From Financial to Real Misallocation: Evidence from a Global Sample

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Abstract

Financial market imperfections are a key determinant of the large differences in aggregate productivity across countries. This study leverages a novel methodology proposed by Whited and Zhao (2021) to measure the allocative efficiency of financial liabilities across firms and applies it to a database of 25 European countries. It finds a strong negative correlation between finance misallocation and economic development, with the productivity gains from achieving the efficient allocation ranging between 40% and 80%. Inspecting the distribution of financing costs, the paper shows these to be lower at older and larger firms than younger and smaller ones. The paper also quantifies the association between financial misallocation and real-input allocative inefficiency. It finds that a decrease in finance misallocation from the median to the 25^{th} percentile of the cross-industry distribution increases aggregate productivity by 7.1% on average and by 8.2% in industries with high external finance dependence.

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1. Introduction

Financial market imperfections are at the forefront of research studying the origin of large differences in allocative efficiency across countries. A recent and novel methodology developed by Whited and Zhao (2021) allows to measure the efficiency of allocation of financial liabilities across firms. In this paper, we leverage on this methodology and explore the link between financial and real misallocation using data from 25 European countries. We have two main goals. First, we seek to establish a broader characterization of the cross-country differences in finance misallocation and its impact on aggregate productivity. Our data set allows us to validate the relationship between the measure of finance misallocation at the sector level and the level of economic development and characterize the heterogeneous impact of financial market imperfections across firms of different sizes and ages. Second, we aim to establish a bridge between the measured misallocation of financial liabilities that follows from Whited and Zhao (2021) and the misallocation of physical inputs computed following Hsieh and Klenow (2009). Concretely, we ask the following question: how much of the observed dispersion in the marginal revenue products of physical inputs are attributable to dispersion in the marginal returns to debt and equity across firms within narrowly defined industries?

We find that there is a strong negative correlation between finance misallocation and economic development. The aggregate productivity gains that would accrue from efficiently reallocating finance across firms are more than twice as high in countries with the lowest per capita income in the sample relative to the richest counterparts. At a more disaggregated level, and exploiting a rich set of country, sector, and time fixed effects, we identify a substantial discount in the shadow cost of finance for larger and older firms. A 10% increase in the total assets of a firm is associated to a 5.3% reduction in the shadow cost of finance, whereas a 1-year gap in a firm's age corresponds to a reduction in the order of 1.25%. While this result has been documented earlier in the literature in different contexts and through different methodologies, we arrive at this conclusion from the direct observation of the distribution of financial liabilities interpreted through the lens of an efficient theory of finance allocation.

Our second contribution involves the quantification of the association between financial misallocation and real-input allocative inefficiency. Following Rajan and Zingales (1998), we classify industries into high and low dependence on external sources of finance. We then regress the standard deviation of the marginal revenue products of real inputs (i.e., real inputs misallocation) within a country, industry, and year, against the standard deviation of the marginal return to financial liabilities (i.e., financial misallocation) and its interaction with the external finance indicator. We find that a decrease in financial misallocation from the median to the 25^{th} percentile of the cross-industry distribution induces an improvement in the allocation efficiency of real inputs that in turn increases aggregate productivity by 7.1% on average and by 8.2% in industries with higher dependence on external finance.

The theoretical framework providing the benchmark of an efficient allocation of real and financial resources is drawn directly from Hsieh and Klenow (2009) and Whited and Zhao (2021). At the core of the framework is the notion that, unless frictions and distortions are in place, the maximization of aggregate output requires that real resources and financial liabilities are distributed across firms in a way that equalizes the marginal returns to additional units of real and financial inputs.[1] A more fundamental connection between the two methodologies is the assumption that the mechanism through which financial misallocation generates losses in aggregate productivity is by causing a misallocation of real inputs. Despite this strong link, the quantitative strength of this mechanism is not obvious, since firms may appeal to internal funding resources to circumvent financial frictions and mitigate their disruptive effect.[2] Therefore, the quantitative effect of finance misallocation on the misallocation of real resources is ultimately an empirical question, which we address in this paper.

[1]A set of assumptions must be adopted to ensure that this is indeed the efficient prescription. Among the most important ones are the imposition of a common technology across firms within a narrow industry, and the frictionless reallocation of resources in the absence of friction.

[2]This insight plays a key role in the quantitative papers in the macro-development literature assessing the aggregate effects from financial frictions, such as Buera et al. (2011), Midrigan and Xu (2014), and Moll (2014). We discuss the literature in greater detail below.

Our empirical strategy to conduct such an assessment involves estimating the relationship between two model-based summary measures of misallocation: the standard deviation of the logarithm of firms' marginal revenue product of real resources relative to the industry mean, yielded by the application of the Hsieh and Klenow (2009) methodology; and the standard deviation of the logarithm of firms' marginal revenue products of financial resources relative to the industry mean, yielded by the application of the methodology in Whited and Zhao (2021). Besides controlling for time, industry, and country fixed effects, we strengthen the identification by classifying industries into high or low external finance dependence, based on the external finance dependence of the industry being above or below the median across U.S. sectors and estimating the differential impact of finance misallocation on the highly external-finance dependent industries. We find a statistically significant decline in real-input misallocation resulting from reducing the dispersion of marginal returns to financial resources from the median to the $25th$ percentile value. Moreover, we find the reduction to be 0.7 percentage points higher in industries with high external finance dependence.

The regression described above allows us to predict the reduction in the real-input misallocation associated with a particular improvement in financial misallocation but is silent about the aggregate productivity gains associated with such reduction. To make this extra step, we leverage the richness of our data to estimate the effect of an industry's real misallocation on the aggregate productivity gains associated with its reversal. Equipped with this estimate, we then find that reducing finance misallocation from the median to the $25th$ percentile of the cross-industry distribution yields an aggregate productivity gain of 7.1%, accruing through an improvement in the allocative efficiency of real inputs. In industries with high external finance dependence, the aggregate gains are 1.5 percentage points higher. Interestingly, these results fall within the range of estimates reported in the macro-development literature appealing to radically different quantification strategies.

Several studies attempt to analyze the link between financial frictions and productivity growth. Finance is needed to buy production inputs (capital, labor, research, and development) and it affects firm entry and exit, all of which in turn influence a firm's productivity. The presence of financial frictions may generate misallocation of resources, lowering firm productivity (Buera et al., 2011; Midrigan and Xu, 2014; and Moll, 2014). Frictions can also generate misallocation across sectors because they increase barriers to entry in more productive sectors. Furthermore, capital misallocation can derive from credit constraints (Banerjee and Duflo, 2005) and inefficient contract monitoring and enforcement (Cole et al., 2016). These studies quantify the aggregate effect of financial frictions pursuing an approach that, unlike us, dispenses from the direct observation of the distribution of financial liabilities. They postulate a specific financial friction, typically a collateral constraint, and calibrate it to match measures of aggregate credit to GDP or moments from the distribution of firm dynamics across age and size. Despite the methodological differences, we find aggregate productivity gains from alleviating financial frictions that are within the same range identified in these macro-development studies. We interpret the similarity of the results as giving reassurance to the validity of our empirical approach.

The purpose of our analysis is not to identify the source of financial misallocation but rather to understand how the sub-optimal allocation of financial liabilities may translate into real-input allocative inefficiency. One such channel is weaknesses in the banking sector. Banks with narrow capital buffers over the minimum required by regulation may engage in "zombie lending" in that they continue to finance weak or insolvent borrowers. Evidence from Japan and European banks in the aftermath of the global financial crisis shows that following the bursting of an asset price bubble and widespread losses in the financial sector, banks with lower capital buffers were more likely to provide frequent rounds of loan restructuring – also known as "evergreening" (Peek and Rosengren, 2005 and Giannetti and Simonov, 2013) and to reduce lending to weak borrowers significantly less than to stronger ones (Acharya et al., 2018; Acharya et al., 2019; Schivardi et al., 2022; and Özlem Dursun-de Neef and Schandlbauer, 2021). When banks' capital gets locked up in troubled sectors and companies, this may prevent some second-round business failures, but it also diverts funds away from more productive sectors of the economy. Inefficient firms could thus have a dominant impact on the functioning of input and output markets, generating lower economic output, investment, and employment (Caballero et al., 2008). Another important channel works through the structure and maturity of a firm liabilities. Departing from the Modigliani and Miller (1958) framework, empirical studies point to a reduction on long-term productive investment due, for example, to excessive reliance on short-term debt (Vermoesen et al., 2013). Sudden credit rationing may also affect disproportionately firms relying on debt financing affecting productivity through a reduction in investment in innovation.[3] We contribute to this literature by employing an identification strategy that allows us to identify the effect of finance on real misallocation. We show that improvements in capital market imperfections can trigger an average aggregate productivity gain of 7.1% and that these gains are larger in industries more dependent on external finance (an additional 1.1 percentage point gain).

The remainder of the paper is organized as follows. In section 2 we introduce and summarize the data, and present the theoretical framework underlying the identification of real and financial misallocation. In section 3 we discuss the aggregate results and then in section 4 we present the heterogeneous effects based on firm age and size. Section 5 we present and implement our empirical strategy to connect financial with real misallocation. In section 6 we conclude.

2. Empirical approach

In this section, we summarize the model, and the data, and provide some stylized facts about our sample.

2.1. Model

Assessing the misallocation of financial and real resources requires an explicit notion of efficiency against which to compare the observed distribution of these inputs.

[3]For example, Granja and Moreira (2021) show that in the aftermath of the global financial crisis, disruption in the credit market caused a decrease in product innovation.

To this end, we follow closely Hsieh and Klenow (2009)'s methodology for the identification of real-input distortions and Whited and Zhao (2021)'s application of this methodology to the case financial inputs. Given that both types of misallocation feature prominently in our analysis, we introduce the methodologies in parallel.

We assume there is a single final good Y produced under perfect competition combining output from all industries, Y_s, under a Cobb-Douglas technology:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} \text{ with } \sum_{s=1}^{S} \theta_s = 1 \tag{1}$$

We consider each industry s to be populated by a large number of monopolistically competitive firms (M_s). Each sector's output Y_s is a constant elasticity of substitution (CES) aggregate of differentiated varieties, given by:

$$Y_s = \left[\sum_{v=1}^{M_s} Y_{sv}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where Y_{sv} is the quantity produced of variety v in sector s and σ is the elasticity of substitution.

The differentiated varieties, in turn, are produced by combining physical capital and labor input in a Cobb-Douglas production function with sector-specific factor shares:

$$Y_{si} = A_{si} L_{si}^{1-\alpha_s} K_{si}^{\alpha_s} \tag{3}$$

The physical productivity of the firm i, also referred to as $TFPQ$, is denoted with A_{si}. Notice that the capital and labor factor shares are assumed to be industry-specific.

