year. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 14: Leverage, full sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.	NA's rel.
2008	0.10	52.72	70.14	71.47	85.40	532.47	3,882	0.001
2009	0.19	49.19	67.80	69.09	83.96	479.63	4,042	0.002
2010	0.39	48.33	67.29	68.32	83.09	527.89	4,682	0.002
2011	0.57	48.30	66.25	67.01	82.04	444.44	4,958	0.001
2012	0.26	47.83	65.04	66.08	81.40	535.75	4,788	0.000
2013	0.47	47.16	64.31	65.47	80.05	511.39	4,203	0.001
2014	2.09	47.34	64.22	65.73	79.93	497.30	3,738	0.001
2015	1.17	47.90	64.02	65.14	79.09	491.11	3,601	0.001
2016	3.67	48.14	63.41	63.95	77.48	314.29	3,307	0.001
2017	3.53	48.78	63.08	63.88	76.92	455.88	2,812	0.000
2018	4.02	49.31	62.85	63.88	76.45	310.00	2,463	0.000

Note: Data is based on the full sample, see Section 4.1. "no. obs." refers to the total number of observations (firms) in the respective year and "NA's rel." stands for the relative share of not available data. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 15: Cash holdings, full sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.	NA's rel.
2008	0	0.52	3.11	9.41	12.24	96.13	3,882	0.039
2009	0	0.60	3.40	10.08	13.49	99.63	4,042	0.043
2010	0	0.63	3.72	10.18	13.67	92.88	4,682	0.040
2011	0	0.58	3.39	9.18	12.31	94.04	4,958	0.039
2012	0	0.60	3.43	9.19	12.21	94.54	4,788	0.035
2013	0	0.62	3.30	8.77	11.54	98.92	4,203	0.037
2014	0	0.57	3.38	8.24	10.87	89.49	3,738	0.036
2015	0	0.63	3.36	8.24	11.39	82.65	3,601	0.039
2016	0	0.72	3.78	8.58	12.25	99.18	3,307	0.040
2017	0	0.78	3.94	8.49	11.70	90.88	2,812	0.042
2018	0	0.74	3.87	8.41	11.57	82.43	2,463	0.028

Note: Data is based on the full sample, see Section 4.1. "no. obs." refers to the total number of observations (firms) in the respective year and "NA's rel." stands for the relative share of not available data. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 16: Implied interest rate, full sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.	NA's rel.
2008	0	1.71	3.31	3.48	4.65	46.03	3,882	0.093
2009	0	1.28	2.44	2.76	3.60	38.46	4,042	0.109
2010	0	0.92	1.79	2.26	2.79	44.92	4,682	0.125
2011	0	1.04	1.91	2.31	2.85	46.93	4,958	0.119
2012	0	1.04	1.87	2.29	2.78	47.45	4,788	0.115
2013	0	0.93	1.66	2.05	2.51	40.52	4,203	0.099
2014	0	1.00	1.72	2.05	2.53	33.33	3,738	0.062
2015	0	0.97	1.63	1.98	2.39	44.07	3,601	0.049
2016	0	0.92	1.53	1.83	2.22	30.92	3,307	0.036
2017	0	0.88	1.42	1.67	2.06	35.85	2,812	0.027
2018	0	0.87	1.40	1.65	2.01	25.88	2,463	0.020

