Journal of Productivity Analysis (2022) 57:93–113
https://doi.org/10.1007/s11123-021-00622-z

Capital and labor misallocation in the Netherlands

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Accepted: 1 November 2021 / Published online: 13 January 2022

Abstract

Using firm-level panel data we analyze the misallocation of capital and labor for the Netherlands in the period 2001–2017. We use the dispersion in marginal revenue products of capital and labor to measure the extent of misallocation. Compared to a counterfactual efficient allocation we find that misallocation has had a sizable negative impact on aggregate productivity of around 14 percentage points in the period 2001–2017. Especially capital misallocation has increased over time. Exploiting a panel data error components model we find that capital misallocation has a much more permanent character than labor misallocation. Moreover, it is the permanent component of capital misallocation that has increased over time. Finally, we show that in our sample the measurement of misallocation is largely insensitive to capital adjustment costs and alternative specifications of the production function. The contribution of heterogeneous markups to observed misallocation, however, is non-negligible.

JEL codes C23 · D24 · O47

Keywords Error components · Misallocation · Panel data · Productivity

1 Introduction

Many countries have experienced an aggregate productivity slowdown in the last decades. To shed light on the causal mechanisms behind the stagnation of macro-economic productivity growth, the recent literature has increasingly made use of micro-economic data sets. It is now widely accepted that the large heterogeneity in firm-level outcomes plays a key role in explaining macro-economic developments. An often analyzed micro-founded explanation for the aggregate productivity slowdown is misallocation of resources across firms. The empirical evidence suggests that the productivity loss caused by misallocation can be large, see e.g., Hsieh and Klenow (2009) or Gopinath et al. (2017) among many others.

In this paper we estimate the negative impact of misallocation of labor and capital on aggregate productivity in the Netherlands. To the best of our knowledge the size of resource misallocation in the Dutch business sector has not been analyzed before. In our empirical analysis we use the model of Hsieh and Klenow (2009), further referred to as the Hsieh and Klenow model. This set up is attractive because it estimates distortions in capital and labor misallocation for each year at the firm-level by the Marginal Revenue Product of Capital (MRPK) and the Marginal Revenue Product of Labor (MRPL) respectively. Furthermore, the Hsieh and Klenow model is able to construct counterfactual productivity levels assuming an efficient allocation of production factors in which Revenue Total Factor Productivity (TFPR) is equalized within sectors.

We show that misallocation in the Netherlands has increased by 14 percentage points in the period 2001-2017 compared to the counterfactual. Regarding the variables underlying the misallocation measure, we find an upward

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trend in MRPK dispersion, while MRPL dispersion is more stable over time. We exploit error component models from the earnings dynamics literature (see e.g., Moffitt and Gottschalk 2011 and Doris et al. 2013) to discriminate between the permanent component and the transitory component of the dispersion in marginal revenue products and TFPR. We find that the permanent component of capital misallocation has increased over time and has even become larger than the transitory component in recent years. In contrast, labor misallocation is mostly transitory of nature.

The empirical literature has documented the presence of misallocation of production factors across firms in many different country studies. Hsieh and Klenow (2009) originally applied their model to the United States, India and China. Regarding European countries misallocation has increased in Spain (Gopinath et al. 2017; Garcia-Santana et al. 2020), Italy (Calligaris et al. 2018) and Portugal (Dias et al. 2016), remained pretty constant in France (Bellone and Mallen-Pisano 2013), and declined in Germany (Crespo and Segura-Cayuela 2014), too cite a few.

The recent literature on misallocation has questioned the underlying assumptions of the Hsieh and Klenow model. Crucial question in this literature is whether we should attribute measured distortions to misallocation, or alternative explanations for the observed distortions. In other words, are the estimated distortions due to misallocation or misspecification? We assess the importance of some often raised conjectures (see e.g., David and Venkateswaran 2019) to the modeling framework of Hsieh and Klenow (2009). First, we analyze the importance of capital adjustment costs (see e.g., Asker et al. 2014) and we find that it explains only 5% of the observed misallocation. Second, we show that allowing for heterogeneous production technologies across firms does not have an impact on our empirical results. Also we analyze how our measure of misallocation changes if we allow for non-unitary substitution between the production factors labor and capital. Third, we analyze the impact of heterogeneous markups across firms. Using methodology of De Loecker and Warzynski (2012) we find that firm-level heterogeneity in markups is able to explain a sizable part of the observed variation in marginal revenue products, i.e., approximately 25%. Taken together we conclude that in our case the majority of the measured distortions (around 70%) is a consequence of either capital or labor misallocation.

The remainder of this paper is structured as follows. Section 2 describes our baseline model to measure misallocation and presents empirical results for the Netherlands. Section 3 analyzes the evolution of marginal revenue products over time focusing on permanent and transitory components. Section 4 addresses the sensitivity of our outcomes to recent criticism in the literature. Section 5 concludes.

2 Measuring misallocation

To quantitatively assess the effect of within-industry resource misallocation on aggregate total factor productivity we build on the framework developed by Hsieh and Klenow (2009), recently applied by i.e., Gopinath et al. (2017), Gamberoni et al. (2016), Calligaris (2015), Calligaris et al. (2018) and others. The Hsieh and Klenow model formally shows that frictions distorting the marginal revenue products of capital and labor lower aggregate factor productivity. We estimate the model using a rich and tailored data set containing the annual balance sheet and the profit and loss statements of all Dutch firms that are legally obliged to declare corporate income tax. Our final data set contains 1,831,5757 firm-year observations for the period 2001–2017, and contains 342,245 unique firms. The Appendix contains a detailed description of the sources and cleaning procedure used to construct this data set.

2.1 Model

In the Hsieh and Klenow model the aggregate economy wide output is defined by a Cobb Douglas (CD) production technology, while at the industry level the output is a Constant Elasticity of Substitution (CES) aggregate of differentiated products. For comparability with Hsieh and Klenow (2009) and Gopinath et al. (2017) we set the elasticity of substitution σ in the latter equal to 3.[1]

Each individual firm produces its unique good according to a standard CD production function:

$$Y_{is,t} = A_{is,t} K_{is,t}^{\alpha_s} L_{is,t}^{1-\alpha_s}, \tag{1}$$

where $A_{is,t}$, $K_{is,t}$ and $L_{is,t}$ are total factor productivity, real capital and labor input of firm i, in industry s at time t, respectively. We measure the firm's nominal value added $P_{is,t} Y_{is,t}$ as the difference between gross turnover minus materials used in production. Real firm-level output $Y_{is,t}$ equals nominal value added deflated with a firm-specific output price deflator $P_{is,t}$. Since we do not observe prices at the firm-level in our data set, we revert to using two-digit industry deflators, following e.g., Dias et al. (2016), Gorodnichenko et al. (2018) and Gopinath et al. (2017). This implies we calculate $Y_{is,t}$ actually as $P_{is,t} Y_{is,t}/P_{s,t}$

[1] Note that as σ goes to ∞ the economy leaves monopolistic competition and approaches perfect competition.

where $P_{s,t}$ is the industry deflator.[2] We measure labor input $L_{is,t}$ as the firm's wage bill deflated by the same two-digit industry deflators used to deflate nominal firm-level output, i.e., $W_{is,t}L_{is,t}/P_{s,t}$. We use the nominal wage bill instead of employment to control for differences in the quality of the workforce across firms, as argued in e.g., Hsieh and Klenow (2009) and Gopinath et al. (2017). Finally, we measure the firm-specific real capital stock $K_{is,t}$ with the book value of fixed tangible assets deflated with the total deflator of non-financial corporations gross fixed capital formation, P_t^K. This implies we actually calculate $K_{is,t}$ as $P_{is,t}^K K_{is,t}/P_t^K$.

Each firm acts a monopolist in its differentiated product and faces two types of distortion: a capital wedge $\tau_{is,t}^K$, that changes the relative marginal revenue product of capital with respect to labor, and an output wedge $\tau_{is,t}^Y$, that changes the marginal product of capital and labor by the same proportion. Market distortions appear in the firm's profit equation:

$$\pi_{is,t} = (1 - \tau_{is,t}^Y)P_{is,t}Y_{is,t} - w_{s,t}L_{is,t} - (1 + \tau_{is,t}^K)R_{s,t}K_{is,t}, \tag{2}$$

where $w_{s,t}$ is the wage faced by all firms and $R_{s,t}$ is the industry-specific time-varying real rental price of capital.

As a result of the wedges $\tau_{is,t}^Y$ and $\tau_{is,t}^K$, there will be differences in the marginal products of labor and capital across firms. The first order conditions for profit maximization with respect to labor and capital, are given by:

$$MRPL_{is,t} = P_{is,t}\frac{\partial Y}{\partial L} = (1-\alpha_s)\left(\frac{\sigma-1}{\sigma}\right)\left(\frac{P_{is,t}Y_{is,t}}{L_{is,t}}\right) = \left(\frac{1}{1-\tau_{is,t}^Y}\right)w_{s,t}, \tag{3}$$

$$MRPK_{is,t} = P_{is,t}\frac{\partial Y}{\partial K} = \alpha_s\left(\frac{\sigma-1}{\sigma}\right)\left(\frac{P_{is,t}Y_{is,t}}{K_{is,t}}\right) = \left(\frac{1+\tau_{is,t}^K}{1-\tau_{is,t}^Y}\right)R_{s,t}. \tag{4}$$

We estimate MRPL and MRPK in (3) and (4) exploiting the firm-level data on value added, labor and capital. We furthermore calculate α_s by one minus the five-digit sectoral shares of labor costs in value added. The substitution elasticity between varieties is assumed the same for all firms, sectors and years and set equal to $\sigma = 3$. Assuming that this elasticity is sector-specific is more realistic but this will not affect the dispersion of MRPs in a sector. However, the development of the dispersion is affected when the elasticity is not constant in time, for example due to pro-competitive effects of globalization. Note that an increase in σ induces an increase in dispersion for both MRPK and MRPL. However, this upward trend is not observed for the latter, as we shall see.

The estimated distortions to capital ($\tau_{is,t}^K$) and output ($\tau_{is,t}^Y$) are estimated relative to labor. An observationally equivalent expression is in terms of distortions in absolute levels of capital and labor denoted by $\tau_{is,t}^{K*}$ and $\tau_{is,t}^{L*}$ respectively. Hsieh and Klenow (2009) show that the firm's first order conditions are identical to those with $\tau_{is,t}^K$, $\tau_{is,t}^Y$ assuming $1 - \tau_{is,t}^Y = 1/(1 + \tau_{is,t}^{L*})$ and $1 + \tau_{is,t}^K = (1 + \tau_{is,t}^{K*})/(1 + \tau_{is,t}^{L*})$. Substituting these expressions into (3) and (4) and taking logarithms results in:

$$log(MRPL_{is,t}) = log(1 + \tau_{is,t}^{L*}) + log(w_{s,t}), \tag{5}$$

$$log(MRPK_{is,t}) = log(1 + \tau_{is,t}^{K*}) + log(R_{s,t}), \tag{6}$$

which shows that within-sector dispersion in the log marginal revenue products is equal to the dispersion in firm-level labor and capital wedges.

Following Foster et al. (2008) the Hsieh and Klenow model makes a distinction between revenue productivity (TFPR) and physical productivity (TFPQ), i.e., the Solow-residual. Using this terminology we can define TFPQ by rewriting Eq. (1):

$$TFPQ_{is,t} = A_{is,t} = \kappa_{s,t}\frac{P_{is,t}Y_{is,t}^{\frac{\sigma}{\sigma-1}}}{K_{is,t}^{\alpha_s}L_{is,t}^{(1-\alpha_s)}}, \tag{7}$$

Where the scalar is $\kappa_{s,t} = (P_{s,t}Y_{s,t})^{\frac{1}{\sigma-1}}/P_{s,t}$. The calculation of $TFPQ_{is,t}$ warrants some explanation. We do not observe each firm's real output $Y_{is,t}$, but only its nominal output $P_{is,t}\,Y_{is,t}$, i.e., we lack data on firm's prices ($P_{is,t}$), and only have information on sectoral prices ($P_{s,t}$). Plants with high real output, however, must have a lower price to explain why buyers would demand the higher output. Following the assumption of an isoelastic inverse demand curve[3] we raise $P_{is,t}\,Y_{is,t}$ to the power $\sigma/(\sigma-1)$ to arrive at $Y_{is,t}$. That is, we infer price versus quantity value added from revenue and our assumed (constant) elasticity of demand. Elegantly, Eq. (7) requires only the assumptions about technology and demand plus maximization. Then TFPR is defined as:

$$TFPR_{is,t} = P_{is,t}A_{is,t} = \left(\frac{\sigma}{\sigma-1}\right)\left(\frac{MRPK_{is,t}}{\alpha_s}\right)^{\alpha_s}\left(\frac{MRPL_{is,t}}{1-\alpha_s}\right)^{1-\alpha_s}. \tag{8}$$

[2] Industry deflators are publicly available data from Statistics Netherlands

[3] Haltiwanger et al. (2018) provide a critical assessment of this assumption and show that part of the observed dispersion in TFPR can be traced back to demand shifts.

