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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Misallocation and Productivity Growth: a Meta-analysis*

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Abstract

We use a meta-analysis to quantify the impact of misallocation of production factors on aggregate productivity. A key estimate in empirical studies on misallocation is the implied aggregate total factor productivity (TFP) loss due to the sub-optimal allocation of resources across firms. In our meta-analysis, we correlate this effect size with various study characteristics. First, we find that the TFP growth effect size is smaller than the level effect size. Second, we make a distinction between studies following a direct or indirect approach, where the former relates misallocation to one or more specific factors while the latter quantifies the overall effect of all possible sources. We find that studies following a direct approach generally report a smaller TFP loss than those using an indirect approach. Third, we find that the extent of misallocation and the corresponding productivity loss depends on the country of analysis. In particular, there is a negative correlation between TFP loss and the level of income.

Keywords: meta-analysis; misallocation; productivity.
JEL-Codes: C40, D24, O47.

*The views expressed in this paper are solely those of the authors and may differ from official views of Bank of Canada, De Nederlandsche Bank or the Eurosystem. No responsibility should be attributed to these institutions.

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1 Introduction

Misallocation of production factors has been the dominant explanation of productivity differences across countries (Hsieh and Klenow, 2009; Bartelsman et al., 2013; Jones, 2016). Misallocation occurs when there are distortions that affect the allocation of production factors, i.e. capital and labor, across heterogeneous producers of the same good. Some firms are taxed while others may be subsidized. In this context, misallocation of production factors results in a lower aggregate productivity level because the economy does not operate at the efficient frontier. Misallocation at the level of the firm is especially harmful for aggregate productivity when it is correlated with the level of firm level productivity (Restuccia and Rogerson, 2008). The empirical evidence suggests that the productivity loss caused by misallocation can be large, see e.g. Hsieh and Klenow (2009) among others.

Many countries have experienced an aggregate productivity slowdown in the last decades. The observed increase in misallocation over time could be an important factor behind the declining Total Factor Productivity (TFP) growth rates. Recent studies have shown that empirical measures of misallocation, based on the dispersion in marginal revenue products, have increased over time within countries (Gamberoni et al., 2016, Gopinath et al., 2017; Calligaris et al., 2018; Bun and de Winter, 2022). In this study we carry out a meta-analysis of the extensive empirical literature quantifying the TFP impact of misallocation. The key estimate in empirical studies on misallocation is the TFP loss due to misallocation. This loss is calculated by comparing realized TFP with a counterfactual efficient TFP in an economy without input factor distortions. We correlate the TFP loss estimates with study characteristics to explore which of the characteristics of the empirical analyses are most important and relevant. The analysis facilitates the assessment of the "true" impact of misallocation on TFP growth. By "true" we refer to the average impact found in empirical studies after controlling for all characteristics of those studies that might bias the result. In our meta-analysis we quantify both the differences between countries and development over time.

The remainder of our paper is structured as follows. Section 2 describes the sources of misallocation. Section 3 provides the set up and methodology for the meta-analysis. Section 4 reports the empirical results and some robustness checks. Section 5 concludes.

2 A Primer on Sources of Misallocation

Misallocation occurs when there are distortions that affect the allocation of production factors across firms. Such allocative distortions originate from many sources and often arise from government policies. Examples include taxes, tariffs, restrictions, regulation and uncertainty.[1] For instance, tariffs and other forms of trade protection may distort the allocation of resources across firms. Guner and Xu (2008) analyse the impact of size-dependent policies leading to output distortions. As another example, Misch and Saborowski (2018) suggest that potential reforms which aim at reducing distortions close to the domestic frontiers would increase TFP by some 13 percent in Mexican States.

Financial frictions are typically seen as an important source for the misallocation of capital (Banerjee and Duflo, 2005; Buera et al., 2015; Gilchrist et al., 2013). Due to credit market imperfections, many firms have limited access to capital markets and hence, they rely on other forms of financing. For instance, Midrigan and Xu (2014) use plant-level data for Korean manufacturing and find that borrowing constraints contribute to losses from misallocation by 4.7 percent of the TFP decline. Firms subject to such financial frictions are often smaller, and face higher borrowing costs.

Another source of misallocation is distortions due to capital or labour adjustment costs. In this respect, corporate tax policy is an important determinant of firms' investment decisions. More generally, changing the level of capital within a firm implies adjustment costs due to installation and training as well as time-to-build. An example of labour adjustment costs resulting from government policy are the firing costs as analysed by Hopenhayn and Rogerson (1993). They empirically show that a tax equal to one year's wage reduces TFP by more than two percent in United States (US) manufacturing.

The effects of firm-level uncertainty are typically considered to be a distortion on firms' investment activities. Bloom (2009) shows that high uncertainty leads firms to temporarily halt their investment and hiring operations. This pause in activity results in slower input reallocation across units and consequently in productivity growth. David and Venkateswaran (2019) show that uncertainty about future productivity, although significant, reduce aggregate TFP by 1-3 percent only. Hosono et al. (2017) emphasize the role of product differentiation and study the effects of uncertainty on aggregate TFP in Japan. Industries of less differentiated goods can achieve significantly larger TFP gains from less uncertainty, ranging between 1.5 and 6 percent, compared to industries of more differentiated goods.

[1] See Restuccia and Rogerson (2017) for an extensive overview.

Finally, the extent of a firms' market power is a significant driver of misallocation. Firm level markups in a monopolistic competition framework imply a sub-optimal allocation of production across firms. Recent studies (David and Venkateswaran, 2019; Ruzic and Ho, 2021; Bun and de Winter, 2022) find an important role for heterogeneous markups in explaining the dispersion of firm-level distortions.

The recent literature on productivity has also questioned the underlying model assumptions related to measurement of distortions and hence, misallocation. A crucial question is whether one should attribute measured distortions to misallocation, or alternative explanations for the observed distortions. In other words, are the estimated distortions due to misallocation or model misspecification? For example, Hsieh and Klenow (2009) assume that all firms charge the same markup and have constant returns to scale. Using this model, Ruzic and Ho (2021) find an increase of misallocation over time in the US. In a generalized setup, however, they find declining misallocation instead. As another example, Bun and de Winter (2022) show that allowing for heterogeneous production technologies across firms, as well as allowing for a non-unitary substitution between the production factors labor and capital, does not have an impact on the measured distortions. Therefore, model assumptions generally matter for the quantitative results and the estimated degrees of misallocation. The contribution of pure misallocation becomes smaller when model misspecification is controlled for.

Other recent studies combine multiple sources of misallocation in a unifying framework, instead of restricting their analysis to each one separately. David and Venkateswaran (2019) investigate the contributions of adjustment costs, uncertainty and policy distortions to capital misallocation in the US and China. Their findings suggest that adjustment costs and informational frictions have economic influence in observed investment dynamics. However, these factors account for a small fraction in the estimated misallocation (less than 10 percent), leading to only moderate losses in aggregate TFP. Similarly, uncertainty over future productivity is significant but not large enough to explain a considerable part of the dispersion in average revenue products, which are typically used as estimates of misallocation. Firm-specific factors such as variation in markups or production technologies account for a larger share, i.e. 27 and 58 percent for China and US, respectively. Overall, in both economies, factors other than technological and informational frictions play a significant role in determining capital allocations. Unobserved heterogeneity, i.e. firm level variation in markups or technologies, is a possible indicator of the observed misallocation in US. However, other market frictions or institutional/policy-related distortion are the main drivers of misallocation among Chinese firms.