Note: Data is based on the full sample, see Section 4.1. "no. obs." refers to the total number of observations (firms) in the respective year and "NA's rel." stands for the relative share of not available data. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 17: Cashflow, full sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.	NA's rel.
2008	-99.89	-18.67	1.63	1.68	20.00	181.06	3,882	0.012
2009	-97.70	0.36	9.70	9.52	20.15	188.13	4,042	0.078
2010	-93.41	1.41	9.31	9.86	18.30	172.48	4,682	0.310
2011	-99.29	1.09	8.52	9.85	17.44	173.61	4,958	0.375
2012	-102.19	1.56	8.67	10.30	17.46	185.14	4,788	0.185
2013	-100.08	2.48	9.40	10.80	17.42	170.10	4,203	0.049
2014	-103.55	2.71	9.30	10.91	17.17	177.77	3,738	0.007
2015	-88.06	3.27	9.57	11.20	17.65	125.99	3,601	0.003
2016	-90.46	4.08	9.99	11.86	17.94	122.85	3,307	0.002
2017	-65.66	3.73	9.76	11.29	17.13	123.53	2,812	0.002
2018	-66.51	3.39	9.25	11.13	16.95	116.41	2,463	0.002

Note: Data is based on the full sample, see Section 4.1. "no. obs." refers to the total number of observations (firms) in the respective year and "NA's rel." stands for the relative share of not available data. For details about data cleaning procedures, refer to Sections 4.1 and A.

B.2 Summary statistics, variables of interest, permanent sample

Table 18: Value-added (nominal), permanent sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	293	4,932.75	12,361.0	31,636.51	28,774.50	1,449,839	380
2009	315	4,695.25	12,075.5	29,875.92	28,781.50	1,301,131	380
2010	395	5,170.50	12,228.5	29,780.94	29,692.75	1,124,128	380
2011	535	5,445.75	14,281.0	31,495.08	31,520.00	1,241,160	382
2012	351	5,554.00	14,675.0	32,912.15	32,527.25	1,130,312	382
2013	411	5,680.50	14,900.0	33,621.01	32,646.00	1,220,941	383
2014	433	5,987.00	15,686.0	34,697.55	34,438.50	1,261,122	383
2015	375	5,872.00	15,646.0	35,653.54	35,365.00	1,353,297	383
2016	444	6,434.00	16,335.0	37,107.84	36,758.00	1,380,737	383
2017	610	6,806.00	17,568.5	38,754.53	35,536.75	1,397,951	382
2018	581	7,239.00	17,918.0	41,552.35	38,122.75	1,705,255	382

Note: Data is based on the permanent sample, see Section 4.1 where the slight variation in the number of observations (”no. obs.”) per year is due to a small number of firms that changed industry classification from an excluded industry mid-sample and are thus excluded only in some years. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 19: Capital (real), permanent sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	17.32	2,153.45	5,893.76	18,678.07	15,284.22	1,479,859	380
2009	13.08	2,341.97	5,899.01	19,292.13	16,133.76	1,594,783	380
2010	12.00	2,452.50	6,137.50	19,520.43	16,664.50	1,601,458	380
2011	15.70	2,446.76	6,230.16	18,724.95	16,228.05	1,494,537	382
2012	11.44	2,664.31	6,453.85	18,647.63	16,008.99	1,396,261	382
2013	16.87	2,705.87	6,725.89	19,135.32	16,655.30	1,390,434	383
2014	13.83	2,727.24	7,150.58	20,112.02	16,461.83	1,449,856	383
2015	21.67	2,827.17	7,361.72	20,503.61	17,473.63	1,458,768	383
2016	27.05	2,854.58	7,380.55	21,066.96	17,055.87	1,428,455	383
2017	10.71	3,207.84	7,071.61	22,223.16	17,583.61	1,356,089	382
2018	4.40	3,365.52	7,599.29	23,245.13	17,875.29	1,270,970	382