In the model of Hsieh and Klenow (2009) TFPR does not vary across firms within an industry unless firms face output and/or capital distortions.[4] The idea is that in a friction-less economy more capital and labor should be allocated to firms with higher physical productivity, $A_{is,t}$, to the point where higher output results in lower price and the same TFPR compared to firms with lower physical productivity. When there are frictions, however, economy wide output can be (much) lower.

Imagine an economy with two firms that have identical technology but in which one firm benefits from subsidized credit (say from a state-owned bank), and the other firm can only borrow at high rates from informal capital markets. Assuming that both firms equate their MRPK with the interest rate, the marginal revenue product of the firm with access to subsidized credit will be lower than the MRPK of the firm that only has access to informal financial markets. This is a clear case of capital misallocation: aggregate output would be higher if capital was reallocated from the firm with a low MRPK ($\tau^{K^*} > 0$, $\tau^K > 0$) to the firm with a high MRPK ($\tau^{K^*} < 0$, $\tau^K < 0$). The misallocation of capital results in lower aggregate output per worker and TFPQ (see e.g., Gopinath et al. 2017).

Regarding MRPL recent studies explain wedges in the first-order condition by labor market power, see Dobbelaere and Kiyota (2018) and Mertens (2020). The first study derives first-order conditions for three settings of the labor market. They show that under efficient bargaining, the MRPL is smaller than the wage ($\tau^{L^*} > 0$, $\tau^Y > 0$), while the reverse holds under monopsony ($\tau^{L^*} < 0$, $\tau^Y < 0$). Indeed we empirically find both negative and positive values for the labor wedges.

We follow Hsieh and Klenow (2009) and estimate the impact of misallocation thus defined on the TFPQ level by defining the "efficient" level of TFPQ, as the TFPQ-level we would observe in the allocation in absence of dispersion in MRPK, MRPL and TFPR such that $TFPR_{is,t} = \overline{TFPR}_{s,t}$, where:

$$\overline{TFPR}_{s,t} = \frac{P_{s,t} Y_{s,t}}{K_{s,t}^{\alpha_s} L_{s,t}^{(1-\alpha_s)}}, \tag{9}$$

It can then be shown that the difference in log(TFPQ) arising from misallocation—the misallocation-gain $\Lambda_{s,t}$—can be written as a combination of the variables introduced in Eqs. (1)–(9). See e.g., Eqs. (1)–(11) in Gopinath et al. (2017) for a more detailed derivation of this misallocation measure.

Note that the calculation in (9) only takes into account within-sector misallocation. It therefore disregards that the nation-wide allocation and aggregate TFP can be improved by shifting resources between sectors. Calligaris et al. (2018) show, however, that the within-sector TFPR dispersion and, hence, the TFP loss due to within-sector misallocation is relatively large. Applying their TFPR variance decomposition, see Eq. (2) of Calligaris et al. (2018), we find a very similar result for the Netherlands. On average over the sample period, the within component accounts for 80% of the TFPR dispersion.

Our misallocation measure represents an upper limit to intra-industry misallocation, given that all variation in the marginal revenue products is attributed to misallocation. This is assuming that firms are at their long-term static equilibrium at any given moment in time, irrespective of the scope, type and frequency of firm-specific shocks. Each diversion from the equilibrium is regarded as misallocation, which constitutes a substantial assumption. The Hsieh and Klenow (2009) model assumptions are relatively strict: all firms have a productivity level with the same mark-up and the same capital intensity, adjustment costs are absent, and the substitution elasticity with respect to capital and labor is equal to a CD-production function with constant revenues of scale. Moreover, input composition effects are neglected. For example, firms using a different mix of high-skilled and low-skilled labor with different marginal productivities will lead to MRPL dispersion. This result is misleading, however, as the allocation is optimal. Insofar such input composition effects do not change over time, we can still interpret the changes in MRPL as changes in misallocation. Despite these limitations, the model is still suitable enough to measure misallocation in the economy in our view. We elaborate on the sensitivity of our misallocation measures to some of the model assumptions in Section 4.

2.2 Estimation results misallocation total economy

Figure 1 shows the allocative efficiency for both factors of production, labor and capital, in the period 2001–2017

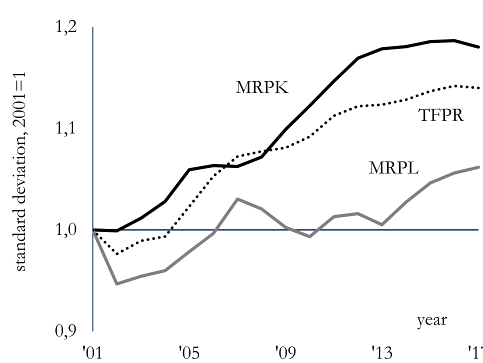


Fig. 1 Evolution of MRPK, MRPL and TFPR dispersion, 2001–2017, the Netherlands

[4] Note that zero dispersion in MRPK, MRPL and TFPR only requires that the wedges are the same for all firms in a sector. There might still be a distortion that affects all firms equally, however.

according to the Hsieh and Klenow model outlined above, reflecting the standard deviation of the log of the marginal revenue product of capital (black line) and the log of the marginal revenue product of labor (gray line). In the remainder of the text we will also refer to these measures as capital misallocation and labor misallocation.[5] The larger the standard deviations, the higher the degree of misallocation. To better show the development over time, we standardize cross-sectional standard deviations to 1 in 2001.

Capital misallocation shows a clearly discernible upward trend over the period 2001–2013, interrupted briefly between 2005 and 2007. After 2013 misallocation of capital has leveled out. On balance, capital misallocation in the Netherlands increased by 18% in the period 2001–2017. Labor misallocation developed quite differently. Labor misallocation increased much less strongly than capital misallocation but fluctuated much more. In the period 2002–2006 labor misallocation even dropped below the level recorded in 2001. In 2017 the level of labor misallocation exceeded the 2001 level by a “mere” 6%. We also report the standard deviation of the log of TFPR, which is the combined measure of both capital and labor misallocation (see Eq. (8)). Note that log(TFPR) is proportional to a weighted average of log(MRPK) and log(MRPL), see Hsieh and Klenow (2009), hence its dispersion is proportional to that of log(MRPK) and log(MRPL).

The pattern for MRPL dispersion is rather different from that of MRPK. Gopinath et al. (2017) note that such empirical results are inconsistent with changing elements in the model that affect both capital and labor misallocation equally. As an example they mention heterogeneity in price markups for which we do not find increased dispersion over time (see also Section 4.3 below). Other examples are the elasticity of substitution or effective tax rates. Regarding the latter we do not find evidence of increased dispersion in effective corporate tax rates, which are calculated from the firm-level balance sheets as the taxes on profit divided by the earnings before taxes.

Figure 2 shows the possible gain from reducing capital and labor misallocation to zero using our misallocation-gain measure $\Lambda_{s,t}$ introduced in Section 2.1. We express the misallocation-measure $\Lambda_{s,t}$ in percentage point differences with respect to the allocation in absence of dispersion in MRPK, MRPL and TFPR in 2001. According to this measure, removing all distortions would increase aggregate TFPQ in the Netherlands by 43% in 2001. This gain increases to 57% in 2017, indicating that since 2001 there has been a decline in allocative efficiency by 14

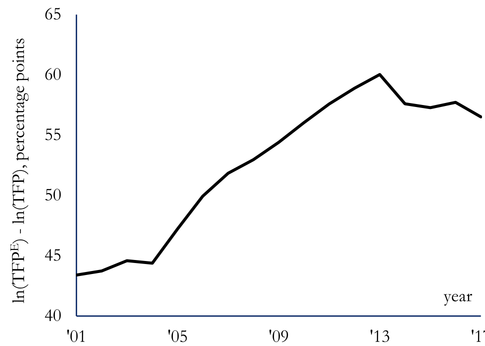


Fig. 2 Evolution of misallocation in the Netherlands, 2001–2017

percentage points. Interestingly, the worsening of allocative efficiency started long before the Great Recession (2008) and the European Debt crisis (2011). During these crisis-years misallocation losses kept rising. After 2013, the misallocation loss dropped somewhat and has been fluctuating around 57% in the period 2014–2017. Comparing our results to recent findings in the literature seems to indicate that the measured increase in misallocation is more comparable to the Southern EU-member states than the Northern EU-member states. Similar to the Netherlands, Gopinath et al. (2017) observe significant increased in misallocation in Spain and Italy, but quite stable levels of misallocation in Germany, France and Norway. Calligaris (2015) and Calligaris et al. (2018) also find steadily increasing misallocation in Italy.

2.3 Between and within sector misallocation

In the period 2001–2017, the level and development in misallocation was not evenly spread across industries. The level of our misallocation measure in the services sector clearly exceeds that in the manufacturing sector.[6] This is clear from Fig. 3, which plots the measured misallocation in the total economy, the manufacturing sector (dashed line) and the services sector (dotted line). Panels A, B and C show the evolution of MRPK, MRPL and TFPR dispersion, respectively. These results confirms the outcomes of earlier studies addressing misallocation in the services sector. For Portugal, Dias et al. (2016) find that the level of misallocation in the services sector exceeds that in the manufacturing sector by a large amount. Busso et al. (2013) find the same result for a number of Latin American countries. Dias et al. (2016) suggest that the relatively high

[5] Economy-wide measures are calculated by the weighted mean, using real industrial value added weights, calculated as the average share in real value added over the period 2001–2017, according to the National Accounts.

[6] The manufacturing sector is comprised of (NACE-industry two-digit codes in brackets): manufacturing (10–33) and construction (41–43). The services sector is comprised of: wholesale and retail trade; repair of motor vehicles and motorcycles (45–47), transportation and storage (49–53), accommodation and food services (55–56), information and communication (58–63), professional, scientific and technical activities (69–75) and administrative and support service (77–82).