Bun and de Winter (2022) use the model of David and Venkateswaran (2019) to perform a sensitivity analysis of their main results on capital and labor misallocation in the Netherlands. They account for adjustment costs of capital, firm-level heterogeneity in the production function and heterogeneous markups. Their findings indicate that capital adjustment costs lower misallocation loss with 5 percentage points, and firm-level heterogeneity in the production function with 1 percentage point. The most sizeable effect on the measure stems from heterogeneity in markups (25%). Taken together, these factors—not taking into account interdependencies of the factors—would explain roughly 31% of the measured level of misallocation.

Le (2022) examine multiple sources of misallocation for Vietnam: adjustment costs, uncertainty and policy distortions. The contribution of adjustment costs and transitory policy distortions are negligible, accounting for 1.1 percent and 0 percent of total capital misallocation. On the contrary, permanent policy distortions account for 81 percent of capital misallocation and lead to a TFP gap of 110 percent. Uncertainty makes up 26.1 percent of capital misallocation and causes a TFP loss of 35.4 percent. As a robustness check, the paper exploits the specification of David and Venkateswaran (2019) and the empirical results are benchmarked against China and US. The largest source of misallocation in all three countries comes from permanent policy distortions.

3 Data collection and meta-analysis

The key estimate in empirical studies on misallocation is the TFP loss due to misallocation. This TFP loss is calculated by comparing realized TFP with a counterfactual efficient TFP in an economy without input factor distortions. We collect estimates of misallocation from 72 primary studies, where the effect size is measured by the reported TFP loss.[2] Some studies report an estimated level of TFP loss for the study period, while others focus on the growth rate of TFP over time. In this paper we distinguish the level and growth effects of misallocation, and report our results on both accounts. The primary studies have been published over the period 2008-2022.

The number of estimates of the TFP loss per study varies from 1 to 187, with a total of 1786 observations. We correlate the TFP loss estimates with study characteristics to explore which of the characteristics of the empirical analyses are most important and relevant.

An important goal of the meta-analysis is to estimate the “true” effect size of misal-

[2]The full list of references is available in Appendix B.

location on aggregate TFP. If all studies in the meta-analysis were equally precise and independent, we could simply compute the mean of the effect sizes. In our sample, the average TFP loss is equal to 40.18% (standard error [s.e.] is 1.16%). This is a rather substantial effect size and depends largely on particular study characteristics. However, the majority of the 72 studies report multiple estimates, and estimates from the same study are likely to be correlated.

Figure 1 provides a funnel plot to examine the presence of potential small study biases in our database. Because we do not observe estimated standard errors in most primary studies in our sample, we use the inverse number of firms in each primary study as a measure of standard errors. The larger the number of firms, the higher the precision of the estimated effect size. The funnel plot suggests that some studies in our sample report large misallocation effect sizes relative to their standard error. This results in an asymmetric distribution, which could indicate some evidence of publication bias as large TFP losses seem over-represented in the data. However the asymmetric distribution could also be a result of heterogeneity across the studies. We explore this heterogeneity for the remainder of our paper with the meta-regression analysis.

One can view the data as a highly unbalanced panel dataset with the number of cross-section units equal to the number of primary studies. We take into account intra-study correlation of reported effect size by a random effects panel data model. We assume that due to unobserved heterogeneity, each primary study has its own effect size, which by itself is a random draw of an underlying distribution. The generalized least squares estimate of its population mean is equal to 38.6% (s.e. is 4.21%). Although smaller than the unweighted sample mean, this estimate still indicates that the TFP loss from misallocation can be potentially large.[3]

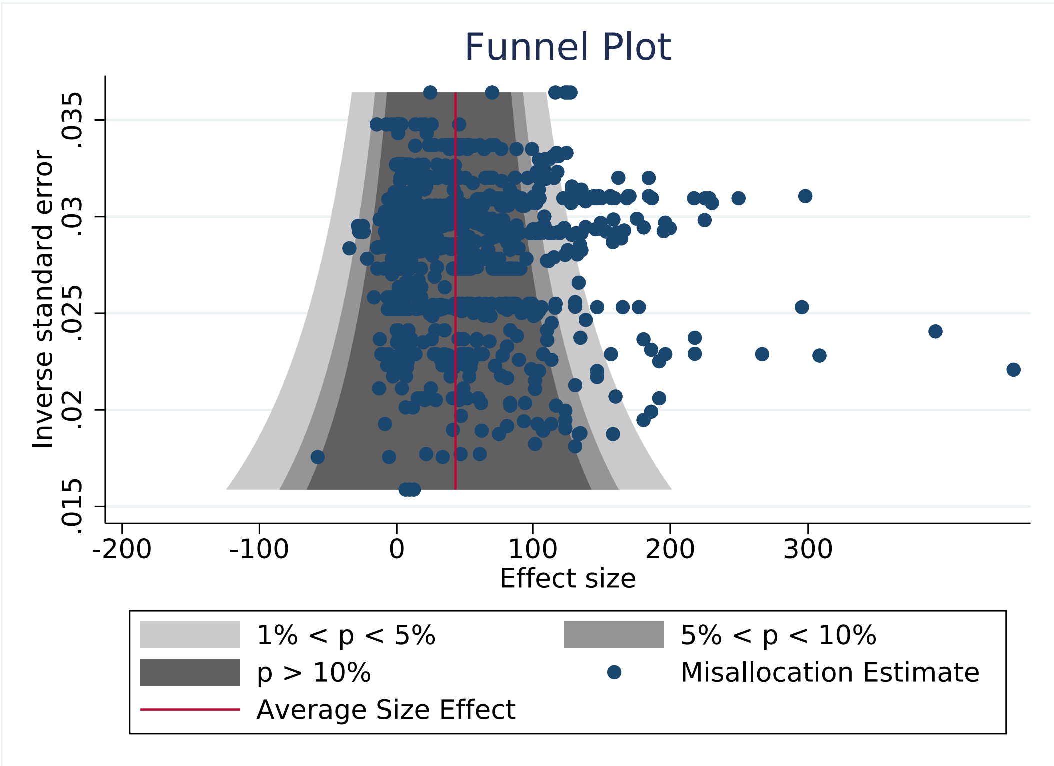
In the next section we use meta-regressions to explain why the estimated TFP loss varies within and between primary studies. We follow as much as possible the best available practices for meta-analysis as described by Nelson and Kennedy (2009). We exploit the following regression model to analyse the methodological differences between misallocation studies:

$$y_{ij} = \mu + \beta^T x_{ij} + \alpha_i + \epsilon_{ij}, \tag{1}$$

where y_{ij} is the j^{th} productivity loss estimate of primary study i, x_{ij} are meta-regressors measuring study characteristics and β their marginal effects, μ is the overall mean effect size, α_i is a study specific effect and ϵ_{ij} is an idiosyncratic error term. The meta-regressors

[3]It should be noted, however, that in the literature there is a debate going on focusing on the (mis)specification of the models underlying such TFP loss calculations (Haltiwanger et al., 2018; Ruzic and Ho, 2021; Bils et al., 2020; Bun and de Winter, 2022).