Note: Data is based on the permanent sample, see Section 4.1 where the slight variation in the number of observations (”no. obs.”) per year is due to a small number of firms that changed industry classification from an excluded industry mid-sample and are thus excluded only in some years. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 20: Wage costs (real), permanent sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	31.93	2,131.75	5,675.15	12,724.83	13,005.73	564,176.7	380
2009	27.89	2,068.14	5,371.32	11,260.13	12,360.58	434,684.9	380
2010	29.00	2,316.00	5,508.00	11,803.09	11,897.00	430,729.0	380
2011	32.03	2,358.97	6,099.97	12,418.71	12,674.23	468,365.3	382
2012	48.34	2,357.81	6,520.85	12,885.20	12,257.03	459,699.1	382
2013	51.16	2,482.04	6,662.08	13,717.11	13,268.03	525,448.1	383
2014	50.17	2,629.59	7,053.36	13,986.75	13,657.89	516,261.9	383
2015	61.24	2,650.25	6,751.59	14,159.01	13,967.59	573,606.2	383
2016	52.35	2,713.73	7,196.61	14,409.13	14,162.32	509,976.4	383
2017	87.68	2,923.99	7,389.50	14,892.55	15,386.68	518,473.3	382
2018	69.33	2,925.53	7,531.40	15,521.34	16,275.82	512,163.0	382

Note: Data is based on the permanent sample, see Section 4.1 where the slight variation in the number of observations (”no. obs.”) per year is due to a small number of firms that changed industry classification from an excluded industry mid-sample and are thus excluded only in some years. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 21: MRPK, permanent sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	0.05	0.41	0.78	2.03	1.56	31.19	380
2009	0.04	0.38	0.72	2.06	1.57	36.20	380
2010	0.04	0.40	0.75	2.33	1.63	62.07	380
2011	0.05	0.41	0.77	2.69	1.80	117.69	382
2012	0.06	0.39	0.83	3.03	1.84	288.29	382
2013	0.06	0.41	0.82	2.69	1.67	157.52	383
2014	0.08	0.44	0.82	2.55	1.65	83.99	383
2015	0.08	0.41	0.80	2.65	1.84	93.49	383
2016	0.10	0.42	0.82	2.83	1.81	134.34	383
2017	0.09	0.42	0.81	2.52	1.75	53.94	382
2018	0.10	0.44	0.82	2.80	1.83	125.57	382

Note: Data is based on the permanent sample, see Section 4.1 where the slight variation in the number of observations (”no. obs.”) per year is due to a small number of firms that changed industry classification from an excluded industry mid-sample and are thus excluded only in some years. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 22: MRPL, permanent sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	0.27	0.48	0.59	0.73	0.79	8.14	380
2009	0.24	0.48	0.62	0.72	0.80	5.70	380
2010	0.24	0.48	0.60	0.71	0.79	4.65	380
2011	0.25	0.48	0.60	0.71	0.79	5.07	382
2012	0.28	0.48	0.61	0.72	0.78	5.33	382
2013	0.29	0.47	0.58	0.71	0.79	6.04	383
2014	0.30	0.47	0.59	0.74	0.78	7.66	383
2015	0.31	0.48	0.61	0.75	0.82	6.67	383
2016	0.32	0.49	0.61	0.75	0.82	6.35	383
2017	0.29	0.50	0.61	0.75	0.83	7.30	382
2018	0.32	0.50	0.62	0.76	0.85	6.76	382

Note: Data is based on the permanent sample, see Section 4.1 where the slight variation in the number of observations (”no. obs.”) per year is due to a small number of firms that changed industry classification from an excluded industry mid-sample and are thus excluded only in some years. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 23: Age, permanent sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	0	8	18	21.31	29	98	380
2009	1	9	19	22.31	30	99	380
2010	2	10	20	23.31	31	100	380
2011	3	11	21	24.25	32	101	382
2012	4	12	22	25.25	33	102	382
2013	5	13	23	26.22	34	103	383
2014	6	14	24	27.22	35	104	383
2015	7	15	25	28.22	36	105	383
2016	8	16	26	29.22	37	106	383
2017	9	17	27	30.25	38	107	382
2018	10	18	28	31.25	39	108	382