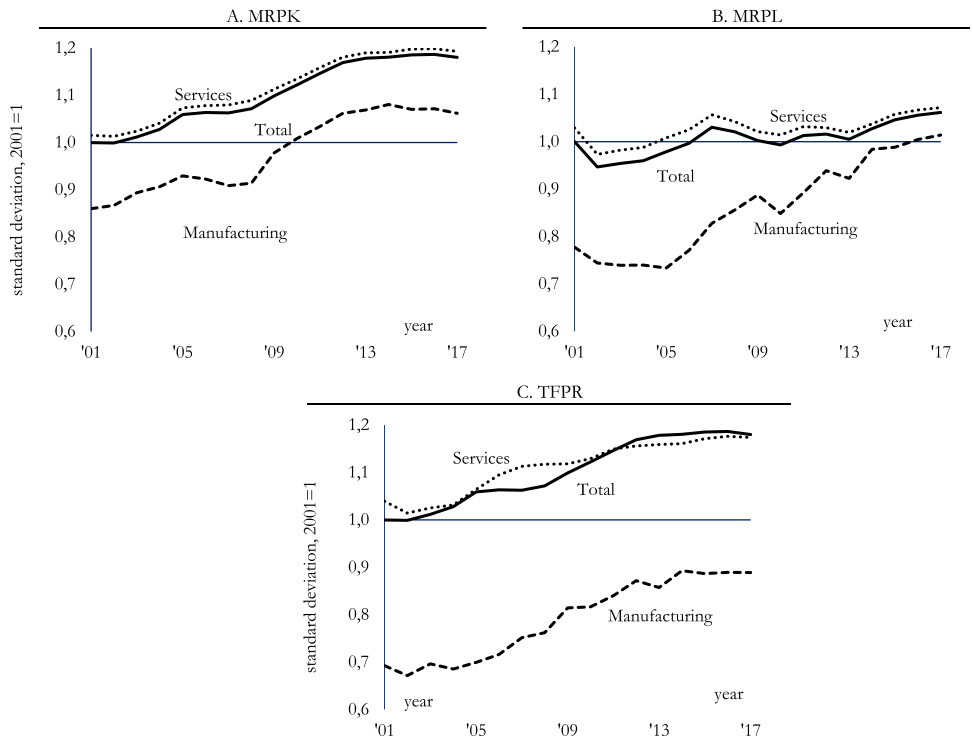
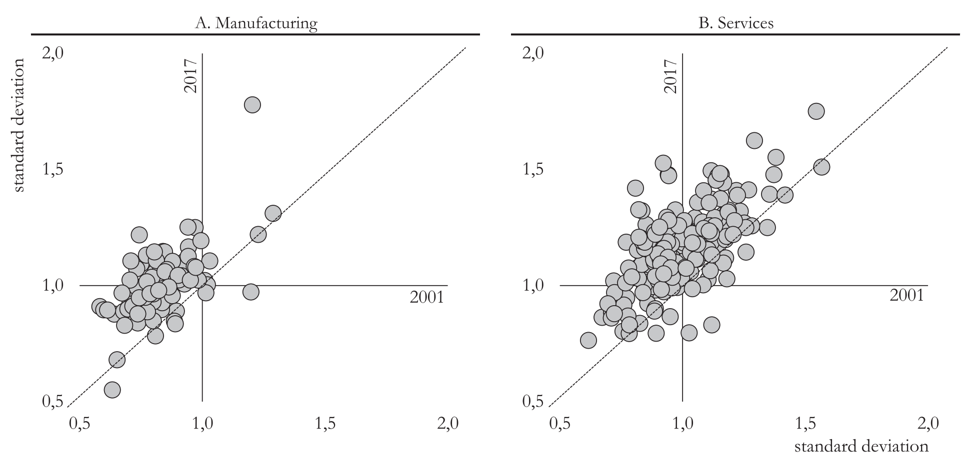


Fig. 3 Evolution of MRPK, MRPL and TFPR dispersion in the manufacturing sector and the services sector, 2001–2017, the Netherlands



Note: standardized with MRPK dispersion total economy in 2001.

Fig. 4 Evolution of MRPK dispersion in the manufacturing sector and services sector, 2001 vs. 2017, NACE five-digit level, the Netherlands

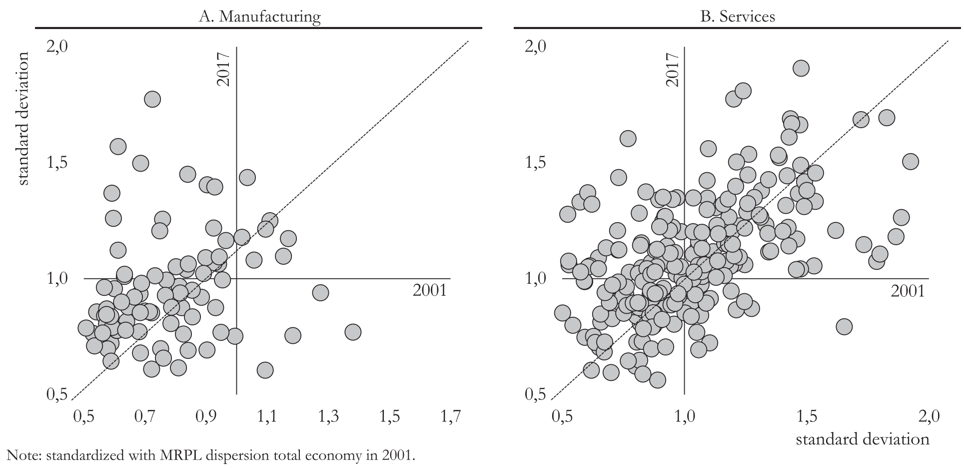
misallocation in the services sector vis-à-vis the manufacturing sector could be driven by lower competition, limited international trade-ability, relatively high regulatory barriers an the location-specific nature of services.[7]

Moreover, the evolution of labor misallocation in manufacturing is markedly different from the services sector (Panel B of Fig. 3). In the manufacturing sector labor misallocation has steadily increased in the period 2005–2017, whereas misallocation in the services sector more or less stabilized during this period. Unlike the diverging evolution of labor misallocation in the manufacturing and services sector, capital misallocation rose in roughly the same amount in both the manufacturing sector and services sector.

Figure 4 shows a more detailed picture of capital misallocation at the five-digit industry level in 2001 and 2017, respectively. Our data set contains 93 industries in the manufacturing sector and 240 industries in the services sector. In both 2001 and 2017 most firms were active in the services sector, i.e., 78% and 81% of all firms in our sample, respectively. Panel A and B show scatter diagrams

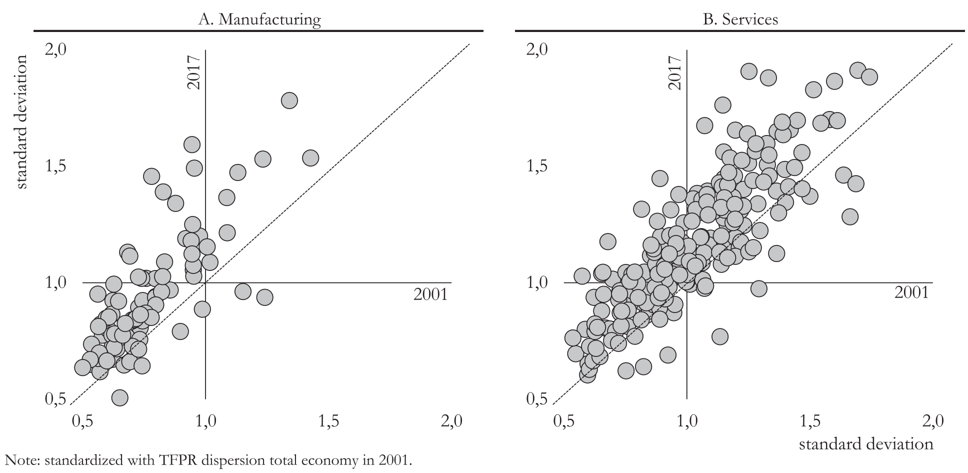
[7] As pointed out by Restuccia and Rogerson (2017) the difference in the level of misallocation between the manufacturing and services sector might also be partly driven by measurement problems specific to the services sector due to e.g., quality changes.

Fig. 5 Evolution of MRPL dispersion in the manufacturing sector and services sector, 2001 vs. 2017, NACE five-digit level, the Netherlands



Note: standardized with MRPL dispersion total economy in 2001.

Fig. 6 Evolution of TFPR dispersion in the manufacturing sector and services sector, 2001 vs. 2017, NACE five-digit level, the Netherlands



Note: standardized with TFPR dispersion total economy in 2001.

of capital misallocation for each five-digit industry in manufacturing and services, respectively. The gray dots show capital misallocation measures in 2001 and 2017, expressed against the same misallocation measure for the total economy in 2001. Dots lying above/below the 45°-line indicate that capital misallocation has increased/decreased. The main take-away from Fig. 4 is that capital misallocation increased in the period 2001–2017 for the vast majority of industries in both the manufacturing and services sector, i.e., most gray dots are above the 45°-line. We observe increases of capital misallocation in 90% and 93% of all five-digit industries in the manufacturing and services sectors, respectively.

Figure 5 shows the same measures as plotted in Fig. 4, but for labor misallocation instead of capital misallocation. In contrast to capital misallocation, the number of industries showing an increase or decrease in labor misallocation is approximately the same in the services sector. This implies that the industry-level heterogeneity in labor misallocation is larger than capital misallocation. Inspecting TFPR dispersion, however, Fig. 6 shows that most industries have experienced an increase in misallocation.

To shed some light on within-sector differences in distortions, we regress firm-level marginal revenue products and TFPR on firm size and TFPQ controlling for sector and year fixed effects. Regarding firm size, Guner et al. (2008) show that size-dependent taxes lead to lower aggregate TFP, while Gopinath et al. (2017) analyse the detrimental impact of size-dependent financial constraints. Regarding TFPQ, Restuccia and Rogerson (2017) and Hsieh and Klenow (2009) note that firm-level distortions would be particularly costly if they are positively correlated with a firm's physical productivity. The estimation results corroborate these theoretical predictions and show that smaller and more productive firms face relatively high capital and labor distortions.

3 Persistence in misallocation

The results of the previous section indicate that capital misallocation is trending upward, while the dispersion of the return to labor is more stable over time. A related question is how long these observed firm-specific differences in the returns to capital and labor persist. Are firm-level differences in marginal revenue products and revenue productivity permanent or do they gradually disappear over time?

3.1 Permanent versus transitory misallocation

Theoretical models on capital misallocation (Banerjee and Moll 2010; Midrigan and Xu 2014) find that in case of financial frictions the dynamics of capital misallocation on the intensive margin are transitory. The empirical results of Midrigan and Xu (2014) show that firm-level productivity shocks only temporarily induce capital misallocation. Financial frictions alone therefore cannot explain the large TFP losses over time due to misallocation. Credit constraints matter most for the extensive margin, i.e., new entrants. In other words, differences in the marginal revenue product of capital of existing firms do not persist. Numerical experiments in Banerjee and Moll (2010) show that the speed of convergence of different marginal products is fast. Banerjee and Moll (2010) also note that by focusing on stationary states a large part of observed misallocation may be missed. Starting from an initial condition far away from the steady state in combination with higly autocorrelated shocks, equalizing marginal products may take a long time and observed misallocation can be substantial.

Adjustment costs typically are viewed transitory of nature. In Asker et al. (2014) capital adjustment costs and time to build lead to the prediction that a firm's MRPK should be mean reverting, i.e., there is no role for a permanent component. They estimate an AR(1) specification for MRPK controlling for industry and years fixed effects. The empirical results indeed show mean reversion, i.e., the estimated autoregressive coefficient is well below unity.

To model persistent misallocation Restuccia and Rogerson (2008) assume the existence of firm-level taxes or subsidies that are permanently fixed over time. Their impact on aggregate TFP is largest when correlated with firm level TFP. Bartelsman et al. (2013) and David and Venkateswaran (2019) generalize this specification and assume an error component structure for firm level distortions (labeled $y_{i,t}$), which consists of both time-invariant (η_i) and idiosyncratic terms ($v_{i,t}$):

$$y_{i,t} = \eta_i + v_{i,t}. \tag{10}$$

Bartelsman et al. (2013) interpret both error components as any output distortions that impacts the revenues of a firm. Both error components have a cross-sectional dimension and are meant to model either firm-specific regulation or the fact that regulation is enforced unevenly across firms. David and Venkateswaran (2019) adopt the same specification, but the time-variant error component $v_{i,t}$ is the sum of an AR(1) process and i.i.d. disturbances. The AR(1) process models autoregressive productivity shocks, hence firm-level distortions are potentially correlated with productivity like in Restuccia and Rogerson (2008).

3.2 Empirical results

We analyze the permanent and transitory nature of capital and labor misallocation empirically by exploiting panel data specifications from the literature on individual earnings dynamics, see e.g., Guvenen (2009), Moffitt & Gottschalk (2011) and Doris et al. (2013). This estimated error component model encompasses earlier specifications adopted in the literature on misallocation and allows for identification of the permanent and transitory components of the observed capital and labor misallocation. We use the following decomposition:

$$y_{i,t} = y_{i,t}^P + y_{i,t}^T, \tag{11}$$

where $y_{i,t}$ is log(MRPK), log(MRPL) or log(TFPR) of firm i in year t.[8] The first and second term in (11) are the permanent and transitory components, respectively.