Firms need to issue debt and raise equity to finance the acquisition of the physical capital, the labor input, and the series of expenses that go into the determination of its $TFPQ$. Rather than imposing a specific theory for why debt and equity are not perfectly substitutable and for how the total amount of financing is distributed into its various applications, we postulate a direct mapping from financial liabilities into real value added that captures these unmodeled elements in reduced form. The imperfect substitutability between debt and equity is reflected in a Constant Elasticity of Substitution specification, which we estimate from the data, and the distribution of finance into capital, labor, and innovation is subsumed in a finance-based measure of productivity which we label Total Finance Benefit (TFB), which we will also back-out from the data. Formally:

$$F_{si} = Z_{si}\left[\alpha_s D_{si}^{\frac{\gamma_s-1}{\gamma_s}} + (1-\alpha_s)\, E_{si}^{\frac{\gamma_s-1}{\gamma_s}}\right]^{\frac{\gamma_s}{\gamma_s-1}} \tag{4}$$

where Z_{si} denotes the Total Finance Benefit, γ is the industry-specific elasticity of substitution between debt and equity, and α_s is the industry-specific weight of debt in real value added. Notice that, for the sake of differentiating notation with respect to the real-input representation, the real value added here is denoted with F_{si}. Empirically, however, we shall extract information about real output from the same observable in the data, the value added of the firm.

In terms of the optimal determination of the capital and labor inputs, we assume these are chosen every period taking the capital rental rate and the wage rate in factor markets as given. To capture frictions and policies in these markets, we introduce wedges that distort the aggregate scale of the firm and the relative price between capital and labor. These are the output wedge $\tau_{y_{si}}$ and the capital wedge $\tau_{k_{si}}$. Importantly, the wedges are assumed to be idiosyncratic to the firm, capturing the idea that the frictions and policies may exert a heterogeneous impact on the firms' input choices. Given the monopolistically-competitive behavior of the variety producers, each firm maximizes

$$\pi_{si} = (1 - \tau_{Ysi})P_{si}Y_{si} - wL_{si} - (1 + \tau_{Ksi})RK_{si} \tag{5}$$

$$s.t.$$

$$P_{si} = Y_{si}^{-\frac{1}{\sigma}} P_s Y_s^{\frac{1}{\sigma}} \tag{6}$$

where equation 6 is the demand for variety i in sector s and where the firm's output is given by equation 3. Solving the optimization problem yields

$$L_{si} \propto \frac{A_{si}^{\sigma-1}(1 - \tau_{Y_{si}})^{\sigma}}{(1 + \tau_{K_{si}})_s^{\alpha}(\sigma - 1)} \tag{7}$$

$$\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{(1 - \alpha_s)} \frac{w}{R} \frac{1}{(1 + \tau_{k_{si}})} \tag{8}$$

Equations 7 and 8 shows the direction in which the wedges distort the decisions away from the efficient level. Under no distortions, firm size is determined by the firm's $TFPQ$, A_{si}, and capital-labor ratios are equalized within industries. With distortions, both properties break down.

An implication of the optimality conditions in the model is that the revenue productivity of the firm, $TFPR$, represents a summary statistic of the mix of capital and output wedges. Through a simple rearrangement of terms, it can be shown that revenue productivity, defined as $TFPR_{si} = \frac{P_{si}Y_{si}}{L_{si}^{1-\alpha_s}K_{si}^{\alpha_s}}$, becomes proportional to the ratio of distortions in the following fashion :

$$TFPR_{real,si} \propto \frac{(1 + \tau_{k_{si}})_s^{\alpha}}{(1 - \tau_{Y_{si}}} \tag{9}$$

This representation of $TFPR$ turns out to be very useful for the characterization of the misallocation in an economy. Since, in the efficient allocation with no distortions, the $TFPR$ must be equalized across firms, any dispersion in revenue productivity is a sign of misallocation. Furthermore, the level of a given firm's $TFPR$ reveals information on the direction in which the distortions are affecting the firm relative to the average in its industry. A high $TFPR$ is indicative of an inefficiently low level of labor and capital flowing to the firm, whereas the opposite is true if $TFPR$ is lower than the average.

One can arrive at an equivalent characterization of the optimal levels of debt and equity in a firm as a function of prices and distortions in capital markets. In this case, the profit maximization problem confronted by the firm is:

$$\pi_{si} = P_{si}F_{si} - r(1+\tau_{D_{si}})D_{si} - (1+\tau_{E_{si}})\lambda E_{si} \tag{10}$$

$$s.t.$$

$$P_{si} = F_{si}^{-\frac{1}{\sigma}} P_s Y_s^{\frac{1}{\sigma}} \tag{11}$$

where r and λ are the prices of debt and equity and $\tau_{D_{si}}$ and $\tau_{E_{si}}$ are the distortions in each market. Static optimization yields the following optimality conditions:

$$\alpha_s \frac{(\sigma-1)}{\sigma} \frac{P_{si}F_{si}}{\alpha_s D_{si} + (1-\alpha_s) D_{si}^{\frac{1}{\gamma_s}} E_{si}^{\frac{(\gamma_s-1)}{\gamma_s}}} = r(1+\tau_{D_{si}}) \tag{12}$$

$$\alpha_s \frac{(\sigma-1)}{\sigma} \frac{P_{si}F_{si}}{(1-\alpha_s) E_{si} + \alpha_s D_{si}^{\frac{(\gamma_s-1)}{\gamma_s}} E_{si}^{\frac{1}{\gamma_s}}} = \lambda(1+\tau_{E_{si}}) \tag{13}$$

As it was the case when choosing real inputs, profit maximization requires that the marginal revenue products of equity and debt are equalized to their marginal costs. Under no distortions, our assumption of price-taking in capital markets would require that these marginal returns are equalized across firms. Therefore, any dispersion in marginal returns would once again constitute evidence of misallocation, in this case of financial liabilities

The CES structure of finance-based real value added precludes a transparent characterization of $TFPR$ as a function of distortions as it was possible for real inputs. For this reason, we define the finance-based marginal returns ($TFPR_{fin}$) as the following weighted average of the debt and equity distortions:

$$TFPR_{fin,si} = \frac{D_{si}}{D_{si} + E_{si}}(1 + \tau_{D_{si}}) + \frac{E_{si}}{D_{si} + E_{si}}(1 + \tau_{E_{si}}) \tag{14}$$

In the empirical and quantitative analysis that follows, we characterize the logarithm of the demeaned values of the firm-level marginal returns, $log\left(\frac{TFPR_{real,si}}{\overline{TFPR_{real,s}}}\right)$ and $log\left(\frac{TFPR_{fin,si}}{\overline{TFPR_{fin,s}}}\right)$. By demeaning the marginal returns with the industry average we are acknowledging that the only type of misallocation we are capturing is within a sector, being silent about any misallocation of real and financial inputs across industries. Lastly, following the literature, we conduct the within-sector average at the lowest level of aggregation allowed for by the data.

The last piece in the characterization of the equilibrium that feeds directly into the empirical analysis relates to the aggregation of firm-level outcomes. Since we are ultimately interested in the aggregate productivity gains that are reaped from efficiently reallocating real and financial inputs from the observed to the undistorted allocation, we must therefore characterize the aggregate output of an industry under no distortions. The real-input-based aggregation in the undistorted economy is simplified by the Cobb-Douglas nature of the production function and boils down to the following expression:

$$TFP_s = \left(\sum_{i=1}^{M_s} \left[A_{si}\frac{\overline{TFPR_s}}{TFPR_{si}}\right]^{\sigma-1}\right)^{\frac{1}{\sigma-1}} \tag{15}$$

where A_{si}, the firm-level $TFPQ$, can be backed out from the observation of the firm's value-added, the real inputs, and the CES structure fo the demand system as:

$$A_{si} \propto \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{(wL)_{si}^{1-\alpha_s} K_{si}^{\alpha_s}} \tag{16}$$

Notice that the aggregate productivity under the efficient allocation can be easily computed from equation 15 recalling that in such allocation, $TFPR$ is equalized across firms, so that equation 15 becomes:

$$\widehat{TFP}_{real,s} = \left(\sum_{i=1}^{M_s} (A_{si})^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$$

The aggregate productivity gain from reversing all the real-input misallocation in a given industry, then, is given by the ratio of the observed and the efficient aggregate productivity.

The CES structure of the function mapping the financial liabilities into real value added does not allow for a simple characterization of the aggregate total benefit as a function of demeaned marginal returns. Therefore, we must construct it for the undistorted and the observed allocations separately. Solving a benevolent social planner's problem of maximizing aggregate real value added subject to a given aggregate amount of debt and equity in the industry yields the following solution to the optimal debt and equity allocations:

$$\widehat{D}_{si} = \frac{Z_{si}^{\sigma-1}}{\Sigma_{i=1}^{M_s} Z_{si}^{\sigma-1}} D_s \tag{17}$$

$$\widehat{E}_{si} = \frac{Z_{si}^{\sigma-1}}{\Sigma_{i=1}^{M_s} Z_{si}^{\sigma-1}} E_s \tag{18}$$

where $\widehat{D}_s$ and $\widehat{E}_s$ stand for the aggregate debt and equity holdings allocated to industry s. Both expressions show the well-established result that, in an undistorted allocation, the more productive firms are assigned higher amounts of debt and equity, limited by the degree of substitutability between product varieties in the industry.

Given the definitions of efficient debt and equity holdings, the efficient real value added at the firm level is given by:

$$\widehat{F}_{si} = Z_{si}\left[\alpha_s \widehat{D}_{si}^{\frac{\gamma_s-1}{\gamma_s}} + (1-\alpha_s)\,\widehat{E}_{si}^{\frac{\gamma_s-1}{\gamma_s}}\right]^{\frac{\gamma_s}{\gamma_s-1}} \tag{19}$$

which can be obtained by plugging in the efficient debt and equity levels derived in equations 17 and 18 and appealing to the finance-based measure of the firm's $TFPQ$, Z_{si}, which is given by:

$$Z_{si} \propto \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{\left[\alpha_s D_{si}^{\frac{\gamma_s-1}{\gamma_s}} + (1-\alpha_s)\,E_{si}^{\frac{\gamma_s-1}{\gamma_s}}\right]^{\frac{\gamma_s}{\gamma_s-1}}} \tag{20}$$

The aggregate real value added of an industry under the efficient allocation is simply $\widehat{Y}_s = \left[\sum_{i=1}^{M_s} \widehat{F}_{si}^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$. As was the case for the real-input allocative gains, in the quantitative analysis we shall focus on the aggregate gains from resolving financial misallocation as given by the ratio between the aggregate real value added in the undistorted economy and the one observed in the data.

2.2. Data and stylized facts

We use firm-level information from Bureau van Dijk's Orbis global database, the largest cross-country database containing information on firms' financial statements, production activity, and firm ownership (Kalemli-Ozcan et al., 2019). We consider all industrial sectors, including financial companies and services (see table **??** in A.1). We observe European firms over a full economic cycle between 2010 and 2016. To clean up the data for our intended purposes, we follow Cusolito and Didier (2022) and select firms for which we have information on the key variables in our study, namely total sales, compensation of employees, interest payments, taxes, paid-in shareholder equity, total debt and date of establishment. Our final sample comprises information on approximately 6.5 million observations across 25 European countries.