Note: Data is based on the permanent sample, see Section 4.1 where the slight variation in the number of observations (”no. obs.”) per year is due to a small number of firms that changed industry classification from an excluded industry mid-sample and are thus excluded only in some years. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 24: Leverage, permanent sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.
2008	4.41	55.71	68.40	68.75	80.59	318.60	380
2009	7.77	53.68	66.36	66.79	79.10	279.65	380
2010	12.79	53.51	67.06	65.89	77.39	203.59	380
2011	13.45	53.51	66.61	65.93	77.73	213.95	382
2012	14.46	51.71	65.60	65.03	77.01	210.00	382
2013	12.96	50.98	65.03	64.40	75.39	151.80	383
2014	13.30	50.77	64.60	63.59	75.58	141.52	383
2015	12.22	51.89	64.09	62.89	74.54	118.51	383
2016	15.28	50.32	61.70	60.63	72.39	116.01	383
2017	10.36	48.53	60.26	59.46	71.14	114.33	382
2018	11.57	48.81	60.45	59.28	71.24	120.87	382

Note: Data is based on the permanent sample, see Section 4.1 where the slight variation in the number of observations (”no. obs.”) per year is due to a small number of firms that changed industry classification from an excluded industry mid-sample and are thus excluded only in some years. For details about data cleaning procedures, refer to Sections 4.1 and A.

Table 25: Cash holdings, permanent sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.	NA's rel.
2008	0	0.39	1.80	5.99	6.91	58.05	380	0.021
2009	0	0.52	1.79	5.97	7.39	56.28	380	0.024
2010	0	0.44	2.00	5.91	8.23	52.06	380	0.016
2011	0	0.34	1.98	5.66	6.95	48.49	382	0.024
2012	0	0.33	1.96	5.21	6.80	59.96	382	0.016
2013	0	0.46	1.88	5.52	7.30	42.95	383	0.021
2014	0	0.39	2.15	5.25	6.13	52.21	383	0.018
2015	0	0.47	2.51	5.53	7.45	52.30	383	0.013
2016	0	0.45	2.42	5.95	8.29	50.15	383	0.016
2017	0	0.47	2.26	6.26	8.93	45.34	382	0.016
2018	0	0.48	2.43	6.66	8.97	73.36	382	0.016

Note: Data is based on the permanent sample, see Section 4.1 where the slight variation in the number of observations (”no. obs.”) per year is due to a small number of firms that changed industry classification from an excluded industry mid-sample and are thus excluded only in some years. For details about data cleaning procedures, refer to Sections 4.1 and A. ”NA's rel.” stands for the relative share of data not available.

Table 26: Implied interest rate, permanent sample

year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.	NA's rel.
2008	0.04	2.70	3.82	3.85	4.82	18.00	380	0.011
2009	0.01	1.76	2.57	2.81	3.42	16.31	380	0.008
2010	0.02	1.26	1.81	2.05	2.43	11.99	380	0.011
2011	0.01	1.39	1.96	2.20	2.62	13.83	382	0.008
2012	0.02	1.27	1.90	2.18	2.54	14.75	382	0.013
2013	0.02	1.11	1.67	1.85	2.20	13.32	383	0.005
2014	0.01	1.07	1.65	1.90	2.25	16.35	383	0.005
2015	0.00	0.95	1.56	1.79	2.07	18.68	383	0.008
2016	0.00	0.87	1.45	1.68	1.93	11.13	383	0.008
2017	0.01	0.74	1.30	1.56	1.86	12.66	382	0.008
2018	0.01	0.73	1.20	1.49	1.69	15.37	382	0.008

Note: Data is based on the permanent sample, see Section 4.1 where the slight variation in the number of observations ("no. obs.") per year is due to a small number of firms that changed industry classification from an excluded industry mid-sample and are thus excluded only in some years. For details about data cleaning procedures, refer to Sections 4.1 and A. "NA's rel." stands for the relative share of data not available.

