The Role of Financial (Mis) Allocation on Real (Mis) Allocation: Firm-level Evidence for European Countries

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Abstract

This paper quantifies the extent of financial misallocation and its transmission into real resource misallocation across firms in 23 European countries between 2010 and 2016. Using firm-level data, we measure financial misallocation as the dispersion in marginal returns to debt and equity, and assess its impact on the allocation of real inputs through standard misallocation frameworks. Three key patterns emerge: financial misallocation is larger in lower-income countries, disproportionately affects more productive firms, and is more severe for younger and smaller firms. We show that approximately 40% of financial distortions translate into distortions in the returns to labor and capital. In a counterfactual scenario where finance-induced real misallocation is eliminated, total factor productivity increases by 2% to 7%.

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1. Introduction

Credit and capital markets play a central role in financing productive inputs, shaping resource allocation, and influencing aggregate productivity. Hsieh and Klenow (2009) pioneered a methodology to quantify the aggregate effects of resource misallocation by examining dispersion in marginal returns to labor and capital. Building on this approach, Whited and Zhao (2021) extended the analysis to the provision of finance by quantifying the impact of dispersion in marginal returns to debt and equity. Despite the close connection between real and financial resource allocation, a key question remains unanswered: how much of the observed misallocation of real resources can be attributed to financial distortions? Addressing this question is the central contribution of this paper.

We begin by presenting a broad cross-country characterization of financial misallocation. While resource misallocation has been extensively studied across different contexts, the application of financial misallocation methodologies has so far been limited to a small number of countries. To expand the scope of analysis, we implement the framework developed by Whited and Zhao (2021) using firm-level data from ORBIS, covering 23 European countries from 2010 to 2016. In this approach, financial misallocation is captured by the dispersion in the marginal returns to debt and equity, which we estimate directly from the data.

We document three main findings. First, consistent with the resource misallocation literature, we find a strong correlation between financial misallocation and economic development. Aggregate productivity gains from efficiently reallocating finance across firms are more than twice as large in countries with the lowest per capita income compared to the richest. Moreover, most of these gains arise from reallocating the overall level of finance (which can be interpreted as access to finance), rather than from optimizing debt-to-equity ratios (which reflect the available mix of financial sources). Second, regressions of financial distortions on firm-level productivity show that more productive firms face higher relative financing costs, suggesting that financial distortions are systematically related to productivity. This elasticity declines with economic development—a pattern consistent with the notion that sophisticated financial markets mitigate misallocation. Third, in line with prior research, we find that the shadow cost of finance is higher for younger and smaller firms.

We then turn to real resource misallocation and its relationship with financial distortions. Our analysis proceeds in two steps. First, we regress the firm-level measure of real misallocation from Hsieh and Klenow (2009)—the log of demeaned total factor revenue productivity ($TFPR$)—on our computed measure of financial misallocation, the log of demeaned cost of finance. We find that a 10% increase in a firm's financial distortion translates into a 4% increase in its distortions in output and factor markets. Second, we input the predicted values from this regression into a model of firm heterogeneity under an undistorted allocation to quantify the associated TFP losses. We find that finance-induced TFP losses from real resource misallocation range from 2% to 7%, depending on the level of financial distortion.

The theoretical framework that defines the benchmark for an efficient allocation of real and financial resources is drawn from Hsieh and Klenow (2009) and Whited and Zhao (2021). The model features multiple sectors, each with heterogeneously productive firms that supply differentiated varieties under monopolistic competition. We assume that real and financial resources can move freely across firms so that, in the output-maximizing allocation, the marginal returns to labor and capital, and debt and equity, are equalized across producers in each sector. Distortions in real and financial markets are thus defined as wedges that prevent such equalization.