Table 1 reports the number of countries and firms in our sample. Out of 25 countries, according to the 2021 World Bank classification of countries into income groups, 19 are high-income countries and 6 are upper-middle-income countries. Italy is the country with the largest number of firms (22% of the sample) and Luxembourg the lowest (0.002% of the sample). On average, more than 60% of total assets are financed through debt. Liabilities to total assets range from 41% (North Macedonia) to 77% (Italy). The ratio of value-added (VA) to total assets is on average around 1, varying between a minimum of 45% (Bosnia and Herzegovina) to a maximum of 150% (Finland).

Table 1: Summary Statistics

Country name	Firms	Liabilities to Assets	VA to Assets
Austria	10,323	0.62	0.97
Belgium	79,603	0.59	0.79
Bosnia and Herzegovina	29,245	0.51	0.45
Bulgaria	365,933	0.44	1.42
Croatia	187,792	0.59	0.73
Czech Republic	382,278	0.50	0.84
Estonia	96,724	0.44	1.08
Finland	138,442	0.58	1.39
France	851,560	0.61	1.22
Germany	127,275	0.62	1.12
Hungary	63,549	0.53	0.90
Italy	2,011,357	0.74	0.82
Latvia	6,518	0.47	0.99
Luxembourg	2,825	0.57	0.88
Montenegro	7,544	0.48	0.65
North Macedonia	73,500	0.41	1.36
Norway	92,419	0.64	1.41
Poland	52,987	0.49	0.92
Portugal	577,537	0.60	0.73
Romania	647,202	0.55	0.92
Serbia	150,549	0.54	0.81
Slovak Republic	257,111	0.58	0.99
Slovenia	147,632	0.54	1.11
Spain	1,651,423	0.58	0.79
Ukraine	79,935	0.41	1.32
Total	8,091,263	0.61	0.93

Table 2 summarizes the cost of financing through debt of firms classified according to their size. In all years, smaller firms face a higher cost of financing through debt.

Moreover, not only the average cost of finance appears to be higher for smaller firms, but there is also a higher dispersion suggesting potentially greater misallocation. Table 3 shows similar patterns but with some distinctions. The cost of equity financing is still greater for smaller firms but variability within size clusters appears to be elevated also for larger firms.

Table 2: Cost of Debt (by Size)

	0-5		5-15		15-30		30-50		50-70		70-85		85-95		95-100	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2010	1.24	3.28	0.80	1.35	0.63	2.27	0.50	0.91	0.42	0.82	0.36	0.74	0.30	0.38	0.23	0.32
2011	1.30	15.76	0.82	2.72	0.63	1.57	0.50	1.54	0.41	1.22	0.35	0.70	0.30	0.48	0.23	0.29
2012	1.16	4.63	0.81	5.40	0.62	2.07	0.48	1.20	0.40	0.77	0.35	0.88	0.30	0.48	0.24	0.35
2013	1.22	9.67	0.81	2.61	0.63	2.03	0.51	2.78	0.41	1.30	0.35	0.81	0.31	0.83	0.26	2.50
2014	1.20	7.26	0.82	3.11	0.63	1.39	0.50	1.15	0.42	1.18	0.36	0.71	0.32	0.59	0.26	0.33
2015	1.21	3.24	0.86	1.71	0.69	4.17	0.55	1.99	0.45	2.49	0.38	0.81	0.36	8.39	0.27	0.72
2016	1.42	13.12	0.93	3.73	0.73	10.58	0.56	2.03	0.45	0.95	0.38	0.67	0.34	1.88	0.27	0.43

Note: This table reports the mean and standard deviation in each year of the cost of debt of firms classified according to their size, from the smallest size (up to the 5th percentile) to the largest size (95th percentile to 100th percentile).

Table 3: Cost of Equity (by Size)

	0-5		5-15		15-30		30-50		50-70		70-85		85-95		95-100	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2010	1.31	3.32	1.01	2.92	0.86	6.83	0.70	4.11	0.59	2.72	0.55	19.46	0.43	4.12	0.41	10.77
2011	1.29	4.09	1.02	3.28	0.88	3.76	0.76	5.55	0.69	14.61	0.54	3.54	0.44	2.58	0.43	10.63
2012	1.34	4.76	1.06	3.93	0.91	5.84	0.77	4.45	0.72	23.50	0.54	4.28	0.44	2.15	0.36	5.22
2013	1.34	3.76	1.13	6.45	0.93	6.84	0.78	5.79	0.68	14.09	0.53	2.09	0.45	2.45	0.40	5.15
2014	1.44	7.38	1.12	4.63	0.93	3.26	0.79	4.94	0.68	6.00	0.55	3.22	0.46	2.66	0.41	7.74
2015	1.49	5.01	1.19	5.26	1.01	11.79	0.85	9.78	0.67	3.15	0.64	35.26	0.66	54.50	0.40	7.27
2016	1.48	3.29	1.19	4.32	0.98	4.46	0.81	4.68	0.67	3.93	0.56	5.47	0.45	2.42	0.37	2.11

Note: This table reports the mean and standard deviation in each year of the cost of equity of firms classified according to their size, from the smallest size (up to the 5th percentile) to the largest size (95th percentile to 100th percentile).

Tables 4 and 5 summarize the cost of debt and equity by age group. We do not observe a clear pattern in the cost of funding among age groups. In general, firms older than 10 years appear to have the lowest mean cost but not necessarily the lowest variability in the cost of funding. For the other age groups, there is not a monotonic relationship among the groups, both in terms of the mean cost of funding and the within-group variability of the cost of debt or equity.

Table 4: Cost of Debt (by Age)

	0-2		2-5		5-10		10+	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2010	0.45	0.61	0.54	0.68	0.59	1.28	0.49	1.38
2011	0.50	0.79	0.71	23.22	0.60	3.22	0.49	1.58
2012	0.60	2.60	0.59	8.95	0.61	2.84	0.47	1.13
2013	0.60	1.19	0.62	1.63	0.64	5.42	0.48	1.85
2014	0.56	0.74	0.64	2.24	0.61	2.99	0.48	1.92
2015	0.56	1.22	0.69	1.60	0.64	3.47	0.51	3.87
2016	0.76	3.06	0.70	7.89	0.63	2.41	0.51	5.03

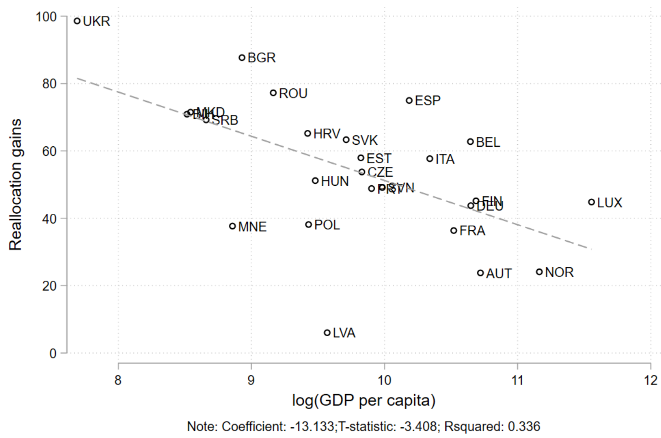
Note: This table reports the mean and standard deviation in each year of the cost of debt of firms classified according their age, from the youngest (up to 2 years) to the oldest (greater than 10 years) firms.

Table 5: Cost of Equity (by Age)

	0-2		2-5		5-10		10+	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2010	0.99	3.02	1.25	3.68	1.09	5.47	0.61	9.41
2011	1.52	10.09	1.41	5.79	1.09	5.55	0.63	8.32
2012	1.48	7.92	1.61	45.60	1.11	6.67	0.62	7.83
2013	1.50	5.57	1.51	11.98	1.04	4.37	0.62	8.10
2014	1.55	4.10	1.48	10.19	0.98	4.18	0.60	3.78
2015	1.47	9.35	1.40	5.78	1.00	13.02	0.66	27.27
2016	1.73	8.91	1.25	5.58	0.93	5.60	0.60	3.18

Note: This table reports the mean and standard deviation in each year of the cost of equity of firms classified according their age, from the youngest (up to 2 years) to the oldest (greater than 10 years) firms.

Figure 1: Productivity Gains from Reversing Finance Misallocation



Note: The figure shows the counterfactual aggregate TFP gain that each country would enjoy if finance misallocation was reversed. The gains are computed based on the methodology described in section 2.1. The GDP per capita is based on the Penn World Tables Database.

3. Aggregate Results

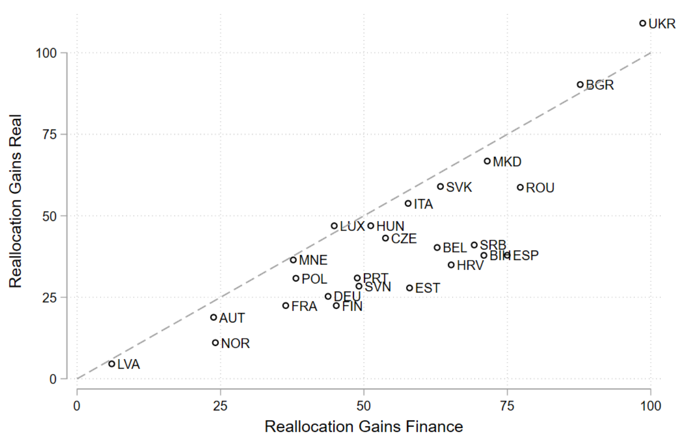
Equipped with a theoretical framework and a suitable global database, we begin the presentation of the aggregate results obtained using our empirical framework. At the aggregate level, the headline object of interest is the aggregate productivity gain that would be obtained from the reversal of the misallocation of financial liabilities. Following Whited and Zhao (2021), the thought experiment underlying this result is the computation of the aggregate TFP under the hypothetical efficient allocation and compare it with the TFP under the observed distribution of debt and equity. In figure 1, we plot the aggregate gains against the log of GDP per-capita, which we take as proxy for the degree of financial development across countries.

Figure 1 shows a strong negative relationship between finance misallocation and economic development. At the bottom of the income distribution, the TFP gains of efficiently reallocating financial liabilities reach approximately 80%, almost doubling the gains to be reaped by the richer countries. As a benchmark, Whited and Zhao (2021) find gains in the order of 11% to 12% in the U.S. and 70% to 80% in China. Not only do these numbers reinforce the plausibility of our findings, but they also imply that the majority of the countries in our sample fall between the polar cases of

China and the U.S.