Table 27: Cashflow, permanent sample

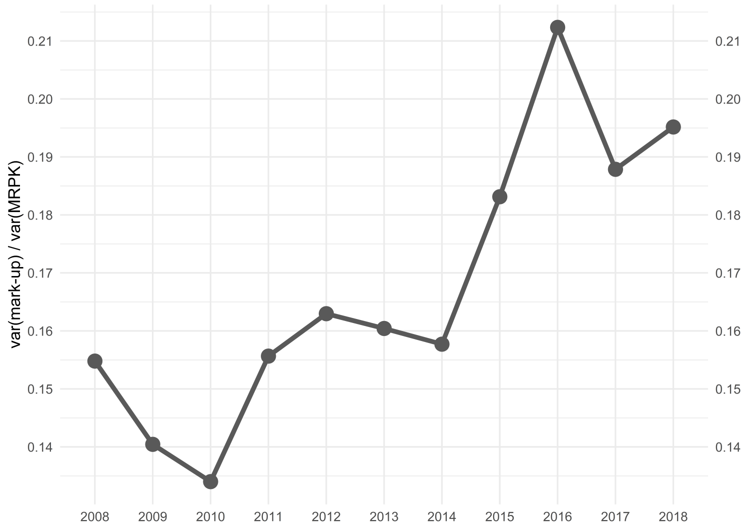
year	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	no. obs.	NA's rel.
2008	-87.44	-18.85	1.33	-1.39	15.74	134.79	380	0.016
2009	-51.76	4.26	10.83	11.22	17.14	67.15	380	0.013
2010	-37.47	3.26	9.27	10.29	16.43	73.99	380	0.063
2011	-30.39	2.66	8.46	9.49	15.38	53.68	382	0.202
2012	-64.31	2.94	9.57	9.68	16.10	65.08	382	0.005
2013	-25.34	4.20	9.60	11.18	15.82	146.49	383	0.000
2014	-49.86	3.84	9.33	9.54	16.52	50.77	383	0.000
2015	-33.66	4.64	10.40	11.11	16.88	94.77	383	0.000
2016	-29.11	5.16	10.39	11.81	17.07	61.60	383	0.000
2017	-21.98	4.51	10.12	10.78	16.56	68.40	382	0.000
2018	-40.26	3.40	8.67	10.48	16.87	65.44	382	0.000

Note: Data is based on the permanent sample, see Section 4.1 where the slight variation in the number of observations ("no. obs.") per year is due to a small number of firms that changed industry classification from an excluded industry mid-sample and are thus excluded only in some years. For details about data cleaning procedures, refer to Sections 4.1 and A. "NA's rel." stands for the relative share of data not available.

C Robustness checks

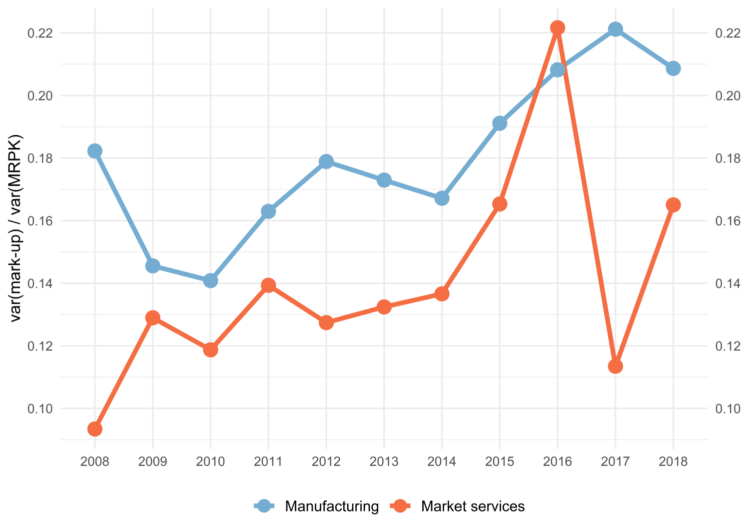
C.1 Variation in markups

Figure 4: Development of the share of variation in MRPK explained by variation in mark-ups, total economy