Figure 1: A funnel plot with misallocation estimates (effect size) on the x-axis, and a measure of the inverse standard error for each estimate on the y-axis. We use the inverse number of firms as our measure of standard error for this figure. The red line corresponds to the average effect size estimated with random effects.



explain systematic variation between studies. We will distinguish the following potentially relevant study characteristics: (1) benchmark TFP; (2) direct and indirect approach; (3) country/area characteristics; (4) year of publication; (5) nuisance parameters.

4 Results

We start our analysis by presenting the average estimates of misallocation growth and level effects for all primary studies in Figure 2. The series are calculated as weighted averages of the primary studies: each data point is assigned a weight of N/m, where N denotes the number of firms in the study, and m denotes the number of data points per primary study. The former ensures that each study receives an equal weight ceteris paribus, while the latter ensures that studies with larger datasets receive more weight.

Figure 2 shows that the growth effect is generally smaller than the level effect over the sample period. The time series are accompanied by fitted linear trend lines, which show that misallocation is persistent and the average estimates have generally tended to increase over time both in the growth and level space.

Next, the empirical results from estimating a random-effects meta-regression (1) are presented in Table I. We consider a number of specifications with different regressors: Column (I) reports the average size effect (i.e. a regression without any study characteristics included), which is 38.6% as discussed above.

Column (II) reports our baseline specification for misallocation, where we include dummy variables for the growth effect size, direct approach, US and EA-specific effect sizes, and publication year as regressors. In columns (III)-(VIII) we consider alternative specifications of the baseline regression: Column (III) includes the nuisance parameter elasticity of substitution;[4] column (IV) further adds per capita income, while column (V) includes a composite macro index;[5] columns (VI) and (VII) estimate the baseline regression again, but for US and EA subsamples; and finally column (VIII) includes dummies for various categories of direct approaches. In what follows, we discuss the effects of each regressor in detail. We further provide robustness checks on our baseline results using fixed-effects OLS, pooled OLS and WLS estimators.

[4]Elasticity of substitution typically appears in papers using the Hsieh and Klenow (2009) approach or extensions thereof, which makes up the majority of our database. Nevertheless, not all papers include this parameter, and therefore we include it in a separate specification.

[5]The macro index is a composite measure constructed with a standard principal components regression. The underlying variables are comprised of comprised of GDP per capita, Gini coefficient, inflation and unemployment.

Figure 2: Weighted averages of estimated misallocation growth and levels over time for all studies. Weights are based on the number of entries and number of firms in each primary study. Studies that do not report the number of firms or observations in their analysis are excluded from the calculations in this figure.