We get a first glimpse on the development over time of permanent and transitory components by applying some simple descriptive statistics. We extract the permanent component in year t as the moving average of the firms annual log MRP (capital or labor) or log TFPR over a 3-year period centered around year t. In other words, we estimate $y_{i,t}^P = \frac{1}{3}(y_{i,t-1} + y_{i,t} + y_{i,t+1})$ for all firms for which complete data are available.[9] Figure 7 shows the cross-sectional variance over time of this moving average, standardized with respect to the first available year. It is clear that the permanent component of the variance in MRPK has increased over time. For MRPL it fluctuates until 2011, while in later years it increases.

Regarding the transitory component we follow Shin and Solon (2011), who propose to use the standard deviation of the changes. They show that this measure is closely related to the variance of the transitory component in a parametric error components model. Figure 8 shows the cross-sectional standard deviations of the 1-year changes or first differences (i.e., $y_{i,t}^T = y_{i,t} - y_{i,t-1}$) in residual MRPK, MRPL and TFPR, again standardized with respect to the first available year. For all three variables the figure shows no clear increasing or decreasing trend in either series. From this preliminary analysis we therefore conclude that the

[8] To be precise we first purge out between sector differences by regressing $y_{i,t}$ on a set of 5-digit sectoral fixed effects.

[9] Alam (2020) applies the Hodrick-Prescott filter, but this cannot be used here due to the short time span and unbalancedness of the available panel data.

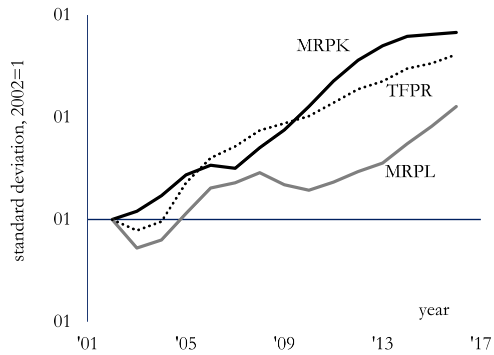


Fig. 7 Cross-sectional standard deviation of 3-year centered moving average, 2002–2016, the Netherlands

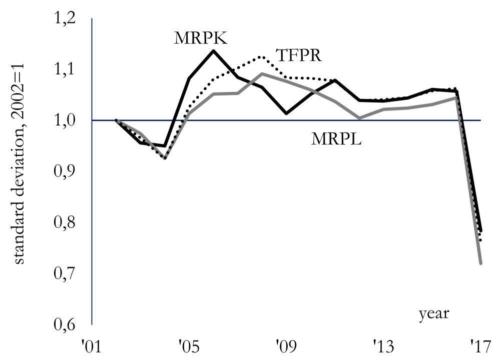


Fig. 8 Cross-sectional standard deviation of 1-year changes, 2002–2017, the Netherlands

observed trends in misallocation are mostly due to the permanent component.

We next analyze the relative importance of permanent and transitory fluctuations in MRPK, MRPL and TFPR dispersion with an error components model. There is a large literature on the precise formulation of such a decomposition and many specifications are possible. For example, the basic random effects model assumes an i.i.d. time-invariant permanent component independent from an i.i.d. transitory component. Extensions allow for (1) a random walk in the permanent component; (2) a stationary ARMA-process for the transitory component; (3) time series heteroscedasticity or factor-loadings for both components; (4) heterogeneity in model parameters across individuals. We note that, irrespective of the chosen specification, there is inevitably some degree of arbitrariness in distinguishing permanent and transitory components.

We use the modeling framework of Doris et al. (2013) and estimate:

$$y_{i,t} = p_t\eta_i + \lambda_t v_{i,t}, \tag{12}$$

where $p_t\eta_i$ and $\lambda_t v_{i,t}$ are defined as the permanent ($y^P_{i,t}$) and transitory error component ($y^T_{i,t}$), respectively. The factor-loadings p_t and λ_t allow the variances of the permanent and transitory misallocation to change over time. Furthermore, $v_{i,t}$ is modeled as a stationary AR(1) process to account for persistence in transitory shocks:[10]

$$v_{i,t} = \rho v_{i,t-1} + \varepsilon_{i,t}. \tag{13}$$

Finally, regarding the initial observation it is assumed that $Var(v_{i1}) = \sigma^2_{v1}$.

The model (12, 13) is very general and encompasses the adopted specifications of firm level distortions in theoretical models on misallocation, see Section 3.1. First, Restuccia and Rogerson (2008) assume that distortions only contain a time-invariant component, i.e., $p_t = 1$ and $\lambda_t = v_{i,t} = 0$. Second, Bartelsman et al. (2013) specify a classical i.i.d. error component model, which implies $p_t = \lambda_t = 1$ and $\rho = 0$. Third, David and Venkateswaran (2019) allow the time-varying component of firm-level distortions to be correlated with and AR(1) productivity process resulting in $p_t = \lambda_t = 1$ and $-1 < \rho < 1$. Fourth, the model of David et al. (2018) implies for MRPK a factor structure in which p_t is the sum of aggregate productivity shocks and time-varying risk and η_i measures the firm-specific exposure to these aggregate conditions. The transitory component of MRPK dispersion is assumed i.i.d., hence $\lambda_t = 1$ and $\rho = 0$.

It is easily seen (Doris et al. 2013) that the cross-sectional variance implied by the model (12,13) is equal to:

$$\begin{aligned} V_{t,\infty} &= p_t^2\sigma^2_\eta + \lambda_t^2\sigma^2_{v1}, \quad t = 1, \\ V_{t,\infty} &= p_t^2\sigma^2_\eta + \lambda_t^2\left(\rho^{2t-2}\sigma^2_{v1} + \sigma^2_\varepsilon\sum_{w=0}^{t-2}\rho^{2w}\right), \quad t > 1. \end{aligned} \tag{14}$$

The permanent component of the cross-sectional variance at time t is given by the first term $p_t^2\sigma^2_\eta$, while the second term is the transitory component. In case of covariance stationarity we have that $p_t = \lambda_t = 1$ and $\sigma^2_{v1} = \sigma^2_\varepsilon/(1-\rho^2)$. Any deviation from these values will cause the cross-sectional variance to change over time. Note that p_t and λ_t are unknown parameters, hence can be trending over time. Note also that when $-1 < \rho < 1$ the impact of a non-stationary initial observation will gradually vanish over time.

We estimate the model by using the Generalized Method of Moments (GMM) estimator of Doris et al. (2013). The parameters are ρ, σ^2_ε, σ^2_η, σ^2_{v1}, $p_1 - p_T$ and $\lambda_1 - \lambda_T$. The coefficient estimates are then used to predict the portion of variance due to the permanent and transitory components, e.g., the former is estimated by $\hat{p}_t^2\hat{\sigma}^2_\eta$. Note that the pattern of p_t fully determines the trend in the permanent component.

[10] We experimented with adding a random walk element to the permanent component and higher-order autoregressive or moving-average processes in $v_{i,t}$, but these components were generally not significant.

Table 1 GMM estimation results of model (12, 13)

	MRPK	*MRPL*	*TFPR*
ρ	0.715 (0.003)	0.653 (0.004)	0.655 (0.003)
σ_{ε}^2	0.298 (0.011)	0.057 (0.003)	0.061 (0.003)
σ_{η}^2	0.686 (0.017)	0.043 (0.002	0.088 (0.003)
σ_{v1}^2	1.574 (0.019)	0.190 (0.004)	0.226 (0.003)
λ_2	1.161 (0.010)	1.084 (0.019)	1.124 (0.014)
λ_3	1.336 (0.019)	1.195 (0.030)	1.267 (0.024)
λ_4	1.459 (0.025)	1.251 (0.037)	1.346 (0.030)
λ_5	1.543 (0.030)	1.259 (0.039)	1.368 (0.032)
λ_6	1.472 (0.029)	1.244 (0.038)	1.371 (0.032)
λ_7	1.460 (0.028)	1.291 (0.039)	1.400 (0.032)
λ_8	1.446 (0.027)	1.244 (0.038)	1.371 (0.031)
λ_9	1.393 (0.026)	1.151 (0.035)	1.293 (0.029)
λ_{10}	1.387 (0.026)	1.153 (0.035)	1.257 (0.029)
λ_{11}	1.421 (0.026)	1.209 (0.036)	1.319 (0.030)
λ_{12}	1.445 (0.027)	1.235 (0.037)	1.343 (0.030)
λ_{13}	1.465 (0.027)	1.269 (0.037)	1.362 (0.030)
λ_{14}	1.518 (0.027)	1.315 (0.039)	1.419 (0.031)
λ_{15}	1.552 (0.028)	1.337 (0.039)	1.447 (0.032)
λ_{16}	1.617 (0.030)	1.394 (0.041)	1.513 (0.034)
λ_{17}	1.635 (0.032)	1.415 (0.043)	1.523 (0.035)
p_2	1.079 (0.010)	1.033 (0.025)	1.069 (0.013)
p_3	1.115 (0.011)	1.002 (0.025)	1.080 (0.014)
p_4	1.150 (0.013)	1.034 (0.030)	1.112 (0.016)
p_5	1.203 (0.014)	1.083 (0.033)	1.177 (0.018)
p_6	1.322 (0.017)	1.206 (0.039)	1.264 (0.020)
p_7	1.354 (0.018)	1.249 (0.042)	1.297 (0.021)
p_8	1.422 (0.019)	1.332 (0.044)	1.374 (0.022)
p_9	1.567 (0.021)	1.356 (0.046)	1.445 (0.024)
p_{10}	1.626 (0.022)	1.324 (0.045)	1.509 (0.025)
p_{11}	1.663 (0.023)	1.307 (0.044)	1.490 (0.025)
p_{12}	1.712 (0.023)	1.268 (0.044)	1.505 (0.025)
p_{13}	1.717 (0.023)	1.182 (0.042)	1.479 (0.025)
p_{14}	1.688 (0.023)	1.143 (0.041)	1.422 (0.024)
p_{15}	1.663 (0.023)	1.151 (0.041)	1.405 (0.024)
p_{16}	1.631 (0.022)	1.147 (0.039)	1.369 (0.023)
p_{17}	1.632 (0.022)	1.194 (0.040)	1.393 (0.023)

Standard errors between parentheses

Regarding the transitory component more parameters are involved, hence there is no one-to-one mapping from parameters to cross-sectional variance.

The GMM estimation results are in Table 1. For MRPK the estimated variance parameters are larger than for MRPL indicating that MRPK dispersion is substantially larger. For MRPK and also TFPR the variance of the firm specific effect σ_{η}^2 is larger than the variance of the idionsyncratic error component σ_{ε}^2, while this is the opposite for MRPL. This indicates that the permanent component of capital misallocation is relatively large compared to the transitory component, while for labor misallocation this is the opposite. For all three misallocation measures the autoregressive coefficient is well below the unit root, which indicates that transitory shocks to both capital and labor misallocation tend to dissipate fairly quickly. Finally, there is a clear upward trend visible in the pattern of the estimated p_t for MRPK with a peak in 2013, while for MRPL the magnitude of these loadings fluctuate over time. Regarding TFPR the estimated p_t increase as well in the earlier years of the sample. As noted above the pattern of p_t fully determines the trend in permanent misallocation.

Figure 9 reports the evolution of the estimated permanent and transitory misallocation. The figure shows some interesting results. First, the permanent component of capital misallocation (Panel A) strongly increased over our sample period, whilst the transitory component was approximately the same size in 2017 as in 2001. From 2008 onwards, the permanent capital misallocation is larger than the transitory misallocation. Second, the relative size and evolution of the permanent and transitory component of capital an labor misallocation are quite different. In contrast to the evolution of capital misallocation, the transitory labor misallocation has been larger than the permanent component over our whole sample period. Third, the transitory nature of labor misallocation has been on a steady increase since 2009. The relative stability of labor misallocation over the whole sample period can therefore be largely ascribed to a simultaneous increase and decrease in the transitory and permanent component, respectively. Fourth, the MRPK and TFPR dispersion seems hardly affected by the Great Recession suggesting that the cleansing effects did not work properly (Bartelsman et al. 2019). Although the decreasing pattern of λ_t for MRPK and TFPR during the crisis years is in line with a cleansing effect, this is offset by the increase in the permanent component as can be seen from Fig. 9. Overall, these outcomes suggest that the Dutch firms have become more adaptive to changing labor demand and supply conditions, i.e., quite effective in removing distortions. The opposite is true for firm's acquisition of capital, where the permanent component of misallocation has increased by much more than the transitory component.