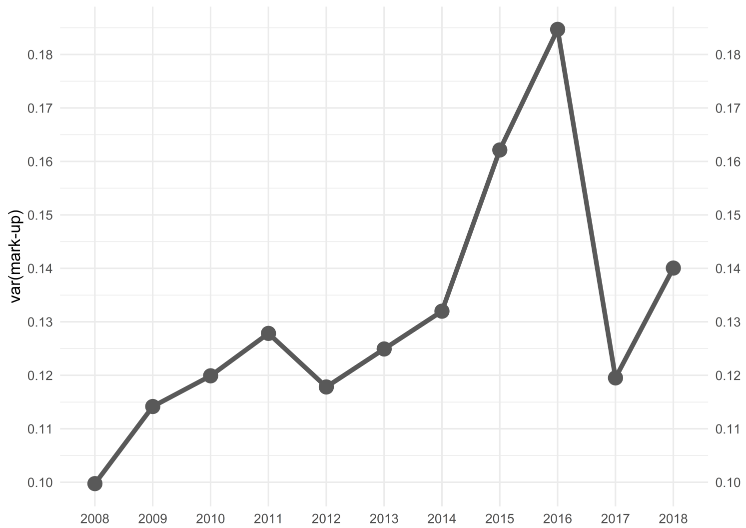
Note: Shares of variation are calculated at the industry level and aggregated to the total economy via constant value-added industry shares. The underlying data is the permanent sample, see Section 4.1.

Figure 5: Development of the share of variation in MRPK explained by variation in mark-ups, industry aggregates



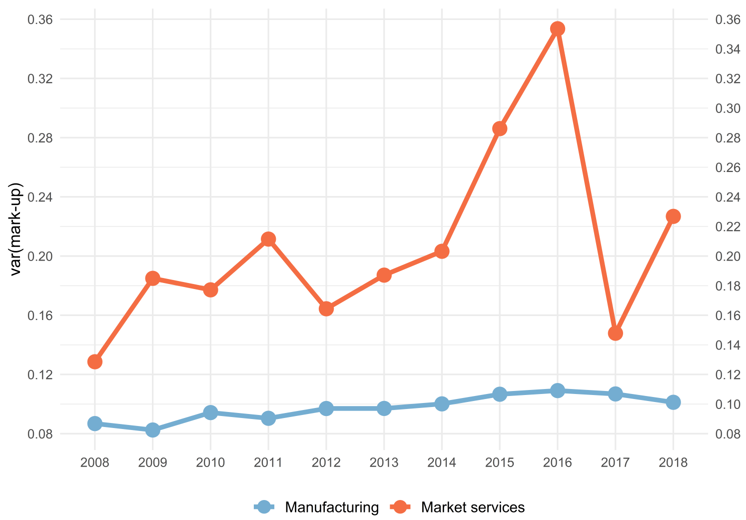
Note: Shares of variation are calculated at the industry level and aggregated to the two macro-sectors via constant value-added industry shares. The underlying data is the permanent sample, see Section 4.1.

Figure 6: Development of the variation in mark-ups, total economy



Note: Variation in mark-ups are calculated at the industry level and aggregated to the total economy via constant value-added industry shares. The underlying data is the permanent sample, see Section 4.1.

Figure 7: Development of the variation in mark-ups, industry aggregates



Note: Variation in mark-ups are calculated at the industry level and aggregated to the two macro-sectors via constant value-added industry shares. The underlying data is the permanent sample, see Section 4.1.