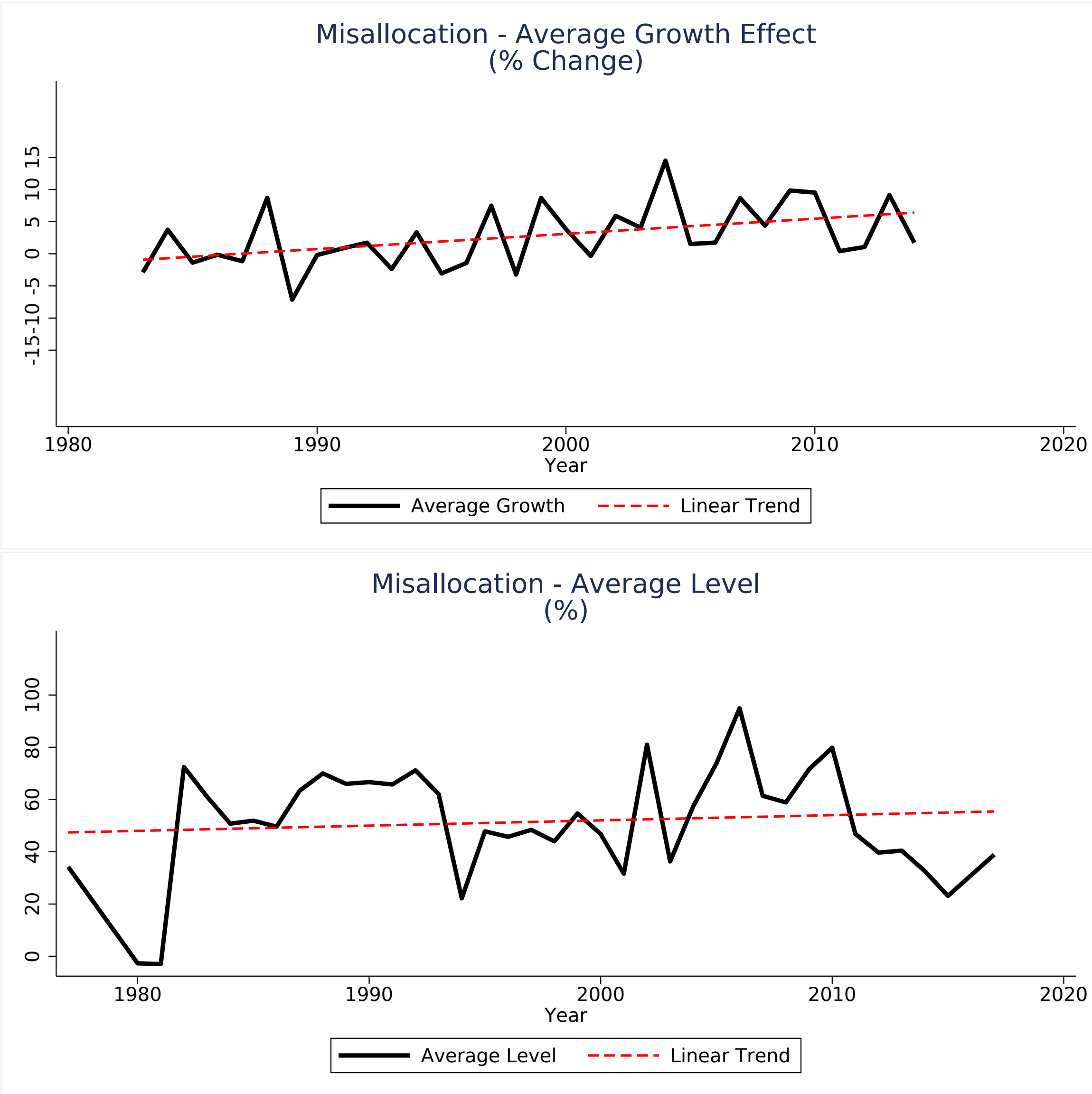


Table I: Random effects meta-regressions

	I	II	III	IV	V	VI - Only US	VII - Only EA	VIII - Including Direct
Growth Effect Size		-50.81***	-53.97***	-53.52***	-53.13***	-27.80***	-40.16***	-52.64***
		(6.65)	(4.59)	(4.74)	(5.05)	(9.10)	(13.01)	(5.31)
Direct Approach		-30.03***	-31.77***	-31.28***	-32.96***	-21.35***	-2.03	
		(5.97)	(9.42)	(9.43)	(11.35)	(8.25)	(3.40)	
US		-26.58***	-33.05***					
		(6.05)	(5.97)					
EA		-14.37***	-17.29***					
		(5.01)	(5.74)					
Pub. Year		0.01	-0.56	-0.36	-1.15	-0.21	-1.29	-0.90
		(1.07)	(1.44)	(1.48)	(1.75)	(1.70)	(2.01)	(1.92)
Elasticity of Subst.			3.12*	3.17*	3.46			3.41
			(1.81)	(1.92)	(2.84)			(2.85)
Per Capita Inc.				-6.96***				
				(2.07)				
Macro Index					-8.12*			-8.01*
					(4.15)			(4.19)
Dummy - Fin. Frictions								-36.94*
								(21.54)
Dummy - Markups								-41.94***
								(15.13)
Dummy - Regulation								-54.96***
								(9.27)
Dummy - Uncertainty								-55.88***
								(14.88)
Dummy - Capital Adj. Costs								-58.50***
								(17.63)
Dummy - Other Sources								-23.81
								(17.43)
Constant	38.60***	66.23***	70.65***	63.13***	66.94***	38.95***	47.83***	66.98***
	(4.21)	(5.06)	(5.57)	(4.70)	(5.79)	(7.85)	(8.68)	(6.27)
Observations	1786	1786	1380	1320	1066	170	351	1066
r2								

Heteroskedasticity-robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

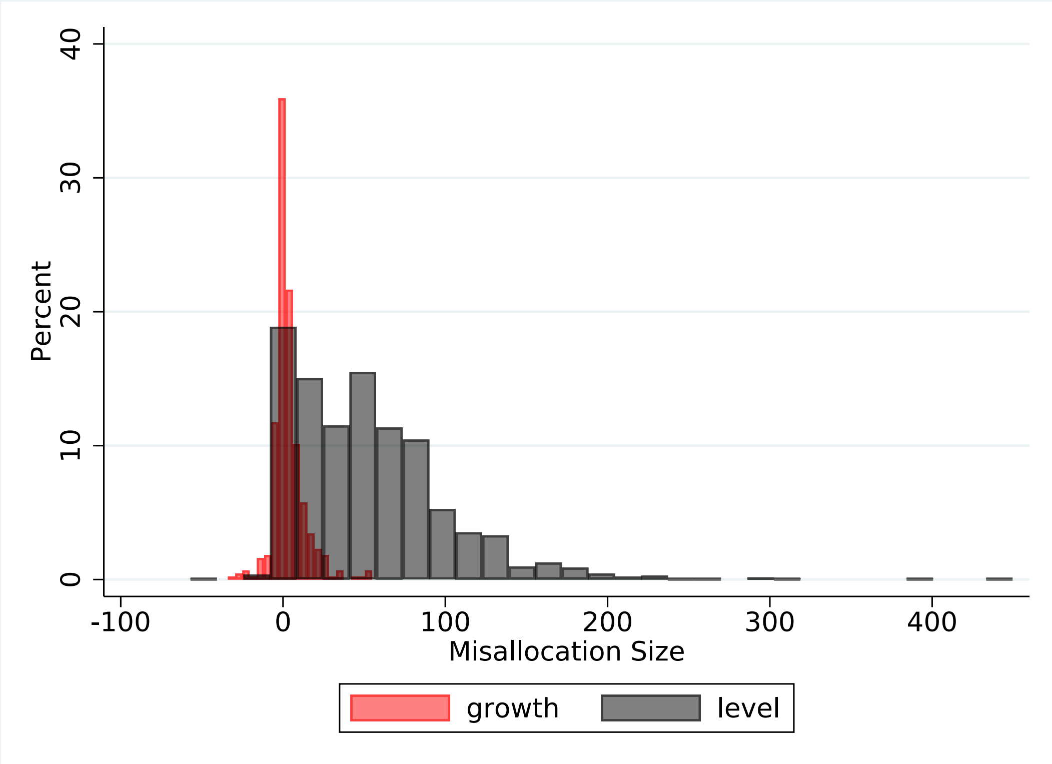
4.1 Level versus Growth Effect Size

We find that the TFP growth effect size is much smaller than the level effect size. For the quantification of the TFP loss due to misallocation, one needs an estimate of a counterfactual TFP level. This is obtained from a hypothetical world without distortions. Many studies follow Hsieh and Klenow (2009) and use their theoretical model to provide the benchmark and to obtain the misallocation level. However, some studies consider the change in TFP loss over a period, rather than an absolute level of misallocation relative to the distortion-free benchmark. This approach controls for the sources of misallocation, which stay constant over time. Therefore, studies focusing on the growth effect typically report smaller estimated effect sizes. For instance, Gopinath et al. (2017) find level and growth TFP effects of 28% and 10% respectively.

To account for the difference between level and growth effect sizes, we include a dummy variable indicating whether the TFP loss is measured against a benchmark TFP level or compared to the TFP loss observed in a base year. Our baseline specification (II) suggests that the growth effect size is 50.81% smaller than the level effect size. This finding is robust across other specifications in Table I and varies between 50.81%-53.13% in the full sample. This is also illustrated in Figure 3, which shows the unconditional distribution of level and growth estimates. It is readily seen that growth estimates are more tightly concentrated around zero compared to level estimates, which have a larger mean and are characterized by more dispersion. The effects are smaller in US- and EA-specific regressions, with 27.8% and 40.16% respectively.

Columns (VI) and (VII) show specifications including only the US and EA studies. EA studies consists of 22 primary studies and 351 observations. The pattern of the estimates is qualitatively the same as before. The growth effect size, measured as the intercept of 47.83% plus the coefficient on the growth effect dummy, -40.16%, can be used as an estimate of the impact of misallocation over time on productivity in the EA. Combining this with the average time span of the primary studies for the EA, which is around 5 years, we find an annual productivity loss of 1.53%. This is a substantial effect given the low productivity growth for many European countries. Note that, this back-of-the-envelope calculation simply provides an upper bound rather than a definitive result, since the majority of the estimates are based on the indirect approach. Regarding the US subsample, we find 1.04% annual productivity loss due to misallocation using similar calculations, while for the full sample this is 2.87%.

Figure 3: Distributions of the level and growth estimates.



4.2 Direct versus Indirect Approach

Studies using the direct approach typically report smaller TFP losses compared to the indirect approach. The direct approach (Restuccia and Rogerson, 2013) consists of identifying one or more explanatory factors of misallocation. This choice depends on a priori conjectures on its empirical relevance and importance as a source of misallocation. This approach also requires an empirical measurement of these factors, and a theoretical model to quantitatively assess the extent to which these factors generate misallocation and have an impact on aggregate TFP. Generally, the TFP loss due to a specific factor is found to be small. For example, Gilchrist et al. (2013) show that variation in effective borrowing rates leads to TFP loss of 2% only.