The variance decomposition of TFPR enables us to disentangle the permanent and transitory contributions to the aggregate productivity loss. We cannot apply the methodology of Hsieh and Klenow (2009) and Gopinath et al. (2017), however, to calculate the level of counterfactual TFP. The reason is that marginal revenue products and, hence, TFPR do not equalize across firms within sectors when either the permanent or transitory component of the distortions is zero. Instead we rely on an approximation from Hsieh and Klenow (2009) when TFPQ and TFPR are

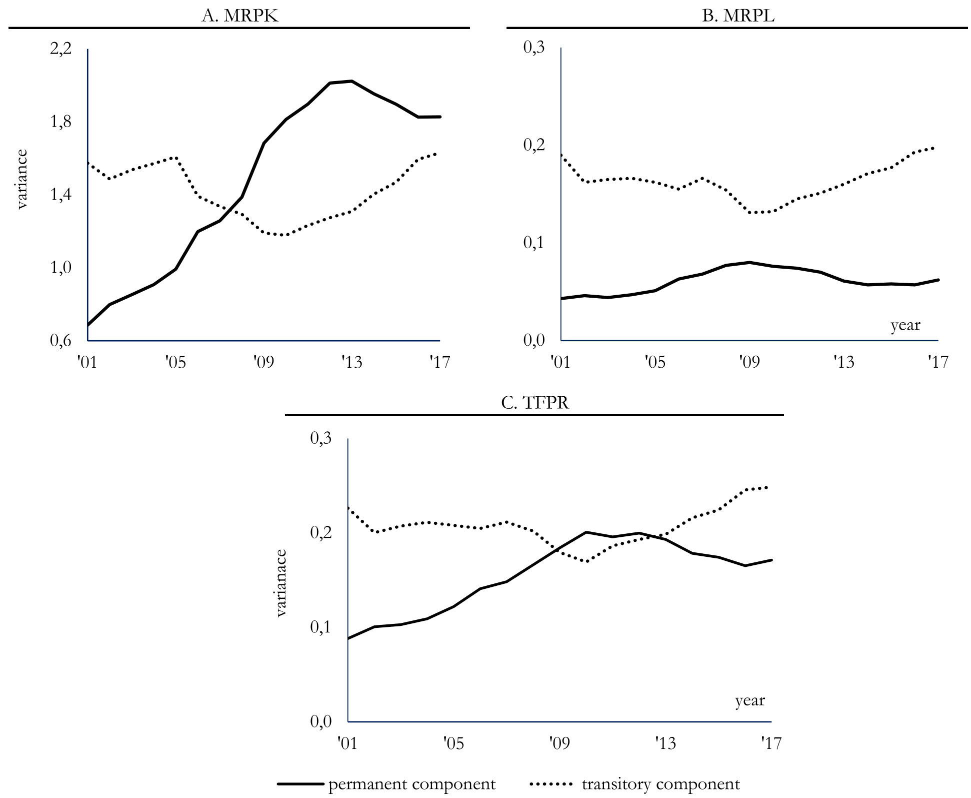


Fig. 9 Evolution of permanent and transitory components of MRPK, MRPL and TFPR dispersion, 2001–2017, the Netherlands

jointly lognormally distributed:

$$\log TFP = \frac{1}{\sigma - 1}\log\left(\sum_i TFPQ_i^{\sigma-1}\right) - \frac{\sigma}{2}Var(\log TFPR_i).$$

In this convenient simplification the TFP loss due to distortions depends entirely on the variance of log(TFPR). We therefore apply the variance decomposition of Eq. (11) to log(TFPR) and calculate for each year in the sample period the fraction due to the permanent and transitory components. Panel C of Fig. 9 shows the resulting variance decomposition for TFPR for each year in the sample. The permanent component attributes, on average, to 42% of the total TFPR dispersion and, hence, to the aggregate productivity loss.

3.3 Manufacturing versus services

We estimated the model (12, 13) separately for the manufacturing and services sectors.[11] Figure 10 shows the evolution of the permanent and transitory components of capital misallocation. In both the manufacturing and services sectors at the end of our sample capital misallocation has a more permanent character. Since 2009 the transitory component and permanent components of capital misallocation are of comparable size in the manufacturing sector, whilst the permanent component of capital misallocation in the services sector has been larger than the transitory component since 2006, albeit the difference has shrunk since 2013. These results imply that the services sector not only has a higher level of capital misallocation (see Fig. 3), but the misallocation has become also more permanent in nature.

Figure 11 shows the evolution of the permanent and transitory components of labor misallocation for the manufacturing and services sector. In contrast to capital misallocation, the evolution of the permanent and temporary components in both sectors is roughly the same, i.e., an increase Fig. 12 of the temporary component after 2009 and a stabilization (manufacturing sector) or small decline (services sector) in the permanent component. Another take-away is that the convergence of the level of labor misallocation in the manufacturing sector to the level of labor misallocation in the services sector, documented in Fig. 3, can be attributed to the combination of a strong increase in the transitory component of labor misallocation in the manufacturing sector and a decline of the permanent component in the services sector. Overall, labor misallocation has gotten a less permanent character in both the manufacturing and services sector.

[11] The pattern of the GMM estimates is qualitatively similar to the full sample estimates in Table 1 and available upon request.

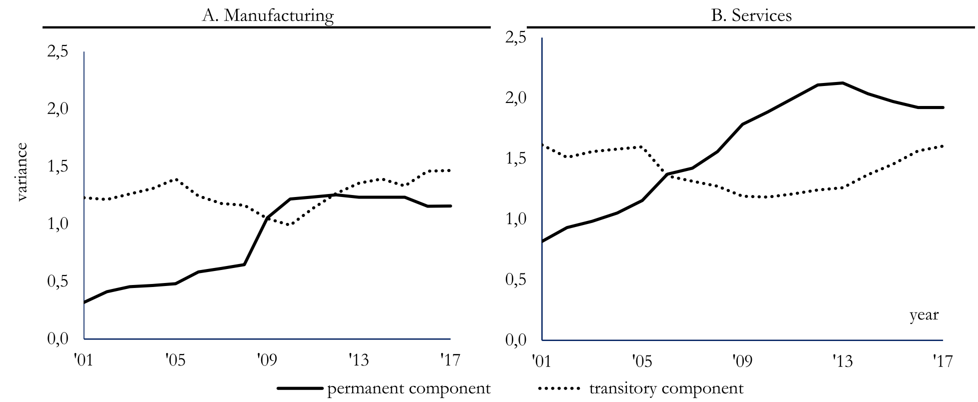


Fig. 10 Evolution of permanent and transitory components of MRPK dispersion, manufacturing and services, 2001–2017, the Netherlands

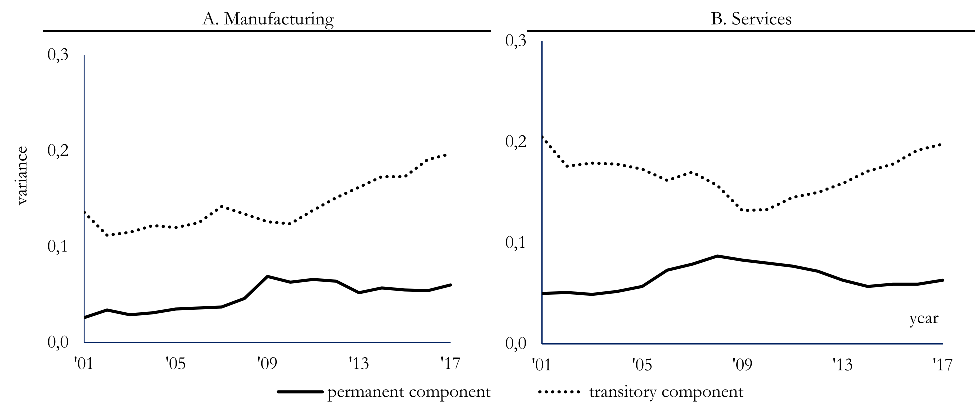


Fig. 11 Evolution of permanent and transitory components of MRPL dispersion, manufacturing and services, 2001–2017, the Netherlands

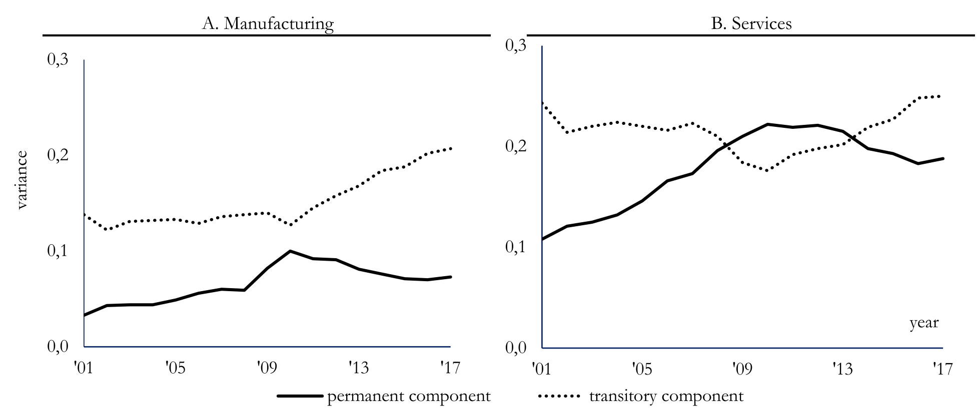


Fig. 12 Evolution of permanent and transitory components of TFPR dispersion, manufacturing and services, 2001–2017, the Netherlands

3.4 Validation by Monte Carlo simulation

To determine if the error components model (12, 13) is capable of reproducing the pattern of the estimation results in Fig. 1 and also the other figures we run a Monte Carlo experiment. We use the estimated model to generate artificial MRPK and MRPL distributions and analyze if the resulting time series pattern of the simulated cross-sectional variances coincides with the empirical cross-sectional variances. The outcome of the Monte Carlo experiments are also used to evaluate the accuracy of the GMM estimator in finite samples.

We generate data according to Eqs. (12,13). For the error components we assume η_i i.i.n.$(0, \sigma_\eta^2)$ independent from ε_{it} i.i.n.$(0, \sigma_\varepsilon^2)$. Regarding the initial observations we assume v_{i1} i.i.n.$(0, \sigma_{v1}^2)$ independent from the error components. For the parameters ρ, σ_ε^2, σ_η^2, σ_{v1}^2, $p_1 - p_T$ and $\lambda_1 - \lambda_T$ we choose the GMM estimates underlying Fig. 9. Finally, we choose $T = 17$ and $N = 10,000$. The cross-sectional dimension is different from the sample size in the empirical analysis, but we get similar results for different N. Other differences with the empirical analysis are that in the simulations we use balanced panel data and calculate unweighted cross-sectional variances.

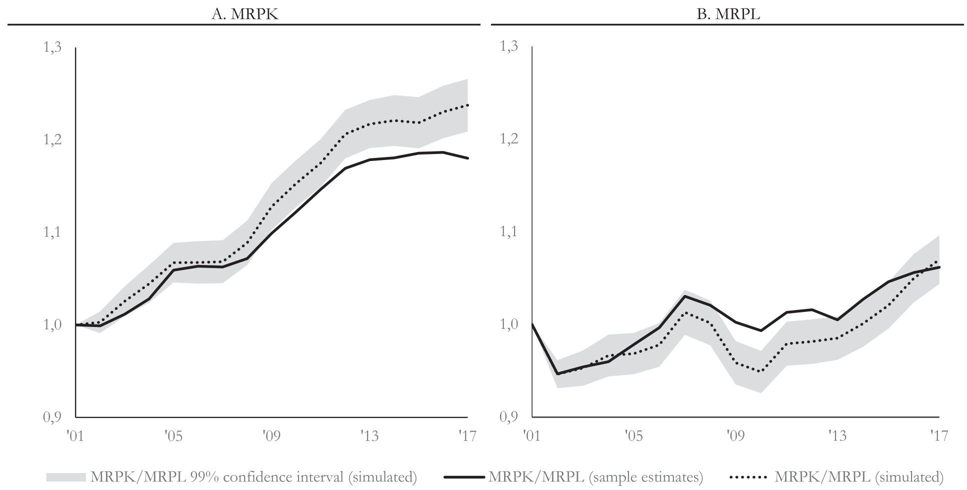


Fig. 13 Empirical and simulated evolution of MRPK and MRPL dispersion, 2001–2017, the Netherlands

For both MRPK and MRPL we create 1,000 data sets and calculate the time series of cross-sectional variances for each replication. The mean of these 1,000 replications is then compared to the empirical cross-sectional variances. Figure 13 shows the empirical MRPK and MRPL variances (normalized at 1 in base year 2001), the average cross-sectional variances of the Monte Carlo replications and the 99%—confidence interval. Panel A shows that the simulated cross-sectional variances implied by the error component model are capable of reproducing the upward trend in the MRPK dispersion. The error components model seems flexible enough to describe the sometimes irregular development, e.g., in the crisis years 2007–2009, of the empirical variances. Panel B shows the simulation results for MRPL, which are also close to the observed empirical measure of labor misallocation. We conclude that the estimated error components model provides an accurate description of the evolution of MRPK and MRPL dispersion.