We turn the focus now to assess the degree of correlation between financial and real measures of misallocation. The theory posits that productivity losses from finance misallocation operate from an induced misallocation of physical capital, labor, and material. Therefore, assessing the extent to which this mechanism is indeed taking place in the data is of great value for the validity of the methodology. Our multi-country database enables us to perform such an assessment. To this end, then, we apply the real misallocation methodology based on Hsieh and Klenow (2009) to our data and investigate the relationship between the productivity gains accruing from the reversal of the real misallocation vis-a-vis the gains resulting from undoing financial misallocation. At this stage, we present a simple correlation between the two measures and later pursue a richer empirical strategy aimed at identifying the causal effect of finance on real misallocation. The relationship between the two outcomes is plotted in Figure 2. It shows that the aggregate gains from reversing financial and real misallocation are strongly correlated, offering some preliminary support to the mechanisms of the finance misallocation theory.

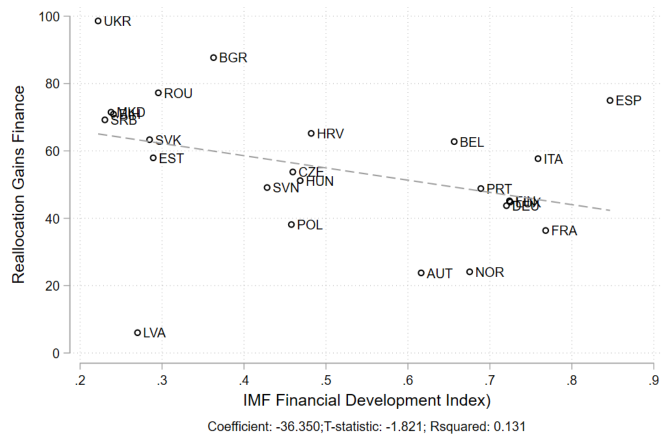
Figure 2: Finance and Real Misallocation



Note: The figure shows the counterfactual aggregate TFP gain that each country would enjoy if finance misallocation was reversed (X-axis, $Reallocation gains WZ$ computed following Whited and Zhao (2021)), against the counterfactual productivity gain that would be obtained from reversing real-input misallocation (Y axis, $Reallocation gains HK$, computed following Hsieh and Klenow (2009).

To provide an intuition of what may cause financial misallocation, we plot the country's measure of financial misallocation against a measure of financial development (Figure 3).

Figure 3: Finance Misallocation and Financial Development

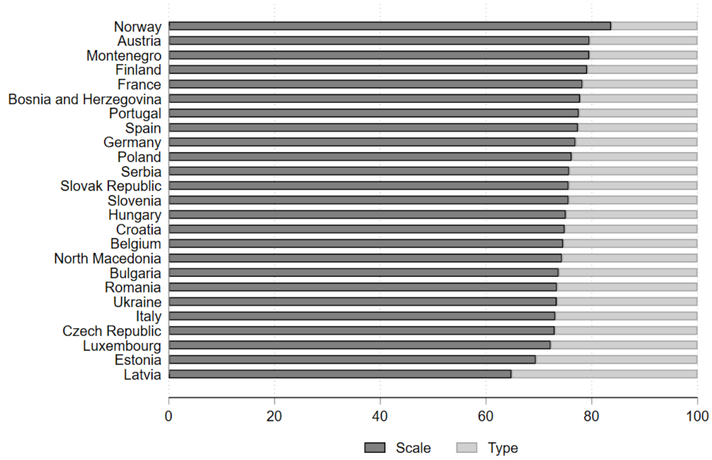


Note: The figure plots finance misallocation (Y axis, *Reallocation Gains Finance*, computed following Whited and Zhao (2021)), against a measure of financial development (X axis, *Financial Development* as computed in Sahay et al. (2015)) .

To close the section with aggregate results, we provide a decomposition of the contribution of the aggregate level vis-a-vis the composition of the distribution of financial liabilities across firms in explaining the overall degree of finance misallocation. We do this by comparing the baseline results under our estimates of the elasticity of substitution between debt and equity across sectors against those emerging from the imposition of perfect substitution between financial liabilities. Since, in the latter case, the ratio of debt and equity is irrelevant for real value added, the extent to which this specification captures the productivity gains from the baseline represents a measure of the contribution of the levels of finance in reaping these gains.

Figure 4 shows that aggregate productivity gains accrue mostly from achieving the efficient level of finance across firms rather than from attaining the efficient composition of liabilities. Keeping debt-to-equity ratios fixed, reallocating funds from the low to the high marginal return firms would reap in all countries more than 60% of the total gains in aggregate productivity. This share is remarkably robust across

Figure 4: The Role of Levels of Finance versus Composition



Note: The figure shows the counterfactual aggregate TFP gain that each country would enjoy if finance misallocation was reversed under the baseline estimation of the elasticity of substitution between debt and equity and under the alternative scenario of perfect substitutability. The gains under perfect substitution are depicted in green, and the difference between the baseline and the perfect substitution, which measure the contribution of the debt-to-equity ratios, is depicted in orange.

our sample of countries and is only slightly below the 79% to 83% share reported by Whited and Zhao (2021) for China.

In short, this section reviewed some of the most salient findings derived from a novel methodology to measure finance misallocation in a broad cross-section of countries. The main conclusion is that the methodology delivers a systematic relationship between the level of economic development and the degree of finance misallocation. We also find suggestive evidence that, as presumed by the methodology, there could be a causal relationship between financial and real-input misallocation, a conjecture that we shall revisit under a richer empirical strategy in the coming sections. Lastly, our examination of the contribution of the levels vis-a-vis the composition of finance in a cross-country setting validates the finding that is documented for China: it is the level rather than the composition that accounts for the largest share of the measured financial misallocation.

4. Heterogeneous Effects: The Role of Age and Size

A long-lasting hypothesis in the macro-finance literature is that the size and the age of the firm constitute important determinants of a firm's access to finance (Beck et al., 2008). Larger firms are better able to pledge collateral in contexts where the relevant financial frictions is a limited commitment problem. Similarly, moral hazard may be attenuated when the borrower is a large firm. A similar reasoning applies to older firms where the accumulation of capital over time and the availability of information reduce financial frictions. In this section, we leverage the richness of the data to explore these hypotheses.

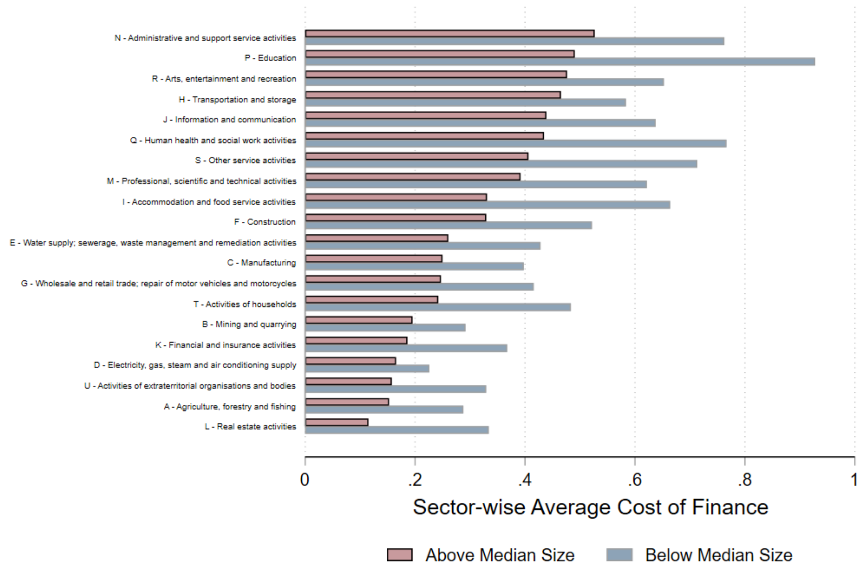
We begin by exploring the differences in the average cost of finance across firms of different sizes. Within an industry in a particular country, we classify firms into small and large based on their asset holdings being above or below the median in the sector-country. Then, we take the model-implied average cost of finance among small and large firms and average it across countries to construct a global measure of the average cost of finance by firm size within each sector. The results are plotted in Figure 5.

Figure 5 reveals a clear pattern: in all industries, the average cost of finance is higher for smaller than for larger firms. A higher cost of finance in our model is reflective of a high marginal return to additional units of finance and is thus suggestive of a scarcity of funds relative to the optimal level. Therefore, our results dictate that in response to a hypothetical reform that liberalizes capital and credit markets, we should expect finance to flow from the larger to the smaller firms. Indeed, this prediction is in accordance with the findings in the recent literature studying the firm-level response to financial liberalization episodes,[4] although in these papers the inference is based on the observation of the reallocation of real inputs.

We turn now to exploring differences in the average cost of finance across firms of different ages. We classify firms within an industry into young and old based on

[4]See, for instance, the work of Larrain and Stumpner (2017), and Bau and Matray (2020)

Figure 5: Heterogeneous Costs of Finance: The Role of Size



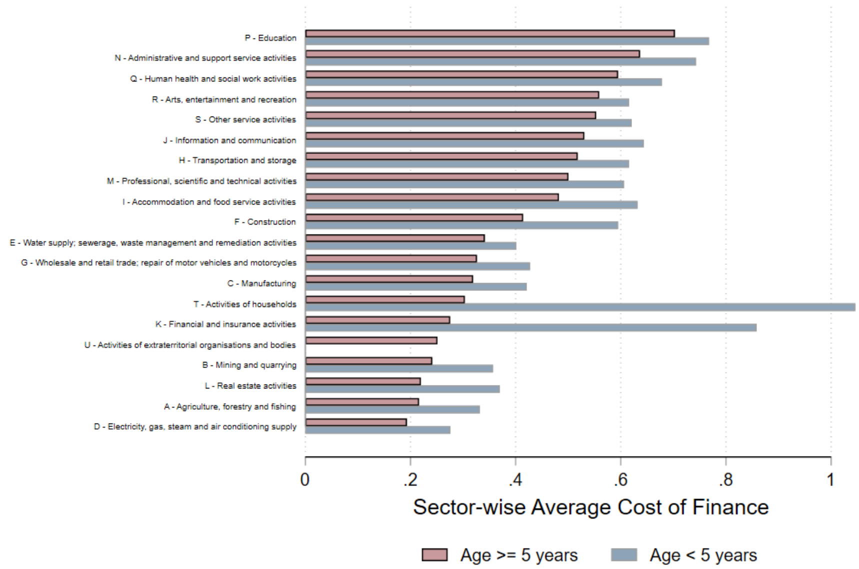
Note: The figure shows the model-based average cost of finance among small (less than the median size of the relevant sector in each country) and large (more than the median size of the relevant sector in each country) firms within each sector classified according to NACE 1.

them being less than or greater than five years old (if exactly five years old, the firm is considered young). We then compute the average cost of finance across young and old firms within an industry in a country and the average across countries.

Figure 6 also shows a common pattern of heterogeneity across firms: Young firms are systematically confronted with higher shadow costs of finance than older firms. As in the case of size, the model-based nature of our measure of the cost of finance is reflective of a higher marginal return to finance among younger firms, and hence funding would be reallocated to these firms in the event of a removal of financial frictions. The same literature tracking real-input reallocation in response to capital market liberalizations also confirms this prediction.