In contrast, the indirect approach does not distinguish across individual determinants, but instead tries to quantify the overall effect of all possible factors on misallocation. The model of Hsieh and Klenow (2009) is a prime example of the indirect approach. In this model, any factor causing misallocation creates a wedge or distortions in the first order conditions of the firms' optimization problem. This cross-sectional dispersion in wedges has a direct impact on aggregate TFP. The estimated TFP loss according to this approach is typically large (>20%). An alternative indirect approach is the within industry sample covariance between firm size and productivity as in Bartelsman et al. (2013). Studies using the sample covariance approach usually do not report the implied TFP loss, and the vast majority of studies using the indirect approach use the Hsieh and Klenow (2009) model or extensions thereof. Therefore we do not distinguish between alternative specifications of the indirect approach, and only focus on the difference between the direct and indirect approach.

Our baseline results suggest that the direct approach yields misallocation estimates that are smaller by 30.03%, with comparable estimates across the full sample specifications. Figure 4 illustrates the distributions of direct and indirect approaches in our sample, which confirms that the estimates for indirect approach tend to be smaller on average. The estimate is smaller when we consider the U.S. sample with 21.35%, and insignificant in the EA sample. The latter is mainly driven by a lack of studies that consider a direct approach in our sample for EA, as we have only 11 such observations in our sample.

In Column (VIII) of Table I we distinguish between different sources of misallocation among primary studies with the direct approach. We categorize the direct approaches in 6 main buckets: 1) financial frictions (e.g. Gilchrist et al., 2013; Midrigan and Xu, 2014; etc.), 2) mark-ups (e.g. Edmond et al., 2015), 3) regulation (e.g. Pavcnik, 2002), 4) uncertainty (e.g. Hosono et al., 2017), 5) capital adjustment costs (e.g. Le, 2022); and 6) other sources (e.g. imperfect information as in David et al., 2019; or land distortions as in Adamopoulos et al., 2022; etc.). Among these categories, we find that capital adjustment costs and uncertainty have the smallest impact on misallocation, which are lower by -58.50% and -55.88% compared to the indirect approach. As opposed to this, other sources and financial frictions have the highest impact, which are lower by only -23.81% and -36.94% compared to the indirect approach.[6]

[6]We have examined the results on direct approach dummies across a variety of specifications using different regressors. These results are omitted here for brevity.

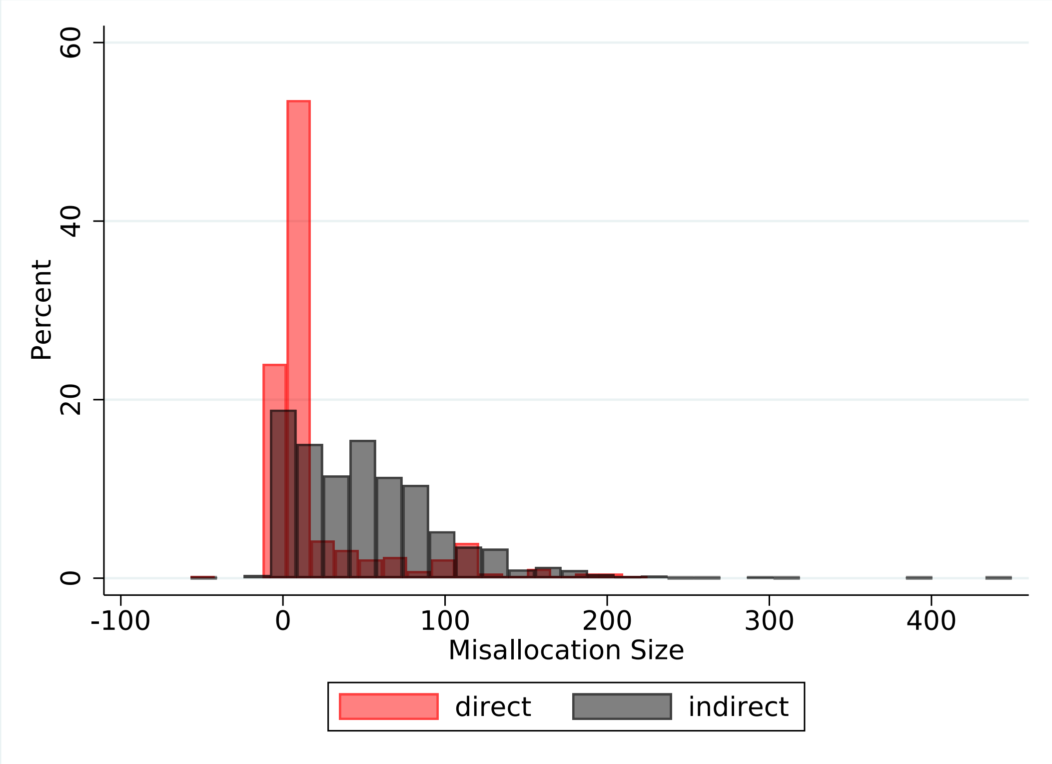


Figure 4: Distributions of the level and growth estimates.

4.3 Country- and Area-specific Effects

The extent of misallocation and the corresponding inefficiency loss depends on the country of analysis. For example, Hsieh and Klenow (2009) find that TFP loss due to misallocation is larger in China and India (100%) compared to US (35%).[7] Gamberoni et al. (2016) analyse 5 European countries (FR, GE, IT, SP, BE) and find the largest TFP loss in France (50%) and smallest in Germany (<10%).

In general, we expect low income countries to exhibit the largest TFP losses from misallocation. First, the literature has shown that TFP differences across countries are a large contributor to income differences. Second, low income countries usually have weaker institutions that prevent an efficient allocation of resources. To see the impact of this, we consider a few specifications in the analysis to account for cross-country differences.

In the baseline regression, i.e. column (II) of Table I, we include two dummy variables for US and the EA respectively. Both coefficients are significantly negative (-26.58% and -14.37%), implying that misallocation in both US and the EA are smaller compared to the full sample average. Furthermore, misallocation in the US is smaller compared the EA. These results are in line with the often adopted view that the US is at the efficiency

[7] Some studies, including Hsieh and Klenow (2009), also calculate the TFP gains relative to that of the United States. In this paper we consider only the absolute TFP gains reported by most studies.

frontier.

In column (IV) we consider a more general approach and replace the US and the EA dummies with the (log of) per capita income. The results indicate that a 1 percentage point (p.p.) increase in per capita income is associated with a 6.96 p.p. reduction in misallocation. In Column (V), we introduce a country-specific *Macro Index*, which is constructed with a principal components analysis using per capita income, the Gini coefficient, inflation and unemployment.[8] The results suggest that a 1 p.p. increase in this index is associated with an 8.12 p.p. reduction in misallocation. Both of these results support the view that lower income is generally associated with larger TFP losses due to misallocation.

In columns (VI) and (VII) of Table I, we repeat the baseline regression (II) for US and EA subsamples respectively. The average level effect (i.e. the constant) is smaller in these specifications compared our baseline in column (II): the level effect is 38.95% and 48.83% respectively for US and the EA, compared with 66.23% in the baseline. This confirms the result that misallocation in both US and the EA are smaller compared to the full sample average. Furthermore, misallocation in the US is smaller compared to the EA.