4 Sensitivity analysis

Recently, several studies have raised concern about the modeling set up of Hsieh and Klenow (2009). A first source of concern is that capital might be subject to adjustment costs in investment ("time-to-build"), which can lead to a higher dispersion simply due to technology-driven adjustment processes, which in itself are not inefficient (see e.g., Cooper and Haltiwanger 2006; Asker et al. 2014; David and Venkateswaran 2019). The Hsieh and Klenow (2009) model neglects this distinction between technology-driven adjustment costs, such as the natural time needed to build a new plant, and wasteful frictions, such as the bureaucratic procedures of authorization that may delay the construction and activation of a new plant. We estimate the importance of these non-wasteful adjustment costs for our measurement in Section 4.1. Another concern is the functional form. Recently Haltiwanger et al. (2018) showed that the model is only valid under quite strict assumptions which generally do not hold in reality. In order to investigate the impact of the functional form we estimate the effect of allowing for firm-specific labor and capital shares, and a different functional form of the production function (i.e., CES instead of a CD functional form) in Section 4.2.[12] Finally, in Section 4.3 we analyze the impact of heterogeneous markups using methodology developed by De Loecker and Warzynski (2012).

4.1 Adjustment costs of capital

In order to explore whether adjustment costs are a significant driver of our measurement of misallocation we use the methodology of David and Venkateswaran (2019). The model is an extension of the Hsieh and Klenow (2009) framework to include dynamic considerations in firm's investment decisions. Furthermore, in the model a number of forces can contribute to the observed dispersion in MRPK and MRPL, i.e.,: (i) capital adjustment costs, (ii) informational frictions, in the form of imperfect knowledge about firm-level fundamentals and (iii) firm-specific factors, meant to capture all other forces influencing investment decisions, such as unobserved heterogeneity in

[12] Another concern with our quantification relates to measurement error in firms' revenues and inputs. As Bils et al. (2018) point out, mismeasurement distorts our analysis because a firm's TFPR is higher when revenues are overstated and/or inpts are understated, the dispersion of measured TFPR is unequivocally biased upward. In our sample this form of mismeasurement is likely not a main concern, since we use tax-data. Though self reported by the firm, these data are thoroughly checked by the tax authorities.

markups and/or production technologies, financial frictions or institutional distortions. The Technical Appendix presents the main model equations. David and Venkateswaran (2019) model capital adjustment costs as a quadratic function:

$$\Phi(K_{is,t+1}, K_{is,t}) = \frac{\hat{\xi}}{2}\left(\frac{K_{is,t+1}}{K_{is,t}} - (1-\delta)\right)^2 K_{is,t}, \tag{15}$$

where δ is the depreciation rate.[13] The coefficient $\hat{\xi}$ determines the slope of the marginal adjustment costs. For example, if $\delta = 0.10$ and capital is doubled form time t tot $t+1$ ($K_{is,t+1} = 2K_{is,t}$), $\hat{\xi} = 1$ implies that the adjustment costs are 60.5% of the investment ($\Delta K_{is,t+1}$). There is a rather large variation in estimates of $\hat{\xi}$ in the literature. Investment-regressions, derived from the Q-theory of investment usually find values for $\hat{\xi}$ (>10), see for instance Hayashi and Inoue (1991). Estimates based on the method of moments are usually much lower, e.g., between 0.8 and 1.6 in Eberly et al. (2008) or close to zero in Cooper and Haltiwanger (2006) and Bloom (2009). This could be partly driven by different country samples. Asker et al. (2014) show that there is quite a large difference in the estimated $\hat{\xi}$ for the US (4.4) on the one hand and France (0.1) on the other.

The relevant model parameters to determine $\hat{\xi}$ can be estimated from the following dynamic model of the capital stock:

$$k_{is,t} = \pi_1 k_{is,t-1} + \pi_2 a_{is,t-1} + \eta_i + u_{is,t}, \tag{16}$$

where $k_{is,t}$ and $a_{is,t}$ are the log of capital $k_{is,t}$ and $TFPQ_{is,t}$, respectively. Moreover, π_1 measures capital adjustment costs, η_i measures firm-specific factors influencing investment decisions and the disturbance term $u_{is,t}$ captures all other possible frictions. In the hypothetical case of no adjustment costs of capital $\pi_1 = 0$ and when there are adjustment costs $\pi_1 > 0$. In the limit, when $\hat{\xi} \to \infty$ it holds that $\pi_1 \to 1$. The relevance of adjustment costs is straightforward to test with the null-hypothesis H_0: $\pi_1 = 0$ versus the alternative hypothesis H_1: $\pi_1 > 0$.

We estimate the dynamic panel data model in Eq. (16) directly using the fixed effects OLS estimator.[14] The estimate for π_1 is 0.62 and the standard error is 0.002, which implies a value of $\hat{\xi} \approx 0.4$. The estimate indicates adjustment costs are a relevant source of misallocation, although the coefficient of 0.4 is on the low-end of the estimations found in the literature. Based on the estimated coefficients David and Venkateswaran (2019) derive a measurement of the empirical relevance of adjustment costs. First, they assume that adjustment costs are the sole source of between-firm variation in MRPK. In that special case, Eq. (16) reduces to:

$$k_{is,t} = \pi_1 k_{is,t-1} + \pi_2 a_{is,t-1}, \tag{17}$$

where $a_{is,t}$ is assumed to follow a stationary AR(1) process is. We can use Eq. (17) to determine the variance of MRPK (σ^2_{MRPK}) when adjustment costs are the only source of misallocation. The Technical Appendix presents the formal derivation of σ^2_{MRPK} in this special case. Using our estimate of π_1 we find $\sigma^2_{MRPK} = 0.16$. This indicated that approximately 5% of the measured total MRPK variance –2.97 in our sample– can be attributed to adjustment costs.

Sector-specific estimates of π_1 in Eq. (16) vary roughly between 0.6 and 0.7. The resulting sector-specific estimates of ξ vary between 0.3 and 0.7. Taking the maximum ξ of 0.7 the adjustment costs still explain only around 5% of the observed dispersion in MRPK. We therefore conclude that capital adjustment costs are not a sizable source of MRPK dispersion in our sample. This outcome is in line with our previous outcome on the persistent nature of capital misallocation as documented in Section 3.

4.2 Alternative functional form

Another concern of the Hsieh and Klenow approach is the strict assumptions on the functional form of the production function, i.e., a CD-production function with firm-invariant capital elasticities and a substitution elasticity of 1 between labor and capital. We relax these assumptions one-by-one in Section 4.2.1 and Section 4.2.2. Our main finding is that only a small fraction of the observed misallocation can be attributed to one of these factors.

4.2.1 Firm-level heterogeneity in the production function

In the standard Hsieh and Klenow model the specified CD-production function has industry varying labor and capital shares, but these shares are constant within an industry, as can be seen from Eq. (1). In other words, the capital and labor elasticities are assumed to be equal for all firms within a five-digit industry. It follows from the model Eqs. (1)–(8) that *all* firm-specific variation in labor or capital-elasticities automatically lead to an increase in misallocation. We are able to relax this strong assumption, because we are able to calculate firm-specific capital shares based on the data. In the Technical Appendix we derive an expression for the dispersion in (the log of) MRPK where misallocation is solely caused by differences

[13] More general specification that also allow non-convex elements can be found in e.g., Cooper and Haltiwanger (2006), Bloom (2009) and Asker et al. (2014).

[14] Our estimation method is a simplification of the method of moments estimator of David & Venkateswaran (2019), who use a set of non-linear moment conditions to estimate the parameters. We are interested only in the adjustment costs parameter, hence the linear model in Eq. (16).

in firm-specific capital elasticities. By comparing this measure with the observed dispersion in (the log of) MRPK in the data we can get a sense of the impact on our results of the assumption of equal capital shares within an industry. We find that the overall impact is rather small. The total variance of MRPK in the data is 2.97, whilst our alternative firm-specific variation is only 0.03. This implies that only approximately 1% of the observed variance of the (log of) MRPK can be attributed to differences in firm-specific capital elasticities.

4.2.2 Constant elasticity of substitution production function

Another possible explanation for the observed misallocation misallocation could be that the assumption of unity substitution in the CD-production function in Eq. (1) is invalid. An alternative –often used– functional form is the CES-production function, where the substitution-elasticity between capital and labor is freely estimated and not a priori equalized to unity, i.e.,:

$$Y_{is,t} = A_{is,t}\left(\alpha_s K_{is,t}^{\frac{\sigma-1}{\sigma}} + (1-\alpha_s)\left(L_{is,t}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{18}$$

where σ is the substitution elasticity between capital and labor. The CES-production function reduces to the Hsieh and Klenow (2009) imposed CD-production function (1) when $\sigma = 1$. MRPK is defined as $P_{is,t}\frac{\partial Y}{\partial K}$, the product of marginal revenue ($P_{is,t}$) and marginal product ($\frac{\partial Y}{\partial K}$). In Technical Appendix we derive that, in the absence of wedges $\tau_{is,t}^{Y}$ and $\tau_{is,t}^{K}$, in this case the MRPK can be written as:

$$MRPK_{is,t} = \alpha_s^{1-\sigma} R_t^{\sigma}\left(\alpha_s^{\sigma} R_t^{1-\sigma} + (1-\alpha_s)^{\sigma} w_t^{1-\sigma}\right), \tag{19}$$

Notice that when $\sigma = 1$ (CD-production function), the expression reduces to $MRPK = R$. In the standard Hsieh and Klenow model the only source of variation in MRPK are the firm-specific wedges $\tau_{is,t}^{Y}$ and $\tau_{is,t}^{K}$. In the case of a CES-production-function ($\sigma \neq 1$) this is not any different since the parameters α and σ are not firm-specific, but only vary between industries.

We also considered a CES-production function with labor-augmenting technological process. In the Technical Appendix we derive that labor-augmenting technology can only have impact on our measure of misallocation if it varies between firms within the same five-digit industry. In policy discussions a concern is the negative impact of industrial robots on employment growth (Acemoglu and Restrepo 2020), which is an example of a labor saving technology. Only if the use of robots has unequal effects on employment growth across firms within an industry, the misallocation estimation based on a CES-production function will lead to different results compared to the base model of Hsieh and Klenow (2009). We leave it to future research to determine how relevant the variation in the adaption of such technologies varies between firms in the same industry.

Finally, we applied the quadratic translog approximation of the CES-production function. We estimated sector-specific translog functional forms, which are linear in the parameters, by OLS and calculated the resulting marginal revenue products of capital and labor. The implied pattern of dispersion in MRPK and MRPL is similar to the Cobb-Douglas specification in Fig. 1, although the increase in MRPK dispersion is less pronounced. We conclude that, relaxing the assumption of a unity substitution elasticity between capital and labor, does not alter our estimate of misallocation substantially.