While figures 5 and 6 are suggestive of a negative relationship between firm size, firm age, and the average cost of finance, we validate these relationships and assess their quantitative magnitude in a controlled regression setting. To this end, then, we estimate the following equation:

Figure 6: Heterogeneous Costs of Finance: The Role of Age



Note: The figure shows the model-based average cost of finance among old (more than five years) and young (less of or equal to five years) firms within each sector classified according to NACE 1.

$$log(TFPR_{i,s,t}/\overline{TFPR_{s,t}}) = \beta_1 log(Assets_{i,s,t}) + \beta_2 Age_{i,s,t}$$
$$+\beta_3 log(TFPQ_{i,s,t}/\overline{TFPQ_{s,t}}) + \alpha_i + \alpha_t + \alpha_c * \alpha_t + \alpha_s * \alpha_t + \epsilon_{i,s,t} \quad (21)$$

where subscripts i, c, t, and s denote the firm, country, year, and industry, respectively; $log(TFPR_{i,s,t}/\overline{TFPR_{s,t}})$ denotes the model-based measure of a firm's cost of finance relative to the average cost in the corresponding industry, and $log(TFPQ_{i,s,t}/\overline{TFPQ_{s,t}})$ stands for the firm's financed-based $TFPQ$ relative to the average in the industry, as defined in equation 20. We use a diverse set of fixed effects to control for both firm-specific and systematic factors that may affect a firm's cost of finance. In particular, we intend to capture the effect of firm-specific risk premiums on the firms' average cost of finance, a factor that would manifest as a financial distortion in the model but is a feature that should also be part of the social planner's economic environment (David et al., 2020).

In addition to isolating the effect of a firm's age and size on its average cost of finance from other factors, the regression specifications also seek to assess productivity dependence in the distribution of financial wedges. This is motivated by the real misallocation literature, where it is a well-established feature of resource misallocation that distortions tend to tax productive firms more heavily than less productive ones. As shown in the literature, idiosyncratic distortions carry larger aggregate effects when increasing with the firms' physical productivity. [5] By including $log(TFPQ_{i,s,t}/\overline{TFPQ_{s,t}})$, in contemporaneous or lagged fashion, we seek to establish if such a relationship manifests as well in the context of financial distortions.

Table 6: Cost of Finance: The Role of Firm Age and Size

	(1)	(2)	(3)	(4)
Age	0.0125***	0.0107***	-0.0042*	-0.0265***
	(0.0032)	(0.0032)	(0.0025)	(0.0086)
Log(Assets)	-0.5336***	-0.5403***	-0.5482***	
	(0.0002)	(0.0002)	(0.0002)	
log(TFPQ)	0.4005***	0.4023***	0.4201***	
	(0.0001)	(0.0001)	(0.0001)	
Log(Assets)$_{t-1}$				-0.1749***
				(0.0009)
log(TFPQ)$_{t-1}$				0.0703***
				(0.0004)
Observations	8091263	8091263	8091263	5494912
Country fixed effects	Y	Y	N	N
Time fixed effects	Y	N	N	N
Industry fixed effects	Y	N	N	N
Firm fixed effects	Y	Y	Y	Y
Industry-time fixed effects	N	Y	Y	Y
Country-time fixed effects	N	N	Y	Y

Note: Standard errors in parentheses. This table presents the results obtained using equation 21. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 confirms that older and larger firms confront a relatively lower cost of

[5] See, for instance, Hsieh and Klenow (2014) and Bento and Restuccia (2017)

financing relative to their younger and smaller peers in the same industry and country. Recall that the cost of finance is measured according to the theory and reflects the cost of acquiring an extra unit of debt and equity that rationalizes marginal returns exhibited by the firm in the data. The results, then, dictate a 10% increase in the size of a firm is associated with a 1.7% reduction in the shadow cost of finance, whereas a 1-year increase in firm age corresponds to a reduction in the order of 2.6%. Column 3 shows that these results are robust to using contemporaneous measures of firm size and TFPQ instead of lagged values.

The productivity dependence of idiosyncratic financial distortions shows prominently in table 6. Comparable to estimates in the real misallocation literature, financial frictions are significantly and strongly increasing in the underlying level of physical productivity of the firm. Even when projecting distortions on lagged values of physical productivity and controlling for a wider range of firm and other types of fixed effects, the positive relationship between productivity and financial distortions is weakened but remains statistically significant.

In summary, in this section, we provided empirical validation for the widely believed and unconvincingly proven idea that firm age and size are important determinants of the ease of access to financing opportunities by firms. We investigated this hypothesis in the context of a novel inference strategy of financial misallocation that relies on the direct observation of the distribution of financial liabilities across firms, applied to a rich firm-level database with rich cross-country and time-series coverage. We found that larger and older firms do face significantly lower costs of external financing.

5. From Finance to Real Misallocation

We now turn to address the second contribution of the paper, namely, answering the question we postulated in the introduction: how much of the observed misallocation of real inputs can be attributed to a misallocation of finance? As stated earlier in the text, the core of the measurement of finance misallocation in our paper lies in the assumption that disruptions in the allocation of finance across firms cause a misallocation of real inputs, which in turn translates into productive inefficiency. While the aggregate evidence presented in section 3 is suggestive of such a relationship being at play, in this section we propose a richer empirical strategy aimed at identifying a causal link between finance and real misallocation.

Our strategy involves estimating the relationship between two model-based summary measures of misallocation: the standard deviation of the logarithm of the demeaned marginal revenue product of real inputs within an industry, yielded by the application of Hsieh and Klenow (2009)'s methodology, and the standard deviation of the logarithm of the demeaned marginal revenue products of financial resources, yielded by the application of the methodology in Whited and Zhao (2021). Financial market imperfections may affect industries in a different fashion, hence the first channel to be explored is whether industries with higher measured finance misallocation are associated with a higher real misallocation, controlling for country, year, and industry fixed effects. Moreover, to get one step closer to identifying a causal relationship, we follow Rajan and Zingales (1998) in splitting industries into high or low external finance dependence, based on a classification applied to industries in the United States. Equipped with this taxonomy, we then also consider the interaction between the high/low external finance indicator and the finance misallocation of an industry as another explanatory variable for the degree of real misallocation. The idea here is that industries that rely more heavily on external credit should exhibit a higher degree of real misallocation, for any given degree of finance misallocation.

Formally, our estimating equation is given by:

$$\begin{aligned} sd(log\_TFPR\_real)_{s,c,t} = \alpha_s + \gamma_c + \tau_t + sd(log\_TFPR\_fin)_{s,c,t} + \\ sd(log\_TFPR\_fin)_{s,c,t} \times \mathbb{1}\{EFD_{s,USA}\} + \epsilon_{s,c,t} \end{aligned} \tag{22}$$

where s denotes industry, c denotes country, t denotes time, EFD denotes external finance dependence of an industry, and $sd(log\_TFPR)_{s,c,t}$ is the standard deviation of log(TFPR/$\overline{TFPR}$) within an industry-country. Subscripts fin and $real$ refer to financial and real distortions, respectively. To attenuate concerns about reverse causality and endogeneity, we consider specifications of the estimating equation where the explanatory variable of interest, the standard deviation of the log of financial distortions, is lagged to the previous period's value.

The external finance dependence within an industry is computed as an average of the following firm-level indicator:

$$EFD_{is} = \frac{(TotalCapitalExpenditure_{is} - TotalCashFlow_{is})}{TotalCapitalExpenditure_{is}} \tag{23}$$

That is, following Rajan and Zingales (1998), we define the external finance dependence of the firm i in sector s as the fraction of its capital expenditures that could not be financed with internal sources of funding. The total cash flow, in turn, is computed as an aggregate of total funds from operations, plus increases in accounts payable decreases in inventories, and decreases in receivables. Importantly, these cash flows are independent of the internal equity of the firm, which we treat as a source of external finance in the measurement of finance misallocation. The sector-wide external finance is the average across firms in the industry. As said, for identification, we apply this indicator to the U.S. economy based on Compustat data. Finally, we classify an industry as highly dependent on external finance if its indicator is above the median across all industries.

Table 7 presents the results from estimating equation 22. We report a positive and statistically significant coefficient for the effect of finance-based on real-based $TFPR$ dispersion. Moreover, we also document a positive and statistically significant coefficient on the interaction between financial misallocation and the high external finance dependence indicator. In industries with a higher reliance on external credit, the misallocation of real resources that are created by the misallocation of finance is

Table 7: From Finance to Real Misallocation

	(1)	(2)
sd(log_TFPR_fin)	0.2647***	
	(0.0099)	
sd(log_TFPR_fin) $\times$ $\mathbb{1}\{EFD_{s,USA}\}$	0.0392***	
	(0.0131)	
sd(log_TFPR_fin)$_{t-1}$		0.1550***
		(0.0098)
sd(log_TFPR_fin)$_{t-1}$ $\times$ $\mathbb{1}\{EFD_{s,USA}\}$		0.0421***
		(0.0136)
Observations	51722	43386
Country fixed effects	Y	Y
Time fixed effects	Y	Y
Industry fixed effects	Y	Y

Note: Standard errors in parentheses. This table presents the results obtained using equation 22.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

about 4 percentage points higher than the average.

Our goal next is to provide an economic interpretation of the regression coefficients reported in table 7. What are the TFP consequences of the real misallocation that results from financial frictions? The question cannot be answered directly from the estimates in the table. The missing piece is a conversion factor that translates changes in the standard deviation of real marginal returns into changes in aggregate productivity. Such a conversion factor can be gauged by running the following regression:

$$TFPgain_{s,c,t} = \alpha_s + \gamma_c + \tau_t + SD_{TFPR_{real},s,c,t} + \epsilon_{s,c,t} \tag{24}$$

which projects a given industry-country's TFP gain from reversing misallocation, $TFPgain_{s,c,t}$, against the given industry-country's degree of real-input misallocation as captured by the standard deviation of the marginal return to real factors, $SD_{TFPR_{real},s,c,t}$

As expected, table 8 reports a strong positive coefficient for the relationship be-

Table 8: TFP Effects of Dispersion in Marginal Returns to Real Inputs

	100*{($Y_{Effective}/Y_{Actual}$)-1}
sd(log_TFPR_real)	186.8481***
	(8.7875)
Observations	63743
Country fixed effects	Y
Time fixed effects	Y
Industry fixed effects	Y

Note: Standard errors in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

tween dispersion in marginal returns and counterfactual gains in aggregate productivity. For instance, reducing $SD_{TFPR_{real}}$ from its median value (0.566) to the 25^{th} percentile (0.407) would imply an aggregate productivity gain of 28%.[6]

We are now ready to answer the question of what is the economic significance of the effect of finance misallocation on real misallocation.[7] Consider a reduction in the dispersion of marginal returns to financial inputs from the median to the 25^{th} percentile of the cross-industry distribution of standard deviations, i.e. a reduction of 0.145.[8]According to our estimates in table 7, such a decline reduces the standard deviation of marginal returns to real inputs by 0.038 in the average industry and by 0.044 in industries with high external finance dependence.[9] Then, feeding these effects on the coefficient mapping real misallocation to aggregate productivity (table 8), we find that the proposed improvement in finance misallocation ends up increasing aggregate productivity by 7.1% on average and by 8.2% in industries with high external finance dependence.[10]

[6]The aggregate productivity gain is computed as follows: (0.55-0.4)*186.8481 = 28.03%.