4.4 Publication Year

In the misallocation literature, there are multiple reasons why the strength of the observed effect size becomes smaller as the empirical evidence accumulates over time. First, the more recent misallocation literature emphasizes restrictive assumptions of earlier models. For example, Hsieh and Klenow (2009) assume that all firms charge the same markup and have constant returns to scale. Applying this model, Ruzic and Ho (2021) find an increase of misallocation over time in the US. In a generalized setup, however, they find declining misallocation instead. Assumptions, therefore, matter a lot for the quantitative results.

Second, the variation in distortions in the indirect approach provides an upper bound for misallocation. In other words, all variation in distortions is attributed to misallocation when the indirect approach is used. Allocative distortions originate from many sources, however. Some of these factors do not strictly cause misallocation like heterogeneity in production technologies. Recent studies (Ruzic and Ho, 2021; David and Venkateswaran, 2019; Bun and de Winter, 2022 disentangle the various sources of dispersion in wedges. Controlling for the various other sources, the contribution of pure misallocation may

[8]The country specific macro variables are extracted from the World Bank Open Database via https://data.worldbank.org/.

become smaller.

In our sample, while the coefficient estimate on the publication year is positive and close to zero in our baseline specification (II), it is typically negative across other specifications. This is in line with the view that the contribution of misallocation may have become smaller over time, though the sign is not robust across all specifications and the coefficient is insignificant across all specifications in Table I.

4.5 Nuisance Parameters

All theoretical models of misallocation depend on nuisance parameters. A prominent example is the elasticity of substitution between varieties, which is typically set equal to 3. However, it can be shown that the TFP loss is increasing in substitution elasticity. Hsieh and Klenow (2009) and Gopinath et al. (2017) also experiment with alternative values. For instance, Gopinath et al. (2017) report a 28% TFP loss when the elasticity of substitution is 3, while increasing it to 5 results in a 46% TFP loss. Such calculations show that the quantitative results are sensitive to the setting of nuisance parameters. We therefore include the value of the substitution elasticity as a meta-regressor. The meta-regression shows a relatively small effect. Increasing this nuisance parameter with one unit (e.g. from 3 to 4) changes the estimated TFP loss by 3.12-3.46 p.p. in Table I. The sign of the estimated coefficient is in line with theory, i.e. in case of higher substitutability the impact of distortions on aggregate productivity is larger. Noting that in the data the minimum and maximum values are 1 and 10 respectively, its economic impact is small.

4.6 Comparison of different estimators

In this section, as a robustness check, we consider alternative methodologies for our random-effects approach. We use our baseline specification (II) from Table I and consider a number of alternatives in Table II. Column (II) shows the results of a pooled OLS regression, i.e. without primary study random effects and, hence, a fixed intercept. In column (III) we replace the heteroskedasticity-robust standard errors with clustered standard errors to take into account the intra-study correlation between effect sizes. In columns (IV) and (V) we consider weighted least squares (WLS) estimators. In (IV), we assign a weight of $\frac{1}{m}$ for each observation, where m denotes the number of data points per primary study. This results in assigning equal weights to each primary study in the sample. In (V), we assign a weight of $\frac{N}{m}$ for each observation, where N is the number of firms in the study. As such, using weights that are proportional to the number of firms also account for the precision of the estimated effect size.[9] Finally, in column (VI) we consider a fixed-effects regression, i.e. for each primary study we include a separate intercept. Because all primary studies report multiple effect sizes, the sample size stays unchanged. The key assumption underlying random effects estimation is that the unobserved heterogeneity in effect-size between primary studies, as represented by the random intercepts, is uncorrelated with the included study characteristics. Both fixed effects and random effects estimators should therefore yield similar coefficient estimates if the random effects assumption is correct.

In general the estimates are consistent with the findings in the baseline regression in Table I, with several exceptions. While the baseline results suggest that the US dummy has a larger impact than the EA dummy (suggesting lower misallocation in US), the coefficients estimates are fairly close to each other under OLS and WLS specifications. Further, the estimate on the publication year is not robust both in terms of its sign and significance. The estimates on the level and growth effect size of misallocation, as well as the direct approach are fairly robust and consistent across all specifications. In Appendix A, we provide a full replication of the Table I with fixed-effects (Appendix A1), OLS and WLS (Appendix A2), and further comparisons between heteroskedasticity adjusted vs. clustered standard errors (Appendix A3). The main pattern of the estimation results is similar across all these specifications, with minor differences.

Table II: Meta-regressions with various sets of controls. Comparison of OLS, WLS, RE and FE regressions.

	(I) Random Effects	(II) Plain OLS	(III) Plain OLS - Cl. Errors	(IV) WLS-I	(V) WLS-II	(VI) Fixed Effects
Growth Effect Size	-50.81***	-54.12***	-54.12***	-39.61***	-48.00***	-51.39***
	(6.65)	(1.51)	(1.86)	(3.38)	(3.35)	(6.86)
Direct Approach	-30.03***	-38.39***	-38.39***	-31.66***	-38.19***	-29.08***
	(5.97)	(2.54)	(2.91)	(4.37)	(6.96)	(7.25)
US	-26.58***	-14.84***	-14.84***	-9.98**	-12.31*	-30.79***
	(6.05)	(2.67)	(2.76)	(4.31)	(6.83)	(6.34)
EA	-14.37***	-15.55***	-15.55***	-13.89***	-27.08***	-15.47***
	(5.01)	(1.99)	(2.10)	(3.51)	(4.61)	(5.63)
Pub. Year	0.01	0.50*	0.50	-0.09	1.72***	
	(1.07)	(0.29)	(0.31)	(0.50)	(0.56)	
Constant	66.23***	66.29***	66.29***	60.82***	72.97***	65.08***
	(5.06)	(1.64)	(1.90)	(2.99)	(4.70)	(2.72)
Observations	1786	1786	1786	1786	1225	1786
r2		0.324	0.324	0.258	0.290	0.279

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[9] Some primary studies in our sample do not report the number of firms/observations used in their estimations. There we have a smaller sample of 1225 in Column (V).

5 Conclusion

Misallocation of production factors has been on the rise in the last decades. Our meta-analysis focuses on the correlation between the estimated TFP loss and primary study characteristics. First, we find that the productivity growth effect size is much smaller than the level effect size. Second, we distinguish between studies following the direct approach, which relates the extent of misallocation to one or more specific sources, and the indirect approach, which tries to quantify the overall effect of all possible sources. We find that on average, the indirect approach results in a larger productivity loss. Within the subset of primary studies using the direct approach, financial frictions, mark-ups and other sources (including imperfect information, misspecification, trade, etc.) are the most important, while capital adjustment costs and uncertainty have the lowest impact on misallocation. Third, we find that the extent of misallocation and the corresponding productivity loss depend on the country of analysis. There is a negative correlation between the productivity loss due to misallocation and the level of income. Finally, we do not find a significant role for publication year.

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Appendix

A. Empirical Results - Robustness Checks

This Appendix provides a replication of our baseline Table I using fixed-effects, OLS and WLS approaches.