4.3 Heterogeneous markups

In the standard Hsieh and Klenow (2009) model all firms within an industry have identical technologies and demand structure. Therefore, markups are identical as well. All dispersion in marginal revenue products is therefore attributed to misallocation, while heterogeneous markups could explain part of the observed MRPK and MRPL variance. To measure dispersion in markups we follow the approach of David and Venkateswaran (2019), which is based on the methodology of De Loecker and Warzynski (2012). We generalize the CD-production function (1) with intermediate inputs $M_{is,t}$, which have an industry specific elasticity ζ_s constant over time. Cost minimization then implies the following optimality condition (David and Venkateswaran 2019):

$$\frac{P_{is,t}^{M} M_{is,t}}{P_{is,t} Y_{is,t}} = (1-\zeta_s)\frac{MC_{is,t}}{P_{is,t}}, \tag{20}$$

where $MC_{is,t}$ are (unobserved) marginal costs of the firm. The optimality condition implies that the dispersion in the log share of intermediate inputs can be used as an estimator of the heterogeneity in log markups. The materials share, i.e., the left hand side of (20), is directly observed in the data. Using this estimator we find that heterogeneous markups explain around 25% of the variation in MRPK. More importantly, the cross-sectional variation in markups, see Fig. 14, is remarkly stable over our sample period corroborating the empirical findings of van Heuvelen et al. (2019).

Overall, the heterogeneity in markups does not drive the observed trend in MRPK dispersion and also not the fluctuations over time in MRPL dispersion. This conclusion is in line with the empirical findings of Gopinath et al. (2017).

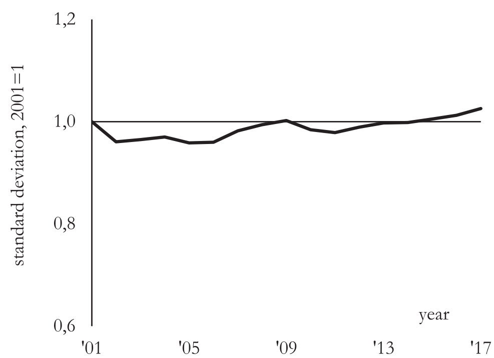


Fig. 14 Cross-sectional standard deviation of markups, 2001–2017, the Netherlands

4.4 Summary

Overall, our sensitivity analysis indicates that the factors raised in recent critique on the misallocation measure of Hsieh and Klenow (2009) seem to have a limited impact on the size of the misallocation loss we measured for the Netherlands. Capital adjustment costs lower our misallocation loss with 5 percentage points, firm-level heterogeneity in the production function with 1 percentage point, whilst the functional form has a negligible effect. The most sizable effect on our measure stems from heterogeneity in markups (25%).

Taken together these factors—not taking into account inter-dependencies of the factors—would lower our measured level of misallocation by roughly 31%, which would lower the estimated efficiency loss from 43% to 30% percent in 2001, and from 56% to 39% in 2017.[15] We have been mindful of the effect of these factors on the level of misallocation in the previous sections by focusing on the differences in misallocation over time, i.e., we normalized on the level of misallocation in the first year of our sample. The idea is that, following Hsieh and Klenow (2009), some "base level" misallocation can be understood as the result of misallocation originating from misspecification, and that a reasonable starting point is to assume that this level is constant over time (Restuccia and Rogerson 2017).

5 Conclusion

Misallocation of capital has been on the rise since the turn of the millennium in several European countries (see e.g., Gopinath et al. 2017, Gamberoni et al. 2016 and Calligaris et al. 2018). Our analysis focuses on the evolution of resource misallocation in the Netherlands. We use a very rich data set containing annual balance sheets as well as profit and loss statements for all Dutch firms that had to declare corporate income tax during the period 2001–2017. Our results shed new light on the evolution of capital and labor misallocation and underlines the importance of looking at the level and persistence of misallocation at the firm-level.

Using conventional measures of misallocation, i.e., the dispersion in firm-level marginal revenue products, we find a combination of steeply rising capital misallocation and relatively stable labor misallocation in the period 2001–2017, indicating that capital frictions account for most of the increase in measured misallocation in the Netherlands. Compared to a counterfactual efficient allocation we find that total misallocation has increased 14 percentage points in the period 2001–2017. The level of capital and labor misallocation is much larger in the services sector than the manufacturing sector. This result might be driven by less competitive pressures in the services sector compared to the manufacturing sector.

We have exploited panel data specifications to analyze the persistence of misallocation over time. Using an error components model we distinguish between permanent and transitory components of misallocation. We find that the observed increase in capital misallocation is permanent rather than transitory. The majority of the observed labor misallocation is transitory in nature. In other words, the persistence of labor misallocation is lower than capital misallocation and, on average, shocks in the allocation of labor die out in a couple of years.

Finally, our findings are quite insensitive to recently raised concerns with the model of Hsieh and Klenow (2009). We show that in our sample the measurement of misallocation is largely insensitive to observed heterogeneity in the production function and to the presence of capital adjustment costs. Although the contribution of heterogeneous markups is non-negligible, we conclude that the majority of the observed dispersion in marginal revenue products can be attributed to misallocation.

Acknowledgements The opinions expressed in this paper are the authors' personal views and do not necessarily reflect the position of De Nederlandsche Bank. This research has been funded by De Nederlandsche Bank. We are grateful to two anonymous referees, Job Swank, Peter van Els and discussants and participants at the International Industrial Organization Conference 2019 and research seminars at the Joint Research Center of the European Commission, Statistics Netherlands (CBS), CPB Netherlands Bureau for Economic Policy Analysis (CPB), and De Nederlandsche Bank for their valuable comments and stimulating suggestions.

Compliance with ethical standards

Conflict of interest The authors declare no competing interests.

[15] We assumed that adjustment costs and firm-level heterogeneity in the production function remained constant in the period 2001–2017.

6 Data set

Our data set contains the complete population of Dutch firms that legally had to declare corporate income tax during the period 2001–2017 (i.e., all firms with a legal person). These confidential micro data are provided by Statistics Netherlands (CBS: Centraal bureau voor de statistiek) and are based on a merger of the Dutch general business register (ABR: Algemeen Bedrijven Register) and corporate tax declarations (NFO: Financiën van niet-financiële ondernemingen). The matched data set includes annual balance sheets as well as profit and loss statements. We restrict our sample to non-agricultural private firms in the non-financial sectors. For multi-establishment firms we take the five-digit industry code (NACE Rev. 2) of the establishment with the largest number of employees. The raw data set contains 2,752,359 firm-year observations, and 491,313 unique firms for the period we analyzed (2001–2017).

The original data come as a repeated cross-section, with unique identifiers for the firm, and can be viewed as highly unbalanced panel data. We clean our data set for outliers and minimum number of observation per industry following previous research of e.g., Gamberoni et al. (2016) and Gopinath et al. (2017) by taking the following steps. First, we drop firm-year observations for which no fixed tangible assets are available. These steps reduce our sample to 2,305,977 firm-year observations and 396,235 unique firms. Second, we drop observation when the ratio of tangible assets to the balance sheet total is greater than one. This step reduces the sample by 915 observations. Next, we drop firm-year observations where the ratio of the wage bill to value added is in the top/bottom 1% of the distribution. This step reduces the sample by 42,798 observations. In addition, following Gopinath et al. (2017), we drop firm-year observations if the wage bill to value added ratio is larger than 1.1 or smaller than 0.1. This step reduces the sample by 265,133 and 55,226 observations, respectively. Finally, we drop industries where the minimum number of yearly observations or the average number of observations over the whole sample is less than 30. This step reduces our sample by 110,330 observations. After cleaning, our final data set contains 1,831,575 firm-year observations and 342,245 unique firms.

7 Technical Appendix

7.1 Misallocation with capital adjustment costs

David and Venkateswaran (2019) develop a model to distinguish the various sources of measured capital misallocation, i.e., dispersion in MRPK. They distinguish capital adjustment costs, informational frictions and firm-specific factors. We first describe the main model equations in David and Venkateswaran (2019). Next, we derive the variance of MRPK when adjustment costs are the only source of misallocation.

7.1.1 Main model equations David and Venkateswaran (2019)

For ease of exposition, we suppress the sector subscript, hence consider a single sector only. The main equations of the model, which are in logarithms, are as follows. An idiosyncratic firm-specific fundamental, which can be interpreted as demand shifter and/or level of efficiency, is generated by:

$$a_{i,t} = \rho a_{i,t-1} + \mu_{i,t}, \quad \mu_{i,t} \sim i.i.d.(0, \sigma_\mu^2), \tag{B.1}$$

where $0 < \rho < 1$ measures the persistence of firm-fundamentals. The capital distortion is modeled as:

$$\tau_{i,t} = \gamma a_{i,t} + \varepsilon_{i,t} + \chi_i, \quad \varepsilon_{i,t} \sim i.i.d.(0, \sigma_\varepsilon^2), \quad \chi_i \sim i.i.d.(0, \sigma_\chi^2), \tag{B.2}$$

where γ models the correlation of the distortion with the firm-fundamental. Furthermore, ε_{it} and χ_i are the uncorrelated time-varying and permanent components respectively. The equation for capital is:

$$k_{i,t+1} = \psi_1 k_{i,t} + \psi_2(1+\gamma)\mathbb{E}_{i,t}\left[a_{i,t+1}\right] + \psi_3\varepsilon_{i,t+1} + \psi_4\chi_i, \tag{B.3}$$

where

$$\begin{aligned} \xi\left(\beta\psi_1^2 + 1\right) &= \psi_1((1+\beta)\xi + 1 - \alpha), \\ \psi_2 &= \tfrac{\psi_1}{\xi(1-\beta\rho\psi_1)}, \\ \psi_3 &= \tfrac{\psi_1}{\xi}, \\ \psi_4 &= \tfrac{1-\psi_1}{1-\alpha}. \end{aligned}$$

The parameter β is the discount rate, which is an element of the optimized dynamic profit function of the firm. The parameter $\alpha = \frac{\alpha_1}{1-\alpha_2}$ where α_1 and α_2 are proportional to the capital and labor elasticities of the firm-level CD-production function. Finally, the marginal revenue product of capital (MRPK) is equal to:

$$MRPK_{i,t} = p_{i,t} + y_{i,t} - k_{i,t}, \tag{B.4}$$

where $P_{i,t}$ is the price of good i and $y_{i,t}$ is firm-level output. The assumed market structure furthermore implies:

$$p_{i,t} = -\frac{1}{\theta}(y_{i,t} - y_t) + \hat{a}_{i,t}, \tag{B.5}$$

where $a_{i,t} = \frac{1}{1-\alpha_2}\hat{a}_{i,t}$ and $\alpha_j = (1-\frac{1}{\theta})\hat{\alpha}_j$, $j = 1, 2$. Furthermore, it can be shown that profit maximization yields the following for labor:

$$l_{i,t} \approx \frac{1}{1-\alpha_2}(\hat{a}_{i,t} + \alpha_1 k_{i,t}), \tag{B.6}$$

where ≈ means that we left out terms without cross-sectional dimension.

7.1.2 Derivation of σ^2_{MRPK} when adjustment costs are the only source of misallocation

Using the model's equations we can rewrite Eq. (B.4) as:

$$\begin{aligned} MRPK_{i,t} &= -\tfrac{1}{\theta}y_{i,t} + \tfrac{1}{\theta}y_t + \hat{a}_{i,t} + y_{i,t} - k_{i,t} \\ &= \left(1-\tfrac{1}{\theta}\right)\left(\hat{\alpha}_1 k_{i,t} + \hat{\alpha}_2 l_{i,t}\right) + (1-\alpha_2)a_{i,t} - k_{i,t} + \tfrac{1}{\theta}y_t \\ &= \alpha_1 k_{i,t} + \alpha_2 l_{i,t} + (1-\alpha_2)a_{it} - k_{it} + \tfrac{1}{\theta}y_t \\ &\approx \alpha_1 k_{i,t} + \alpha_2\left(a_{it} + \tfrac{\alpha_1}{1-\alpha_2}k_{i,t}\right) + (1-\alpha_2)a_{i,t} - k_{i,t} \\ &= \tfrac{\alpha_1+\alpha_2-1}{1-\alpha_2}k_{i,t} + a_{i,t}, \end{aligned} \tag{B.7}$$

where ≈ means that we left out terms without cross-sectional dimension. The reason is that these terms will not contribute to dispersion in MRPK, which is defined as:

$$\sigma^2_{MRPK} = \left(\frac{\alpha_1+\alpha_2-1}{1-\alpha_2}\right)^2\sigma^2_k + \sigma^2_a + 2\left(\frac{\alpha_1+\alpha_2-1}{1-\alpha_2}\right)\sigma_{ka}, \tag{B.8}$$

where

$$\sigma^2_a = \frac{\sigma^2_\mu}{1-\rho^2},$$

due to the assumption that the firm-fundamental follows a stationary AR(1) process.