[7]As a reminder, every time refer to financial misallocation, we mean the within-industry-country dispersion in the log of marginal returns to financial liabilities, demeaned by the industry-country average, i.e. $\log(TFPR_{fin}/\overline{TFPR_{fin}})$. Likewise, with real-input misallocation we mean the dispersion in $\log(TFPR_{real}/\overline{TFPR_{real}})$

[8]The reduction in the dispersion of marginal returns is computed as follows: 0.683-0.538 = 0.145.

[9]The reduction in the standard deviation of marginal returns to real inputs in the average industry is computed as follows: 0.145*0.2647 = 0.038. The value for industries with high external finance dependence is: 0.145*(0.2647+0.0392)=0.044.

[10]0.038*186.8481 = 7.1, 0.044*186.8481 = 8.22

To put the quantitative implications of our identification strategy in perspective, we contrast our results with those found in the macro-development literature. In Buera et al. (2011), Midrigan and Xu (2014), and Moll (2014), salient examples in the literature, the quantification is based on the postulation of specific financial friction (a collateral constraint) in the context of a general equilibrium model of firm dynamics and the quantification of the productivity gains resulting from the alleviation of the friction. Our results fall in the ballpark of their findings. Midrigan and Xu (2014), for instance, document productivity losses in the order of 5% to 10% arising from the misallocation of labor and capital across firms within a sector, including the 8.2% that we estimate in our study.[11] We interpret the proximity of our results to those emerging from alternative quantification strategies as providing reassurance to the validity of our empirical specification.

In short, in this section we constructed a bridge between the finance misallocation methodology proposed in Whited and Zhao (2021) and the real misallocation counterpart pioneered in Hsieh and Klenow (2009). We proposed an identification strategy to tease out the association of finance with real misallocation and ultimately aggregate productivity. We found that a plausible improvement in the degree of capital market imperfections that brings finance misallocation down from the median to the 25^{th} percentile of the cross-industry distribution of financial misallocation would trigger aggregate productivity gain of 7.1% on average, and an extra 1.1% gain in industries with a higher dependence on external credit. We found reassurance for the plausibility of these findings in that they fall in the ballpark of the gains found in macro-development studies under very different quantification strategies.

[11] Midrigan and Xu (2014) and Buera et al. (2011) find larger productivity gains from reversing financial frictions when accounting for compounding forces, such as the effect of these frictions on limiting the adoption of better and more modern technologies. However, since our methodology is designed to capture the allocative channel only, it is not comparable to the magnitudes generated by these magnifying mechanisms

6. Conclusion

Financial frictions play an important role in determining total factor productivity. In this study, we advance the extant literature by providing new evidence on the global properties of financial misallocation and its ability to account for the misallocation of real resources that is observed in the data.

In light of a promising new methodology to measure finance misallocation and its narrow application to a pair of countries, an important goal of the paper was to assess whether such methodology would deliver reasonable implications for the distribution of finance misallocation across countries with different degrees of financial development. Such an assessment is challenged by the data requirements: one must be able to count with firm-level databases offering a wide international and sectoral coverage, as well as rich information on the firm's balance sheet. In this paper, we took this challenge confronting the new methodology with ORBIS database, arguably the only suitable database for the task.

We confirm that the novel measure of finance misallocation proposed in Whited and Zhao (2021) varies systematically with a country's economic development in the direction that one would expect: finance misallocation is twice as severe in the poorest than in the richest countries in our sample.

We also validate a number of well-rooted conjectures in the literature concerning the distribution of financing costs across firms of different ages and sizes. Based on the theoretical implication that younger and smaller firms are more likely to be financially constrained, we show that this is actually the case under our measure of theory-based financing costs: small and young firms confront a significantly higher cost of accessing external finance.

Perhaps the most novel of our contributions was the ability to establish an empirical connection between the novel measure of finance misallocation and the most standard measure of real-input misallocation that has been widely adopted in the literature since the work of Hsieh and Klenow (2009). Establishing such a connection is essential for the validity of one of the central assumptions behind the approach to measuring financial misallocation: that by disrupting the costs of accessing debt and equity markets, firms are in effect unable to acquire the efficient levels of productive factors. We close this gap in this paper and show that there is a strong positive correlation between financial misallocation in an industry and its degree of misallocation of real resources. Our estimates yield significant productivity gains from reducing finance misallocation. Mediated by its implied improvement in real allocative efficiency, we find that reducing finance misallocation generates aggregate gains in Total Factor Productivity in the order of 7% to 8%, in the ballpark of what has been found earlier in the literature.

While the paper builds upon a novel approach to measuring financial misallocation, it remains silent about the potential causes of such misallocation. In future research, we expect to leverage the rich time dimension of our database to identify plausible exogenous natural experiments that can provide us with a clean identification of the effect of a particular type of financial reform on finance misallocation and ultimately aggregate productivity.

Acknowledgements

The views in this paper are those of the authors and do not necessarily represent those of the World Bank, their Executive Directors, or the countries they represent. We thank Tatiana Didier, Leonardo Iacovone, Ha Nguyen, Jean Pesme and the participants to the World Bank authors' workshop of the flagship report for useful suggestions.

Appendix A. Supplementary tables and figures

Table A.1: Classification of firms into industries

Code Value	Description	Industry
01	Agricultural Production - Crops	A. Agriculture, Forestry, & Fishing
02	Agricultural Production - Livestock and Animal Specialties	A. Agriculture, Forestry, & Fishing
07	Agricultural Services	A. Agriculture, Forestry, & Fishing
08	Forestry	A. Agriculture, Forestry, & Fishing
09	Fishing, Hunting and Trapping	A. Agriculture, Forestry, & Fishing
10	Metal Mining	B. Mining
12	Coal Mining	B. Mining
13	Oil and Gas Extraction	B. Mining
14	Mining and Quarrying of Nonmetallic Minerals, Except Fuels	B. Mining
15	Construction - General Contractors & Operative Builders	C. Construction
16	Heamy Construction, Except Building Construction, Contractor	C. Construction
17	Construction - Special Trade Contractors	C. Construction
20	Food and Kindred Products	D. Manufacturing
21	Tobacco Products	D. Manufacturing
22	Textile Mill Products	D. Manufacturing
23	Apparel, Finished Products from Fabrics & Similar Materials	D. Manufacturing
24	Lumber and Wood Products, Except Furniture	D. Manufacturing
25	Furniture and Fixtures	D. Manufacturing
26	Paper and Allied Products	D. Manufacturing
27	Printing, Publishing and Allied Industries	D. Manufacturing
28	Chemicals and Allied Products	D. Manufacturing
29	Petroleum Refining and Related Industries	D. Manufacturing
30	Rubber and Miscellaneous Plastic Products	D. Manufacturing
31	Leather and Leather Products	D. Manufacturing
32	Stone, Clay, Glass, and Concrete Products	D. Manufacturing
33	Primary Metal Industries	D. Manufacturing
34	Fabricated Metal Products	D. Manufacturing
35	Industrial and Commercial Machinery and Computer Equipment	D. Manufacturing
36	Electronic & Other Electrical Equipment & Components	D. Manufacturing
37	Transportation Equipment	D. Manufacturing
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	D. Manufacturing
39	Miscellaneous Manufacturing Industries	D. Manufacturing
40	Railroad Transportation	E. Transportation & Public Utilities
41	Local & Suburban Transit & Interurban Highway Transportation	E. Transportation & Public Utilities
42	Motor Freight Transportation	E. Transportation & Public Utilities
43	United States Postal Service	E. Transportation & Public Utilities
44	Water Transportation	E. Transportation & Public Utilities
45	Transportation by Air	E. Transportation & Public Utilities
46	Pipelines, Except Natural Gas	E. Transportation & Public Utilities
47	Transportation Services	E. Transportation & Public Utilities
48	Communications	E. Transportation & Public Utilities
49	Electric, Gas and Sanitary Services	E. Transportation & Public Utilities
50	Wholesale Trade - Durable Goods	F. Wholesale Trade
51	Wholesale Trade - Nondurable Goods	F. Wholesale Trade
52	Building Materials, Hardware, Garden Supplies & Mobile Homes	G. Retail Trade
53	General Merchandise Stores	G. Retail Trade
54	Food Stores	G. Retail Trade
55	Automotive Dealers and Gasoline Service Stations	G. Retail Trade
56	Apparel and Accessory Stores	G. Retail Trade
57	Home Furniture, Furnishings and Equipment Stores	G. Retail Trade
58	Eating and Drinking Places	G. Retail Trade
59	Miscellaneous Retail	G. Retail Trade
60	Depository Institutions	H. Finance, Insurance, & Real Estate

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Table A.1 – continued from previous page

Code Value	Description	Industry
61	Nondepository Credit Institutions	H. Finance, Insurance, & Real Estate
62	Security & Commodity Brokers, Dealers, Exchanges & Services	H. Finance, Insurance, & Real Estate
63	Insurance Carriers	H. Finance, Insurance, & Real Estate
64	Insurance Agents, Brokers and Service	H. Finance, Insurance, & Real Estate
65	Real Estate	H. Finance, Insurance, & Real Estate
67	Holding and Other Investment Offices	H. Finance, Insurance, & Real Estate
70	Hotels, Rooming Houses, Camps, and Other Lodging Places	I. Services
72	Personal Services	I. Services
73	Business Services	I. Services
75	Automotive Repair, Services and Parking	I. Services
76	Miscellaneous Repair Services	I. Services
78	Motion Pictures	I. Services
79	Amusement and Recreation Services	I. Services
80	Health Services	I. Services
81	Legal Services	I. Services
82	Educational Services	I. Services
83	Social Services	I. Services
84	Museums, Art Galleries and Botanical and Zoological Gardens	I. Services
86	Membership Organizations	I. Services
87	Engineering, Accounting, Research, and Management Services	I. Services
88	Private Households	I. Services
89	Services, Not Elsewhere Classified	I. Services
91	Executive, Legislative & General Government, Except Finance	J. Public Administration
92	Justice, Public Order and Safety	J. Public Administration
93	Public Finance, Taxation and Monetary Policy	J. Public Administration
94	Administration of Human Resource Programs	J. Public Administration
95	Administration of Environmental Quality and Housing Programs	J. Public Administration
96	Administration of Economic Programs	J. Public Administration
97	National Security and International Affairs	J. Public Administration
99	Nonclassifiable Establishments	K. Nonclassifiable Establishments

Appendix B. Historical Financial Data Cleaning Procedure

Following van Dijk (2011), Kalemli-Ozcan et al. (2022), Cusolito and Didier (2023), and Kalemli-Ozcan et al. (2023), we document the steps we apply to clean the financial information.