A1. Fixed Effects Regressions

Table III: Fixed effects meta-regressions

	I	II	III	IV	V	VI - Only US	VII - Only EA	VIII - Including Direct
Growth Effect Size		-51.42***	-54.25***	-53.84***	-52.94***	-25.24**	-41.00***	-52.34***
		(2.12)	(4.65)	(4.77)	(5.20)	(9.78)	(14.03)	(5.48)
Direct Approach		-30.90***	-29.86**	-29.99**	-32.61**	-13.66	6.63	
		(5.18)	(12.15)	(12.17)	(13.62)	(8.84)	(7.60)	
US		-30.85***	-34.39***					
		(5.05)	(6.47)					
EA		-15.47***	-18.79***					
		(4.88)	(6.88)					
Pub. Year		4.32	-0.19	0.73				
		(5.66)	(6.27)	(6.29)				
Elasticity of Subst.			3.35*	3.44*	3.90			3.88
			(1.88)	(2.02)	(3.00)			(3.02)
Per Capita Inc.				-6.65***				
				(2.22)				
Macro Index					-7.27			-7.25
					(4.68)			(4.68)
D - Fin. Frictions								-37.00
								(23.52)
D - Markups								-38.49*
								(22.25)
D- Regulation								-55.44***
								(12.26)
D - Uncertainty								-57.38**
								(21.69)
D - Capital Adjustment Costs								-59.75**
								(24.55)
D - Other Sources								-26.68
								(21.60)
Constant	40.18	65.49***	68.66***	62.55***	64.43***	33.42***	43.33***	63.99***
	(1.08)	(1.83)	(3.35)	(3.11)	(2.17)	(1.44)	(6.87)	(2.57)
Observations	1786	1786	1380	1320	1066	170	351	1066
r2	0.000	0.280	0.293	0.283	0.252	0.103	0.445	0.252

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A2. OLS and Weighted Least Squares Regressions

Table IV: OLS meta-regressions

	I	II	III	IV	V	VI - Only US	VII - Only EA	VIII - Including Direct
Growth Effect Size		-54.12***	-59.68***	-54.29***	-58.44***	-34.39***	-34.26***	-58.28***
		(1.51)	(1.58)	(1.73)	(1.96)	(4.74)	(2.67)	(1.94)
Direct Approach		-38.39***	-31.71***	-40.37***	-36.92***	-21.78***	-7.17*	
		(2.54)	(3.94)	(3.30)	(5.10)	(4.64)	(3.79)	
US		-14.84***	-29.03***					
		(2.67)	(2.81)					
EA		-15.55***	-16.25***					
		(1.99)	(2.02)					
Pub. Year		0.50*	0.51	1.27***	0.43	-1.42**	-2.53***	-0.21
		(0.29)	(0.32)	(0.37)	(0.46)	(0.65)	(0.74)	(0.47)
Elasticity of Subst.			0.50	2.16**	1.70			1.13
			(0.84)	(0.85)	(1.18)			(1.19)
Per Capita Inc.				-10.81***				
				(1.12)				
Macro Index					-10.94***			-8.47***
					(1.72)			(1.70)
D - Financial Frictions								-36.35**
								(15.49)
D - Markups								-48.89***
								(3.68)
D - Regulation								-55.46***
								(5.65)
D - Uncertainty								-56.11***
								(5.44)
D - Capital Adjustment Costs								-59.69***
								(5.86)
D - Other Sources								-5.89
								(8.25)
Constant	37.80***	66.29***	69.58***	63.59***	65.82***	39.39***	43.12***	64.52***
	(1.69)	(1.64)	(1.80)	(1.51)	(1.80)	(3.68)	(2.09)	(1.80)
Observations	1786	1786	1380	1320	1066	170	351	1066
r2	0.000	0.324	0.325	0.390	0.313	0.202	0.413	0.306

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table V: Weighted least squares meta-regressions

	I	II	III	IV	V	VI - Only US	VII - Only EA	VIII - Including Direct
Growth Effect Size		-39.61***	-49.51***	-44.97***	-52.20***	-37.77***	-28.93***	-52.05***
		(3.38)	(2.39)	(2.59)	(3.07)	(10.00)	(3.66)	(2.99)
Direct Approach		-31.66***	-34.65***	-35.22***	-33.10***	-28.09***	-9.31***	
		(4.37)	(5.84)	(6.13)	(6.80)	(7.47)	(3.22)	
US		-9.98**	-21.23***					
		(4.31)	(4.02)					
EA		-13.89***	-12.23***					
		(3.51)	(2.76)					
Pub. Year		-0.09	-0.30	-0.22	-2.05**	0.77	-1.53	-2.00**
		(0.50)	(0.78)	(0.90)	(0.89)	(1.22)	(1.16)	(0.90)
Elasticity of Subst.			-0.32	-0.20	-1.79			-2.58
			(1.95)	(2.16)	(2.38)			(2.35)
Per Capita Inc.				-7.27***				
				(1.54)				
Macro Index					-11.70***			-10.92***
					(2.33)			(2.19)
D - Fin. Frictions								-29.71*
								(17.48)
D - Markups								-43.10***
								(5.69)
D - Regulation								-56.20***
								(5.82)
D - Uncertainty								-42.95***
								(8.73)
D - Capital Adjust. Costs								-54.65***
								(7.22)
D - Other Sources								-12.11
								(8.93)
Constant	37.80***	60.82***	67.34***	60.46***	67.44***	48.44***	40.24***	66.60***
	(1.69)	(2.99)	(3.12)	(2.50)	(2.75)	(6.45)	(3.39)	(2.74)
Observations	1786	1786	1380	1320	1066	170	351	1066
r2	0.000	0.258	0.276	0.297	0.298	0.316	0.396	0.303

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table VI: Weighted least squares meta-regressions by number of firms

	I	II	III	IV	V	VI - Only US	VII - Only EA	VIII - Including Direct
Growth Effect Size		-48.00***	-55.96***	-48.57***	-54.62***	-72.83***	-29.53***	-55.40***
		(3.35)	(3.07)	(3.24)	(3.83)	(7.97)	(4.37)	(3.90)
Direct Approach		-38.19***	-27.62***	-37.95***	-31.42***	-45.66***	-5.99***	
		(6.96)	(8.70)	(8.22)	(8.57)	(7.94)	(1.93)	
US		-12.31*	-18.31**					
		(6.83)	(7.19)					
EA		-27.08***	-23.16***					
		(4.61)	(3.28)					
Pub. Year		1.72***	1.15	1.67*	-1.23	0.94	-0.20	-1.02
		(0.56)	(0.92)	(0.89)	(0.89)	(1.89)	(1.37)	(0.89)
Elasticity of Subst.			5.96*	6.03*	6.16*			6.86**
			(3.13)	(3.23)	(3.55)			(3.45)
Per Capita Inc.				-11.19***				
				(1.86)				
Macro Index					-19.95***			-19.74***
					(2.88)			(2.88)
D - Financial Frictions								-35.63**
								(14.89)
D - Markups								-66.35***
								(3.40)
D - Regulation								-62.80***
								(5.90)
D - Uncertainty								-65.93***
								(17.82)
D - Capital Adjustment Costs								-87.13***
								(9.83)
D - Other Sources								-8.96
								(11.62)
Constant	44.31***	72.97***	78.44***	66.69***	74.70***	63.59***	38.84***	74.87***
	(2.43)	(4.70)	(3.80)	(2.99)	(3.32)	(7.50)	(3.05)	(3.32)
Observations	1225	1225	948	916	782	75	272	782
r2	0.000	0.290	0.301	0.333	0.315	0.341	0.375	0.342

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A4. Heteroskedasticity Adjusted vs. Clustered Standard Errors

Table VII: Heteroskedasticity adjusted vs. clustered standard errors with plain OLS regressions. Columns (H) stand for specifications with heteroskedasticity adjusted standard errors, whereas columns (C) stand for specifications with clustered standard errors.