C.2 Role of age, size and industry for financial constraints

Table 28: Dependent variable is the growth rate of real tangible assets, full sample

	leverage	cash hold.	int. rate	cashflow
log MRPK	1.405***	1.219***	1.409***	1.346***
	(0.423)	(0.424)	(0.424)	(0.425)
log MRPK:Period 2	-0.393	-0.399	-0.348	-0.487
	(0.440)	(0.440)	(0.441)	(0.440)
log MRPK:Period 3	0.823	0.756	0.870	0.721
	(0.491)	(0.491)	(0.492)	(0.492)
log sales t2	0.979	0.085	0.149	-0.927
	(1.685)	(0.969)	(1.116)	(0.907)
log sales t3	2.583	0.660	-1.249	-0.174
	(2.147)	(1.362)	(1.446)	(1.295)
age t2	-3.184	-0.697	-3.138***	-2.150***
	(1.661)	(0.761)	(0.895)	(0.700)
age t3	-4.481**	-1.582*	-2.942***	-2.140***
	(1.683)	(0.782)	(0.922)	(0.725)
fin. constr.	-0.078***	0.453***	-0.462	0.089*
	(0.024)	(0.060)	(0.333)	(0.035)
fin. constr.:log sales t2	-0.023	-0.083	-0.433	0.060
	(0.021)	(0.057)	(0.316)	(0.033)
fin. constr.:log sales t3	-0.049	-0.173**	0.102	-0.040
	(0.026)	(0.062)	(0.305)	(0.034)
fin. constr.:age t2	0.011	-0.200***	0.421	0.004
	(0.023)	(0.055)	(0.278)	(0.031)
fin. constr.:age t3	0.023	-0.134*	0.127	-0.043
	(0.023)	(0.059)	(0.292)	(0.033)
fin. constr.:Market services	0.013	-0.103*	-0.062	-0.002
	(0.020)	(0.049)	(0.242)	(0.029)
log capital	-1.508***	-1.252***	-1.307***	-1.439***
	(0.325)	(0.324)	(0.324)	(0.326)
time-industry FE:	yes	yes	yes	yes
Num.Obs.	22163	22163	22163	22163
R2 Adj.	0.020	0.021	0.018	0.019

Note: Results refer to the baseline specification introduced in Section 3.2 with additional interaction effects included. Sales and age are categorical variables with ”t2” and ”t3” referring to the second and third tertile. Standard errors are given in parentheses. Observations are derived from the full sample and limited to a common sample over all five models where all independent variables are available for each firm. ***, **, and * indicate significant at the 0.5%, 1%, and 5% level, respectively.

C.3 Model results with permanent sample

Table 29: Dependent variable is the growth rate of real tangible assets, permanent sample

	(1)	(2)	(3)	(4)	(5)
log MRPK	3.113***	3.046***	3.174***	3.073***	3.118***
	(0.818)	(0.818)	(0.819)	(0.817)	(0.819)
log MRPK:Period 2	-0.962	-0.981	-0.929	-1.050	-1.098
	(1.100)	(1.099)	(1.099)	(1.099)	(1.099)
log MRPK:Period 3	-2.045	-2.090	-1.984	-2.184*	-2.235*
	(1.099)	(1.099)	(1.098)	(1.100)	(1.100)
log capital	-0.204	-0.128	-0.134	-0.269	-0.194
	(0.410)	(0.410)	(0.410)	(0.410)	(0.412)
age	-0.013	-0.012	-0.013	-0.011	-0.013
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
leverage	-0.033				-0.024
	(0.025)				(0.026)
cash hold.		0.124*			0.069
		(0.059)			(0.062)
int. rate			-0.583*		-0.514
			(0.292)		(0.294)
cashflow				0.095**	0.083*
				(0.034)	(0.035)
time-industry FE:	yes	yes	yes	yes	yes
Num.Obs.	3604	3604	3604	3604	3604
R2 Adj.	0.010	0.011	0.011	0.012	0.013

Note: Results reported refer to the baseline specification introduced in Section 3.2. Standard errors are given in parentheses. Observations are derived from the permanent sample and limited to a common sample over all five models where all independent variables are available for each firm. ***, **, and * indicate significant at the 0.5%, 1%, and 5% level, respectively.