In identifying real and financial distortions, we apply the two methodologies independently. Rather than embedding a specific financial friction into a unified model of misallocation, we estimate the distribution of distortions under their respective frameworks and then use a regression-based approach, with rich controls, to isolate the portion of real misallocation that can be attributed to financial distortions. Although our framework does not explicitly model the origin of financial frictions, it leverages a key advantage: the direct observation of the distribution of financial resources across firms. This feature is typically absent in models where resource misallocation arises from assumed or stylized financial frictions.

Specifically, we quantify the extent to which financial distortions contribute to real misallocation by regressing the log of demeaned firm-level TFPR (a measure of real distortion) on the log of the demeaned average cost of finance (our measure of financial distortion). To isolate the variation of interest, we exploit the richness of our microdata and include a comprehensive set of fixed effects—firm, time and country/time and industry/time. We also explore alternative specifications that incorporate lagged values of financial distortions and additional firm-level controls. In our baseline specification, we find that approximately 40% of financial distortions are transmitted into real distortions.

Armed with this pass-through elasticity, we assess the aggregate implications of finance-induced misallocation. We simulate a counterfactual economy in which predicted real wedges, estimated based on observed financial distortions, are treated as idiosyncratic revenue taxes. We then compute the resulting level of Total Factor Productivity. The simulated productivity losses due to this channel range from 2% to 7%, underscoring the macroeconomic relevance of financial frictions.

A large literature quantifies the aggregate impact of financial frictions using calibrated models that impose specific constraints, such as collateral limits, and match moments from firm dynamics or credit aggregates ((Buera et al., 2011), Midrigan and Xu (2014), Moll (2014), Greenwood et al. (2010)). These models typically abstract from the empirical distribution of finance across firms, focusing instead on the implications of assumed frictions on the allocation of real resources. Our approach offers a complementary view: rather than modeling the source of financial frictions, we directly observe the dispersion of financial liabilities across firms to infer the extent of misallocation. Despite this difference in methodology, our counterfactual estimates of the TFP gains from removing finance-induced real misallocation fall within the range identified in these macro-development studies. This similarity provides additional support for the empirical validity of our approach.

Our work is closely related to Cavalcanti et al. (2021), who use loan-level credit registry data from Brazil to document high dispersion in default-adjusted credit spreads across firms. While we do not observe borrowing costs directly, we infer heterogeneity in the cost of finance by examining the dispersion in marginal returns to debt and equity. We document sizable dispersion in these marginal returns, consistent with the presence of significant financial frictions. Quantitatively, our estimates of the aggregate productivity gains from alleviating financial distortions—derived through their pass-through into real input misallocation—are more conservative and closer in magnitude to those reported by Midrigan and Xu (2014).

2. Empirical approach

In this section, we summarize the model and the data. We also 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. 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 methodology for the case of 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:

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

where Y_{si} is the quantity produced by firm i 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}. Note 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 substitute 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. 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:

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

where Z_{si} denotes the Total Finance Benefit, γ is the industry-specific elasticity of substitution between debt and equity, and α_s^D 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 determining the optimal allocation of capital and labor inputs, we assume that these are chosen at the beginning of 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.

The optimality conditions in the model imply 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:

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

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

As 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, $log\left(\frac{TFPR_{real,si}}{TFPR_{real,s}}\right)$ and $log\left(\frac{TFPR_{fin,si}}{TFPR_{fin,s}}\right)$. By demeaning the marginal returns against the industry average, we acknowledge that we are only capturing misallocation within a sector, while remaining 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 characterizing 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:

$$TFP_{real,s} = \left(\sum_{i=1}^{M_s} \left[A_{si} \frac{\overline{TFPR}_{real,s}}{TFPR_{real,si}} \right]^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{15}$$

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 for 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 an 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:

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

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

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:

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

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:

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

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.

3. Data

Our analysis draws on firm-level data from Bureau van Dijk's Orbis database, the most comprehensive cross-country source of financial statements, production activity, and ownership information for firms worldwide. We focus on European firms across all industrial sectors—including financial services and non-financial services—between 2010 and 2016 (see Table A.1 in Appendix Appendix A).