The model distinguishes three main sources of dispersion in MRPK: (1) capital adjustment costs; (2) imperfect information; (3) distortions. In absence of adjustment costs we have:

$$\psi_1 = 0, \quad \psi_2 = \psi_3 = \psi_4 = \frac{1}{1-\alpha},$$

while in case of perfect foresight we have:

$$\mathbb{E}_{it}\left[a_{i,t+1}\right] = a_{i,t+1},$$

and when there are no distortions we have:

$$\gamma = 0, \quad \sigma^2_\varepsilon = \sigma^2_\chi = 0.$$

Each of these three origins will show up in MRPK dispersion mainly through dispersion in capital (σ^2_k).

David and Venkateswaran (2019) assume the following:

$$\mathbb{E}_{i,t}\left[a_{i,t+1}\right] = \rho a_{i,t} + s^*_{i,t+1}, \tag{B.9}$$

where the error $s^*_{i,t+1}$ depends on the information a firm has on the next innovation $\mu_{i,t+1}$. We then have:

$$k_{i,t+1} = \psi_1 k_{i,t} + \psi_2(1+\gamma)\rho a_{i,t} + u_{i,t+1} + \psi_4\chi_i, \tag{B.10}$$

where $u_{i,t+1} = s^*_{i,t+1} + \psi_3\varepsilon_{i,t+1} \sim i.i.d.(0, \sigma^2_u)$. Using the lag operator, the model can be written as

$$k_{i,t+1} = \psi_2(1+\gamma)\rho\frac{1}{(1-\psi_1 L)(1-\rho L)}\mu_{it} + \frac{1}{(1-\psi_1 L)}u_{i,t+1} + \frac{\psi_4}{1-\psi_1}\chi_i. \tag{B.11}$$

The development in a firms' capital is the sum of three orthogonal components (μ_{it}, $u_{i,t+1}$ and χ_i are uncorrelated), which are an AR(2), AR(1) and i.i.d. process respectively. The AR(2) process:

$$\phi_{i,t+1} = \frac{1}{(1-\psi_1 L)(1-\rho L)}\mu_{i,t+1}$$

has variance:

$$\sigma^2_\phi = \left(1 - (\psi_1+\rho)\mathrm{corr}\left(\phi_{i,t+1}, \phi_{it}\right) + \psi_1\rho\,\mathrm{corr}\left(\phi_{i,t+1}, \phi_{i,t-1}\right)\right)^{-1}$$

with

$$\begin{aligned} \mathrm{corr}\left(\phi_{i,t+1}, \phi_{i,t}\right) &= \tfrac{\psi_1+\rho}{1+\psi_1\rho}, \\ \mathrm{corr}\left(\phi_{i,t+1}, \phi_{i,t-1}\right) &= \tfrac{(\psi_1+\rho)^2}{1+\psi_1\rho} - \psi_1\rho. \end{aligned}$$

Hence, we find that dispersion in capital is:

$$\sigma^2_k = (\psi_2(1+\gamma)\rho)^2\sigma^2_\phi + \frac{1}{1-\psi_1^2}\sigma^2_u + \left(\frac{\psi_4}{1-\psi_1}\right)^2\sigma^2_\chi.$$

Consider now the case $\sigma^2_u = \sigma^2_\chi = 0$, i.e., only adjustment costs matter for dispersion in MRPK. The model reduces to

$$k_{i,t+1} = \psi_1 k_{i,t} + \psi_2(1+\gamma)\rho a_{i,t}, \tag{B.12}$$

which is basically Eq. (17). By repeated substitution we write:

$$k_{i,t+1} = \psi_2(1+\gamma)\rho\sum_{s=0}^{\infty}\psi_1^s a_{i,t-s}, \tag{B.13}$$

hence the covariance between capital $k_{i,t+1}$ and fundamental a_{it} becomes:

$$\begin{aligned}\sigma_{ka} &= \mathbb{C}\mathrm{ov}\left(\psi_2(1+\gamma)\rho\sum_{s=0}^{\infty}\psi_1^s a_{i,t-s}, a_{i,t+1}\right)\\ &= \psi_2(1+\gamma)\rho\sum_{s=0}^{\infty}\psi_1^s\mathbb{C}\mathrm{ov}\left(a_{i,t-s}, a_{i,t+1}\right)\\ &= \psi_2(1+\gamma)\rho^2\sum_{s=0}^{\infty}\psi_1^s\rho^s\sigma_a^2\\ &= \tfrac{\psi_2(1+\gamma)\rho^2}{1-\psi_1\rho}\sigma_a^2.\end{aligned} \tag{B.14}$$

Substituting σ_a^2, σ_k^2 and σ_{ka} we find the analytical expression for σ^2_{MRPK} for the specific case that only adjustment costs matter for MRPK dispersion.

7.2 Derivation of σ^2_{MRPK} with firm-level heterogeneity in the production function

Consider the following generalized production function:

$$Y_{is,t} = A_{is,t}K_{is,t}^{\alpha_{is,t}}L_{is,t}^{1-\alpha_{is,t}}, \tag{B.15}$$

in which capital intensities are idiosyncratic and time varying. Suppose no distortions exist. The first-order conditions for profit maximization are:

$$P_{is,t}\frac{\partial Y}{\partial L} = w_{s,t}, \tag{B.16}$$

$$P_{is,t}\frac{\partial Y}{\partial K} = R_{s,t}, \tag{B.17}$$

with

$$\frac{\partial Y}{\partial K} = A_{is,t}\alpha_{is,t}K_{is,t}^{\alpha_{is,t}-1}L_{is,t}^{1-\alpha_{is,t}} = \alpha_{is,t}\frac{Y_{is,t}}{K_{is,t}}, \tag{B.18}$$

$$\frac{\partial Y}{\partial L} = \ldots = \left(1-\alpha_{is,t}\right)\frac{Y_{is,t}}{L_{is,t}}. \tag{B.19}$$

Combining Eq. (B.17) and Eq. (B.18) and omitting constants we have:

$$MRPK_{is,t} = \log\frac{P_{is,t}Y_{is,t}}{K_{is,t}} \approx -\log\left(\alpha_{is,t}\right), \tag{B.20}$$

hence,

$$\mathbb{V}\mathrm{ar}\left(MRPK_{is,t}\right) = \mathbb{V}\mathrm{ar}\left(\log\left(\alpha_{is,t}\right)\right). \tag{B.21}$$

Summarizing, in a model without distortions, but including heterogeneous technologies, all dispersion in MRPK is caused by dispersion in production technologies.

Following Hsieh & Klenow (2009) we use 1 minus the labor share to estimate the elasticity of output with respect to capital. For the purpose of estimating dispersion at the level of the firm, we use firm-level labor shares.

7.3 Derivation of σ^2_{MRPK} in case of a CES-production function

For ease of exposition we suppress time subscripts. Consider the same market structure as in Hsieh & Klenow (2009), hence the demand curve and price setting for an individual firm's product follow from the first-order condition:

$$P_sY_s^{\frac{1}{\sigma}}Y_{is}^{-\frac{1}{\sigma}} = P_{is}. \tag{B.22}$$

However, the individual firm has the CES-production function (18) with both a neutral productivity component A_{is} and labor augmenting productivity B_{is} (see e.g., Raval, 2019). Define $\rho = \frac{\sigma-1}{\sigma}$ with σ the substitution elasticity between capital and labor. Then we can express the CES-production function (18) as:

$$Y_{is} = A_{is}(\alpha_sK_{is}^{\rho} + (1-\alpha_s)(B_{is}L_{is})^{\rho})^{\frac{1}{\rho}}. \tag{B.23}$$

Note that the CD-production function is the special case $\sigma = 1$ or $\rho = 0$. The marginal products are:

$$\frac{\partial Y}{\partial L} = A_{is}(\alpha_sK_{is}^{\rho} + (1-\alpha_s)(B_{is}L_{is})^{\rho})^{\frac{1-\rho}{\rho}}(1-\alpha_s)\rho B_{is}^{\rho}L_{is}^{\rho-1}, \tag{B.24}$$

$$\frac{\partial Y}{\partial K} = A_{is}(\alpha_sK_{is}^{\rho} + (1-\alpha_s)(B_{is}L_{is})^{\rho})^{\frac{1-\rho}{\rho}}\alpha_s\rho K_{is}^{\rho-1}, \tag{B.25}$$

hence,

$$\frac{\frac{\partial Y}{\partial L}}{\frac{\partial Y}{\partial K}} = \frac{1-\alpha_s}{\alpha_s}B_{is}^{\rho}\left(\frac{K_{is}}{L_{is}}\right)^{1-\rho}. \tag{B.26}$$

In the absence of distortions profits of each producer are given by:

$$\pi_{is} = P_sY_s^{\frac{1}{\sigma}}Y_{is}^{\frac{\sigma-1}{\sigma}} - w_sL_{is} - R_sK_{is}, \tag{B.27}$$

Each producer chooses L_{is} and K_{is} to maximize profits:

$$\max_{L_{is},K_{is}} \pi_{is}. \tag{B.28}$$

The first order conditions for profit maximization are:

$$P_s Y_s^{\frac{1}{\sigma}} \left(\frac{\sigma - 1}{\sigma}\right) Y_{is}^{-\frac{1}{\sigma}} \frac{\partial Y}{\partial L} = w_s, \tag{B.29}$$

$$P_s Y_s^{\frac{1}{\sigma}} \left(\frac{\sigma - 1}{\sigma}\right) Y_{is}^{-\frac{1}{\sigma}} \frac{\partial Y}{\partial K} = R_s. \tag{B.30}$$

Dividing both equations and rearranging we get for the capital-labor ratio:

$$\frac{K_{is}}{L_{is}} = \left(\frac{\alpha_s}{1 - \alpha_s}\right)^{\frac{1}{1-\rho}} B_{is}^{\frac{-\rho}{1-\rho}} \left(\frac{w_s}{R_s}\right)^{\frac{1}{1-\rho}}. \tag{B.31}$$

Note that when $\rho = 0$, i.e., CD-production function, we get:

$$\frac{K_{is}}{L_{is}} = \frac{\alpha_s}{1 - \alpha_s} \frac{w_s}{R_s}, \tag{B.32}$$

which does not depend on B_{is}.

The firm's output price P_{is} will be set as a fixed mark up $\frac{\sigma}{\sigma-1}$ over the firm's marginal costs. In case of the CES-production function (18), marginal costs are:

$$MC_{is} = \frac{\alpha_s^{\sigma} R_s^{1-\sigma} + (1 - \alpha_s)^{\sigma} \left(\frac{w_s}{B_{is}}\right)^{1-\sigma}}{A_{is}\left(\alpha_s \left(\frac{R_s}{\alpha_s}\right)^{1-\sigma} + (1 - \alpha_s)\left(\frac{w_s}{(1-\alpha_s)B_{is}}\right)^{1-\sigma}\right)^{\frac{\sigma}{\sigma-1}}}, \tag{B.33}$$

and

$$P_{is} = \left(\frac{\sigma}{\sigma - 1}\right) MC_{is}. \tag{B.34}$$

Combining these equations after some algebra we find that:

$$\begin{aligned} MRPK_{is} &= P_{is} \tfrac{\partial Y}{\partial K} \\ &= \alpha_s^{1-\sigma} R_s^{\sigma} \left(\alpha_s^{\sigma} R_s^{1-\sigma} + (1 - \alpha_s)^{\sigma} \left(\tfrac{w_s}{B_{is}}\right)^{1-\sigma}\right). \end{aligned} \tag{B.35}$$

Without component B_{is}, i.e., the standard CES-production function, the result in Eq. (19) follows. The last equation shows that, for labor augmenting or labor saving productivity to cause variation in MRPK, it should vary across firms within the same industry.

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