1. *Fill time-invariant data gaps*: for a given BvD.ID-year combination, with BvD.ID standing for firm unique identifier, replace missing highly-likely time-invariant information with information available for previous years (e.g., US SIC code, NAICS, NACE, NACE main sector, company name, city, region, postal code, legal form, incorporation date, thicker, isin). To perform this step, the team first worked with auxiliary raw tables, which collect legal and sectoral information of the firm, and collapsed the time-invariant variables at the BvD.ID level.

2. *Harmonize timeframe*: convert variable closedate from string to numeric format. Then create a new variable, name it year, and assign a year to the observation according to the following rule. If closing month corresponding to the observation is June or any other month after June, then make Year take the year reported in closedate. Otherwise, make Year the year reported in closedate minus 1.

3. *Drop duplicates*: the raw database presents a large number of duplicates at the BvD.ID-year level. The team noticed that the information was the same, except in the SIC primary code variable. Thus, we collapsed all the SIC primary codes reported by the same BvD.ID-year in one variable, using semicolons to list all the SIC primary codes, and eliminated duplicates.

4. *Drop firms with missing relevant information*: drop all the firms with no information for the following set of variables: US SIC code, NAICS, NACE core code, NACE main sector.

5. *Drop observations with missing information for the currency code*: eliminate observations with missing information for the currency code.

6. *Drop observations with missing information for variable closedate*: eliminate observations with missing information for the close date of the financial statement.

7. *Drop observations with relevant missing information* eliminate observations that at the BvD.ID-year level have missing information in all the following variables: operating revenue (turnover), sales, employment, total assets.

8. *Drop duplicates and keep most updated information*: keep observations with the most recent closing date if there are duplicates at the BvD.ID-year-first letter of consolidation code (e.g., C, U) level.

9. *Drop duplicates and keep information from annual reports*: keep observations with annual report in *Use FillingType* variable if there are still duplicates and keep the standardized information. Using annual reports (IFRS preferred, instead of local reports) guarantees standardization of reporting protocol at international level.

10. *Eliminate firms with noisy data*: drop all the observations corresponding to a specific BvD.ID if any of the following variables has a negative value in a specific year – total fixed assets, tangible fixed assets, intangible fixed assets, other fixed assets, current assets, sales, and employment.

11. *Deflate values*: use country GDP deflators from the World Bank database to deflate nominal variables and set year 2005 as the base year.[12]

12. *Harmonize currencies*: convert values in local currency to USD dollars, using the average of the monthly exchange rate for year 2005.

13. *Validation of final database*: We validate the representatives of the final database by calculating the ratio of the sum of employment and gross output in the

[12]https://data.worldbank.org/indicator/NY.GDP.DEFL.ZS.

database to their corresponding aggregates, in the same manner as **?**. Aggregates for employment and gross output are obtained from Eurostat's Structural Business Statistics Database (SBS). Tables **??** and **??** show the coverage of our sample by country, separately for manufacturing and non-manufacturing sectors. [@Davide: Insert Tables about Here]

Appendix C. Sample representativity

The tables below report information on the representativity of the sample with respect to data collected by Eurostat. Data is reported separadetly for manufacturing and non-manufacturing firms.

Table C.2: Services

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Austria	2010	0%	19%	27%	16%	41%
Austria	2011	0%	21%	29%	18%	44%
Austria	2012	0%	29%	44%	35%	63%
Austria	2013	0%	35%	55%	40%	76%
Austria	2014	0%	29%	50%	35%	70%
Austria	2015	1%	33%	51%	40%	71%
Austria	2016	0%	29%	49%	37%	66%
Belgium	2010	2%	51%	86%	56%	97%
Belgium	2011	2%	51%	86%	56%	93%
Belgium	2012	2%	53%	88%	56%	93%
Belgium	2013	2%	54%	90%	56%	96%
Belgium	2014	2%	53%	89%	56%	94%
Belgium	2015	2%	53%	89%	54%	94%
Belgium	2016	1%	51%	87%	53%	91%
Bosnia and Herzegovina	2010					
Bosnia and Herzegovina	2011	20%	85%	102%	76%	107%
Bosnia and Herzegovina	2012	9%	37%	44%	39%	52%
Bosnia and Herzegovina	2013	20%	78%	96%	72%	103%
Bosnia and Herzegovina	2014	8%	75%	92%	65%	96%
Bosnia and Herzegovina	2015	6%	62%	78%	61%	83%
Bosnia and Herzegovina	2016	8%	70%	86%	63%	92%
Bulgaria	2010	7%	51%	64%	49%	247%
Bulgaria	2011	13%	62%	72%	54%	285%
Bulgaria	2012	14%	77%	77%	57%	305%
Bulgaria	2013	15%	75%	79%	58%	305%
Bulgaria	2014	15%	76%	80%	60%	309%

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Table C.2 – continued from previous page

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Bulgaria	2015	16%	81%	81%	60%	294%
Bulgaria	2016	14%	76%	79%	59%	273%
Croatia	2010	13%	49%	56%	55%	58%
Croatia	2011	15%	53%	62%	59%	62%
Croatia	2012	16%	55%	63%	63%	66%
Croatia	2013	16%	56%	65%	64%	66%
Croatia	2014	17%	58%	69%	67%	69%
Croatia	2015	18%	59%	70%	67%	71%
Croatia	2016	17%	61%	72%	69%	77%
Czech Republic	2010	5%	69%	72%	46%	95%
Czech Republic	2011	5%	75%	74%	45%	97%
Czech Republic	2012	5%	73%	76%	46%	99%
Czech Republic	2013	5%	74%	78%	48%	102%
Czech Republic	2014	5%	71%	80%	50%	104%
Czech Republic	2015	5%	73%	83%	52%	106%
Czech Republic	2016	4%	67%	80%	50%	100%
Estonia	2010	19%	41%	56%	36%	57%
Estonia	2011	20%	43%	57%	37%	56%
Estonia	2012	20%	43%	59%	39%	58%
Estonia	2013	20%	45%	61%	39%	59%
Estonia	2014	20%	45%	62%	41%	58%
Estonia	2015	19%	45%	62%	41%	59%
Estonia	2016	17%	47%	65%	42%	59%
Finland	2010	6%	43%	58%	51%	84%
Finland	2011	8%	45%	63%	56%	95%
Finland	2012	8%	45%	61%	52%	89%
Finland	2013	8%	45%	66%	60%	99%
Finland	2014	8%	46%	67%	59%	100%
Finland	2015	8%	45%	64%	59%	96%
Finland	2016	7%	44%	63%	57%	94%
France	2010	5%	20%	28%	23%	39%
France	2011	5%	19%	27%	22%	37%

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Table C.2 – continued from previous page

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
France	2012	4%	18%	25%	20%	35%
France	2013	4%	23%	30%	26%	45%
France	2014	4%	26%	36%	31%	55%
France	2015	3%	27%	35%	31%	54%
France	2016	2%	24%	33%	30%	51%
Germany	2010	1%	31%	56%	49%	82%
Germany	2011	1%	33%	59%	51%	80%
Germany	2012	1%	34%	60%	51%	82%
Germany	2013	1%	35%	61%	51%	82%
Germany	2014	0%	34%	60%	50%	81%
Germany	2015	0%	34%	60%	47%	82%
Germany	2016	0%	32%	56%	46%	77%
Hungary	2010	1%	39%	78%	68%	160%
Hungary	2011	1%	40%	79%	71%	159%
Hungary	2012	1%	40%	85%	75%	174%
Hungary	2013	2%	41%	87%	78%	177%
Hungary	2014	1%	42%	92%	79%	184%
Hungary	2015	1%	38%	85%	73%	165%
Hungary	2016	1%	37%	83%	73%	169%
Italy	2010	3%	40%	59%	44%	77%
Italy	2011	6%	57%	79%	55%	96%
Italy	2012	6%	58%	80%	53%	99%
Italy	2013	7%	57%	78%	51%	99%
Italy	2014	7%	59%	81%	50%	101%
Italy	2015	7%	62%	83%	52%	104%
Italy	2016	6%	60%	81%	54%	99%
Latvia	2010	0%	2%	4%	5%	13%
Latvia	2011	1%	3%	6%	5%	17%
Latvia	2012	1%	3%	6%	5%	15%
Latvia	2013	1%	3%	6%	5%	16%
Latvia	2014	1%	3%	7%	5%	14%
Latvia	2015	1%	2%	5%	4%	11%

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Table C.2 – continued from previous page

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Latvia	2016	1%	3%	6%	5%	13%
Luxembourg	2010	1%	40%	50%	57%	91%
Luxembourg	2011	1%	41%	46%	64%	100%
Luxembourg	2012	1%	41%	48%	70%	122%
Luxembourg	2013	1%	45%	53%	69%	146%
Luxembourg	2014	1%	49%	60%	69%	138%
Luxembourg	2015	1%	71%	82%	87%	173%
Luxembourg	2016	1%	59%	70%	81%	164%
North Macedonia	2010					
North Macedonia	2011					
North Macedonia	2012	24%	57%	93%	71%	333%
North Macedonia	2013	26%	68%	123%	83%	395%
North Macedonia	2014	27%	68%	114%	83%	400%
North Macedonia	2015	26%	67%	117%	82%	387%
North Macedonia	2016	24%	71%	113%	77%	347%
Norway	2010	0%	10%	12%	9%	16%
Norway	2011	0%	10%	12%	9%	14%
Norway	2012	0%	10%	11%	8%	13%
Norway	2013	0%	7%	7%	7%	13%
Norway	2014	1%	8%	10%	11%	18%
Norway	2015	13%	87%	104%	62%	70%
Norway	2016	14%	87%	104%	69%	81%
Poland	2010	1%	24%	31%	22%	43%
Poland	2011	1%	23%	29%	21%	40%
Poland	2012	1%	15%	19%	14%	26%
Poland	2013	0%	10%	13%	8%	17%
Poland	2014	0%	7%	11%	8%	16%
Poland	2015	0%	6%	8%	6%	14%
Poland	2016	0%	12%	18%	15%	29%
Portugal	2010	8%	43%	59%	47%	80%
Portugal	2011	8%	46%	63%	49%	86%
Portugal	2012	8%	47%	65%	50%	87%

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Table C.2 – continued from previous page