	(H)	(C)	(H)	(C)	(H)	(C)
Growth Effect Size	-58.44***	-58.44***	-34.26***	-34.26***	-58.28***	-58.28***
	(1.96)	(2.32)	(2.67)	(3.11)	(1.94)	(2.34)
Direct Approach	-36.92***	-36.92***	-7.17*	-7.17*		
	(5.10)	(5.91)	(3.79)	(3.81)		
Pub. Year	0.43	0.43	-2.53***	-2.53***	-0.21	-0.21
	(0.46)	(0.50)	(0.74)	(0.80)	(0.47)	(0.52)
Macro Index	-10.94***	-10.94***			-8.47***	-8.47***
	(1.72)	(1.82)			(1.70)	(1.86)
Elasticity of Subst.	1.70	1.70			1.13	1.13
	(1.18)	(1.22)			(1.19)	(1.20)
Dummy - Financial Frictions					-36.35**	-36.35**
					(15.49)	(15.63)
Dummy - Markups					-48.89***	-48.89***
					(3.68)	(4.03)
Dummy - Regulation					-55.46***	-55.46***
					(5.65)	(5.86)
Dummy - Uncertainty					-56.11***	-56.11***
					(5.44)	(5.59)
Dummy - Capital Adjustment Costs					-59.69***	-59.69***
					(5.86)	(6.24)
Dummy - Other Sources					-5.89	-5.89
					(8.25)	(8.65)
Constant	65.82***	65.82***	43.12***	43.12***	64.52***	64.52***
	(1.80)	(2.06)	(2.09)	(2.32)	(1.80)	(2.08)
Observations	1066	1066	351	351	1066	1066
r2	0.313	0.313	0.413	0.413	0.306	0.306

Standard errors in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B. List of Primary Studies, details

Author	Pub. year	Journal	No. firms
Adamopoulos et al.	2022	Econometrica	8000
Alam	2020	Journal of Economic Dynamics and Control	9141
Albagli et al.	2019	Central Bank of Chile Working Paper 835	10363
Bai et al.	2018	NBER Working Paper 24436	100000
Baqaee and Farhi	2019	Quarterly Journal of Economics	Not available
Bartelsman et al.	2013	American Economic Review	Not available
Bastidas and Acosta	2019	Journal of Economic Structures	1322
Bayer et al.	2018	CEPR Discussion Papers	Not available
Bellone and Mallen-Pisano	2013	GREDEG Working Paper No. 2013-38	Not available
Benkovskis	2018	Journal of Productivity Analysis	29374
Bond et al.	2013	Review of Economic Dynamics	Not available
Brandt et al.	2013	Review of Economic Dynamics	Not available
Bun and de Winter	2022	Journal of Productivity Analysis	342245
Busso et al.	2013	The BE Journal of Macroeconomics	Not available
Calligaris	2015	Review of Labor Economics	Not available
Calligaris et al.	2018	Economic Policy	145000
Camacho and Conover	2010	IADB WP Series	4376
Caraiani	2018	Empirica	293
Cette et al.	2016	European Economic Review	Not available
Chen and Irarrazabal	2013	Norges Bank Working Paper	1489.00
Chuah et al.	2018	Working Paper 8368, World Bank Group	Not available
David and Venkateswaran	2019	American Economic Review	Not available
David et al.	2016	Quarterly Journal of Economics	Not available
David et al.	2022	Journal of Financial Economics	Not available

Table VIII: List of primary studies.

Dheera-Aumpon	2014	Asian-Pacific Economic Literature	51330
Di Nola	2016	University of Konstanz, Mimeo	Not available
Dias et al.	2016	Journal of Macroeconomics	36512
Edmond, Michigan and Xu	2015	American Economic Review	95
Ek and Wu	2018	Journal of Development Economies	Not available
Franco	2018	OECD, Mimeo	72907
Fu and Moral-Benito	2018	Banco de Espana Documentos Occasionales 1808	800000
Fujii and Nozawa	2013	DBJ Discussion Paper	1267
Gamberoni et al.	2016	ECB Working Paper No 1981	Not available
Garcia-Santana et al.	2020	International Economic Review	350000
Gilchrist et al.	2013	Review of Economic Dynamics	496
Gong and Hu	2016	Economics Letters	118
Gopinath et al.	2017	Quarterly Journal of Economics	100000
Gorodnichenko et al.	2018	NBER Working Paper 24444	12300
Ha et al.	2016	Asian Development Review	100601
Hagemejer et al.	2017	GRAPE Working Paper #31	1641
Hang, Krishna and Tang	2020	NBER working paper	96296
Ho and Ruzic	2021	The Review of Economics and Statistics	65000
Hosono et al.	2017	Working Paper	Not available
Hsieh and Klenow	2009	Quarterly Journal of Economics	40000
Inklaar et al.	2017	Macroeconomic Dynamics	148
Karabarbounis and Macnamara	2019	FRB Richmond Working Paper	7632
Kim et al.	2017	Federal Reserve Bank of St.Louis Review	Not available
Kumari et al.	2021	Applied Economics	14000

Table IX: List of primary studies, continued.

Le	2022	Economic Record	692
Lenzu abd Manaresi	2019	Bank of Italy Occasional Paper Series	7300
Li and Wang	2021	Economics Letters	Not available
Libert	2016	Working Paper	110000
Maliranta and Maattanen	2013	ETLA Working Papers No 11	107082
Marconi and Upper	2017	Bank of Italy Working Papers 1143	Not available
Martinez et al.	2019	WPAE-2019-1919	18381
Meehan	2016	New Zealand Productivity Commission	82536
Midrigan and Xu	2014	American Economic Review	165137
Misch and Saborowski	2018	IMF working paper	3000000
Newman et al.	2019	WIDER Working Paper No 2019/46	Not available
Nguyen	2016	Working Paper 7780, World Bank Group	6796
Nicola et al.	2020	World Bank Group Policy Research Working Paper No. 9483	Not available
Nishida et al.	2016	CES Working Paper 16-50	300000
Oberfield	2012	Review of Economic Dynamics	Not available
Pavcnik	2002	Review of Economic Studies	3704
Ryzhenkov	2015	Journal of Comparative Economics	47497
Schelkle	2017	Working Paper, University of Cologne	Not available
Song and Wu	2015	Working Paper	107579
Tang	2022	Economic Modelling	Not available
Uras	2014	Journal of Banking and Finance	105
Whited and Zhao	2021	The Journal of Finance	Not available
Yang	2011	JMP, UC Berkeley	20000
Ziebarth	2013	Review of Economic Dynamics	6000

Table X: List of primary studies, continued.

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