Table 30: Dependent variable is the growth rate of the real wage sum, permanent sample

	(1)	(2)	(3)	(4)	(5)
log MRPL	2.350	2.333	2.440	2.304	2.397
	(1.246)	(1.246)	(1.246)	(1.250)	(1.250)
log MRPL:Period 2	-1.644	-1.646	-1.606	-1.687	-1.577
	(1.842)	(1.842)	(1.841)	(1.842)	(1.842)
log MRPL:Period 3	-1.000	-0.972	-1.006	-1.040	-0.933
	(1.831)	(1.831)	(1.830)	(1.831)	(1.832)
log wage	-1.555***	-1.548***	-1.529***	-1.567***	-1.515***
	(0.276)	(0.276)	(0.276)	(0.276)	(0.277)
age	-0.018	-0.018	-0.019	-0.018	-0.018
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
leverage	0.012				0.016
	(0.017)				(0.017)
cash hold.		0.043			0.037
		(0.039)			(0.041)
int. rate			-0.409*		-0.388*
			(0.195)		(0.197)
cashflow				0.011	0.006
				(0.023)	(0.024)
time-industry FE:	yes	yes	yes	yes	yes
Num.Obs.	3604	3604	3604	3604	3604
R2 Adj.	0.097	0.097	0.098	0.097	0.097

Note: Results reported refer to the baseline specification introduced in Section 3.2. Standard errors are given in parentheses. Observations are derived from the permanent sample and limited to a common sample over all five models where all independent variables are available for each firm. ***, **, and * indicate significant at the 0.5%, 1%, and 5% level, respectively.

Table 31: Dependent variable is the growth rate of real tangible assets, permanent sample

	leverage	cash hold.	int. rate	cashflow
log MRPK	3.838***	3.972***	3.979***	3.683***
	(0.990)	(0.992)	(0.991)	(0.993)
log MRPK:Period 2	-0.868	-0.999	-0.826	-1.035
	(1.101)	(1.100)	(1.101)	(1.101)
log MRPK:Period 3	-1.974	-2.085	-1.826	-2.103
	(1.101)	(1.099)	(1.102)	(1.103)
log sales t2	4.949	0.690	-1.322	-0.288
	(4.297)	(1.747)	(2.292)	(1.709)
log sales t3	2.960	-1.223	-3.611	-2.280
	(4.656)	(2.276)	(2.614)	(2.211)
age t2	-0.375	1.129	-0.934	-0.342
	(4.452)	(1.363)	(1.850)	(1.330)
age t3	2.955	-0.766	0.082	-0.363
	(4.098)	(1.405)	(1.830)	(1.400)
fin. constr.	0.039	0.526***	0.134	0.237***
	(0.069)	(0.130)	(0.845)	(0.081)
fin. constr.:log sales t2	-0.107	-0.391***	-0.378	-0.130
	(0.062)	(0.135)	(0.818)	(0.080)
fin. constr.:log sales t3	-0.094	-0.278	0.077	-0.011
	(0.066)	(0.145)	(0.779)	(0.079)
fin. constr.:age t2	-0.007	-0.279*	0.184	0.011
	(0.067)	(0.132)	(0.660)	(0.072)
fin. constr.:age t3	-0.074	-0.115	-0.755	-0.114
	(0.060)	(0.138)	(0.651)	(0.083)
fin. constr.:Market services	0.027	-0.188	-0.960	-0.144*
	(0.055)	(0.125)	(0.609)	(0.070)
log capital	0.526	0.601	0.686	0.295
	(0.670)	(0.667)	(0.671)	(0.674)
time-industry FE:	yes	yes	yes	yes
Num.Obs.	3602	3602	3602	3602
R2 Adj.	0.010	0.014	0.011	0.013

Note: Results refer to the baseline specification introduced in Section 3.2 with additional interaction effects included. Sales and age are categorical variables with ”t2” and ”t3” referring to the second and third tertile. Standard errors are given in parentheses. Observations are derived from the permanent sample and limited to a common sample over all five models where all independent variables are available for each firm. ***, **, and * indicate significant at the 0.5%, 1%, and 5% level, respectively.

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