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Portugal	2013	8%	48%	64%	50%	86%
Portugal	2014	8%	48%	63%	51%	85%
Portugal	2015	8%	48%	63%	52%	86%
Portugal	2016	8%	46%	60%	51%	81%
Romania	2010	16%	43%	64%	53%	94%
Romania	2011	19%	46%	69%	57%	100%
Romania	2012	19%	49%	77%	63%	110%
Romania	2013	18%	50%	79%	64%	103%
Romania	2014	18%	52%	80%	64%	109%
Romania	2015	19%	57%	84%	72%	143%
Romania	2016	18%	56%	85%	73%	137%
Serbia	2010					
Serbia	2011					
Serbia	2012					
Serbia	2013					
Serbia	2014					
Serbia	2015					
Serbia	2016	21%	52%	93%	88%	155%
Slovak Republic	2010	7%	52%	74%	54%	92%
Slovak Republic	2011	7%	55%	80%	60%	98%
Slovak Republic	2012	8%	58%	83%	59%	97%
Slovak Republic	2013	8%	62%	85%	61%	106%
Slovak Republic	2014	9%	64%	92%	61%	122%
Slovak Republic	2015	10%	60%	87%	60%	125%
Slovak Republic	2016	10%	58%	86%	55%	115%
Slovenia	2010	16%	59%	74%	63%	128%
Slovenia	2011	17%	64%	80%	69%	135%
Slovenia	2012	16%	64%	81%	70%	140%
Slovenia	2013	15%	65%	84%	68%	143%
Slovenia	2014	15%	64%	80%	68%	136%
Slovenia	2015	14%	64%	81%	68%	132%
Slovenia	2016	13%	64%	77%	66%	122%

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Table C.2 – continued from previous page

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Spain	2010	8%	42%	55%	45%	58%
Spain	2011	8%	45%	59%	47%	62%
Spain	2012	8%	44%	60%	46%	62%
Spain	2013	8%	45%	61%	48%	63%
Spain	2014	8%	45%	61%	48%	64%
Spain	2015	8%	46%	61%	49%	64%
Spain	2016	7%	44%	62%	47%	63%

Table C.3: Manufacturing

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Austria	2010	0%	14%	15%	12%	20%
Austria	2011	0%	21%	25%	17%	31%
Austria	2012	1%	34%	47%	35%	63%
Austria	2013	3%	41%	60%	51%	90%
Austria	2014	3%	44%	65%	54%	93%
Austria	2015	3%	45%	66%	58%	96%
Austria	2016	3%	47%	69%	58%	97%
Belgium	2010	6%	61%	96%	77%	133%
Belgium	2011	7%	63%	100%	73%	137%
Belgium	2012	7%	63%	98%	75%	140%
Belgium	2013	8%	64%	99%	75%	137%
Belgium	2014	7%	66%	101%	73%	136%
Belgium	2015	7%	66%	101%	77%	137%
Belgium	2016	7%	65%	101%	75%	136%
Bosnia and Herzegovina	2010					
Bosnia and Herzegovina	2011	23%	59%	66%	57%	73%
Bosnia and Herzegovina	2012	14%	42%	53%	46%	65%
Bosnia and Herzegovina	2013	24%	59%	69%	56%	77%
Bosnia and Herzegovina	2014	11%	57%	69%	59%	74%
Bosnia and Herzegovina	2015	11%	59%	68%	63%	74%
Bosnia and Herzegovina	2016	10%	53%	60%	52%	61%
Bulgaria	2010	16%	55%	59%	39%	100%
Bulgaria	2011	28%	65%	67%	40%	98%
Bulgaria	2012	30%	75%	69%	41%	104%
Bulgaria	2013	31%	70%	68%	40%	103%
Bulgaria	2014	32%	70%	69%	42%	101%
Bulgaria	2015	33%	74%	72%	45%	96%
Bulgaria	2016	31%	70%	70%	45%	87%
Croatia	2010	20%	53%	56%	56%	62%
Croatia	2011	22%	57%	61%	62%	66%
Croatia	2012	23%	60%	64%	68%	76%

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Table C.3 – continued from previous page

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Croatia	2013	24%	58%	64%	68%	73%
Croatia	2014	25%	60%	66%	67%	72%
Croatia	2015	27%	63%	68%	66%	74%
Croatia	2016	26%	62%	65%	62%	66%
Czech Republic	2010	6%	73%	72%	48%	84%
Czech Republic	2011	7%	77%	75%	52%	87%
Czech Republic	2012	7%	76%	77%	53%	88%
Czech Republic	2013	7%	77%	79%	54%	89%
Czech Republic	2014	7%	74%	80%	53%	88%
Czech Republic	2015	7%	78%	85%	59%	95%
Czech Republic	2016	6%	72%	83%	58%	93%
Estonia	2010	31%	39%	49%	33%	48%
Estonia	2011	34%	41%	53%	33%	48%
Estonia	2012	34%	41%	52%	33%	49%
Estonia	2013	33%	43%	54%	35%	52%
Estonia	2014	33%	44%	56%	36%	53%
Estonia	2015	31%	43%	56%	36%	54%
Estonia	2016	29%	45%	57%	38%	54%
Finland	2010	13%	39%	49%	32%	72%
Finland	2011	15%	42%	52%	33%	80%
Finland	2012	16%	42%	52%	32%	86%
Finland	2013	16%	42%	54%	31%	81%
Finland	2014	17%	46%	60%	35%	91%
Finland	2015	16%	43%	54%	36%	82%
Finland	2016	14%	44%	58%	39%	86%
France	2010	11%	23%	30%	19%	42%
France	2011	11%	22%	30%	18%	41%
France	2012	8%	19%	26%	15%	36%
France	2013	8%	25%	33%	21%	48%
France	2014	9%	33%	45%	30%	64%
France	2015	8%	34%	47%	32%	68%
France	2016	6%	34%	48%	32%	70%

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Table C.3 – continued from previous page

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Germany	2010	3%	31%	47%	46%	77%
Germany	2011	3%	34%	50%	48%	81%
Germany	2012	3%	34%	50%	48%	82%
Germany	2013	3%	35%	51%	48%	82%
Germany	2014	2%	35%	51%	50%	84%
Germany	2015	2%	34%	53%	50%	86%
Germany	2016	2%	33%	49%	49%	80%
Hungary	2010	4%	58%	87%	76%	119%
Hungary	2011	4%	62%	94%	79%	126%
Hungary	2012	5%	62%	98%	79%	131%
Hungary	2013	5%	62%	102%	83%	136%
Hungary	2014	5%	64%	109%	89%	146%
Hungary	2015	5%	63%	107%	89%	144%
Hungary	2016	4%	59%	103%	90%	145%
Italy	2010	10%	45%	68%	52%	96%
Italy	2011	18%	58%	83%	57%	113%
Italy	2012	20%	59%	83%	56%	114%
Italy	2013	20%	60%	85%	59%	117%
Italy	2014	21%	61%	86%	57%	115%
Italy	2015	22%	64%	87%	58%	115%
Italy	2016	21%	63%	88%	59%	113%
Latvia	2010	1%	5%	8%	8%	13%
Latvia	2011	1%	5%	9%	8%	18%
Latvia	2012	1%	5%	8%	7%	16%
Latvia	2013	1%	4%	7%	8%	15%
Latvia	2014	1%	4%	7%	8%	15%
Latvia	2015	1%	5%	8%	8%	14%
Latvia	2016	1%	5%	7%	8%	14%
Luxembourg	2010	8%	59%	75%	77%	132%
Luxembourg	2011	9%	67%	78%	100%	153%
Luxembourg	2012	9%	64%	74%	95%	150%
Luxembourg	2013	9%	63%	79%	77%	159%

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Table C.3 – continued from previous page

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Luxembourg	2014	9%	61%	74%	76%	154%
Luxembourg	2015	8%	57%	65%	68%	111%
Luxembourg	2016	8%	53%	56%	62%	83%
North Macedonia	2010					
North Macedonia	2011					
North Macedonia	2012	32%	60%	75%	41%	107%
North Macedonia	2013	34%	64%	85%	52%	123%
North Macedonia	2014	33%	66%	84%	49%	116%
North Macedonia	2015	31%	59%	78%	42%	105%
North Macedonia	2016	30%	60%			
Norway	2010	0%	11%	12%	10%	17%
Norway	2011	1%	13%	15%	13%	23%
Norway	2012	1%	17%	15%	12%	21%
Norway	2013	0%	11%	12%	9%	19%
Norway	2014	1%	14%	15%	10%	20%
Norway	2015	23%	56%	64%	47%	74%
Norway	2016	24%	58%	70%	51%	80%
Poland	2010	2%	26%	30%	30%	46%
Poland	2011	2%	22%	26%	25%	39%
Poland	2012	1%	16%	19%	20%	31%
Poland	2013	1%	10%	12%	12%	19%
Poland	2014	1%	7%	10%	10%	17%
Poland	2015	1%	7%	9%	10%	14%
Poland	2016	1%	17%	21%	23%	34%
Portugal	2010	25%	60%	73%	48%	91%
Portugal	2011	26%	64%	77%	49%	100%
Portugal	2012	27%	65%	80%	49%	104%
Portugal	2013	27%	67%	81%	50%	105%
Portugal	2014	28%	68%	81%	52%	108%
Portugal	2015	28%	68%	82%	54%	103%
Portugal	2016	27%	67%	82%	54%	101%
Romania	2010	27%	51%	68%	46%	77%

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Table C.3 – continued from previous page

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Romania	2011	31%	53%	70%	48%	85%
Romania	2012	31%	55%	76%	53%	93%
Romania	2013	31%	58%	78%	54%	97%
Romania	2014	31%	59%	79%	55%	93%
Romania	2015	32%	60%	78%	55%	108%
Romania	2016	31%	58%	77%	55%	101%
Serbia	2010					
Serbia	2011					
Serbia	2012					
Serbia	2013					
Serbia	2014					
Serbia	2015					
Serbia	2016	32%	65%	109%	83%	147%
Slovak Republic	2010	6%	58%	67%	40%	69%
Slovak Republic	2011	7%	57%	73%	45%	79%
Slovak Republic	2012	7%	62%	83%	56%	90%
Slovak Republic	2013	8%	63%	76%	59%	88%
Slovak Republic	2014	8%	61%	80%	53%	82%
Slovak Republic	2015	9%	56%	71%	42%	70%
Slovak Republic	2016	8%	52%	67%	41%	70%
Slovenia	2010	25%	60%	71%	59%	94%
Slovenia	2011	27%	63%	74%	61%	98%
Slovenia	2012	26%	64%	75%	63%	104%
Slovenia	2013	25%	61%	73%	60%	99%
Slovenia	2014	25%	63%	74%	60%	97%
Slovenia	2015	24%	67%	78%	65%	102%
Slovenia	2016	23%	61%	71%	58%	94%
Spain	2010	23%	49%	58%	40%	64%
Spain	2011	25%	52%	62%	40%	67%
Spain	2012	25%	52%	63%	41%	71%
Spain	2013	26%	53%	64%	43%	73%
Spain	2014	26%	55%	67%	42%	73%

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Table C.3 – continued from previous page

Country	Year	Number of firms	Employment	Wage bill	Turnover	Value added
Spain	2015	27%	55%	67%	44%	74%
Spain	2016	26%	54%	67%	45%	75%

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