Data preparation follows cleaning procedures established by Bureau van Dijk (2011), Kalemli-Ozcan et al. (2015), and Cusolito and Didier (2020). We retain firm-year observations with non-missing values for key financial and operational variables essential to our estimation strategy: total sales, employee compensation, interest expenses, tax payments, paid-in equity, total liabilities, and year of establishment. The final dataset consists of approximately 7.8 million firm-year observations spanning 23 European countries. Further details on data cleaning and cross-country coverage are available in Appendices Appendix B and Appendix C.

Table 1 summarizes the sample. Eighteen countries are classified as high-income and six as upper-middle-income, based on the World Bank's 2021 income classification. Italy accounts for the largest share of observations (25%), while Austria contributes the smallest (0.06%). On average, debt accounts for over 61% of total assets, with liabilities-to-assets ratios ranging from 41% in Ukraine to 74% in Italy. The ratio of value added to total assets—a proxy for firm-level productivity—averages 0.91 across countries, with a low of 0.43 in Bosnia and Herzegovina and a high of 1.42 in Bulgaria.

The elasticity of substitution for real value added across firms within an industry is set at 1.77. This parameter reflects the estimated value that aligns the observed

Table 1: Summary Statistics

Country name	Firms	Liabilities to Assets	VA to Assets
Austria	4,589	0.63	0.91
Belgium	64,662	0.60	0.74
Bosnia and Herzegovina	24,041	0.52	0.43
Bulgaria	340,143	0.44	1.42
Croatia	172,877	0.59	0.71
Czech Republic	351,180	0.50	0.81
Estonia	84,864	0.44	1.05
Finland	123,217	0.58	1.37
France	805,018	0.61	1.22
Germany	105,216	0.63	1.08
Hungary	54,594	0.53	0.87
Italy	1,880,721	0.74	0.79
Montenegro	4,654	0.48	0.70
North Macedonia	62,327	0.42	1.33
Norway	79,584	0.64	1.41
Poland	42,428	0.49	0.87
Portugal	534,495	0.61	0.71
Romania	609,699	0.55	0.90
Serbia	140,410	0.54	0.79
Slovak Republic	222,136	0.59	0.95
Slovenia	135,048	0.54	1.11
Spain	1,542,454	0.58	0.76
Ukraine	71,226	0.41	1.28
Total	7,455,583	0.61	0.91

firm size distribution—measured by total assets—with the theoretically efficient distribution in the United States. The underlying assumption is that the U.S. firm size distribution represents an efficient benchmark.

Following Hsieh and Klenow (2009), we assume an undistorted rental price of capital, r, of 10%, comprising a 5% real interest rate and a 5% depreciation rate. Based on this assumption, the undistorted cost of capital is calculated as r×K, where K denotes total fixed assets. Data on employee compensation are directly sourced from Orbis. Using these two components, we compute the capital share for each country-sector as the ratio of the total cost of capital across all firms in a given sector to the sum of total capital and labor costs within that sector.

Consistent with the approach above, we set the undistorted cost of both debt and equity at 10%. This assumption has no bearing on the misallocation analysis itself, which hinges on firm-specific distortions in these costs. At the country-sector level, the CES production function weight on debt is estimated as the undistorted share of debt cost relative to the total cost of debt and equity, with each component adjusted according to the elasticity of substitution.

$$\alpha_s^D = \frac{rD^{1/\gamma_s}}{rD^{1/\gamma_s} + \lambda E^{1/\gamma_s}} \tag{21}$$

We follow Whited and Zhao (2021) in estimating the elasticity of substitution between debt and equity from the CES production function at the country-sector level using the methodology developed by Kmenta (1967):

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

Taking the log of both sides and using a first-order approximation around $\gamma_s = 1$, we obtain the following linear regression specification to estimate the elasticity of substitution at the country-sector level:

$$\ln F_{it} = \beta_A + \beta_B \ln D_{it} + \beta_E \ln E_{it} + \beta_{DE}(\ln D_{it} - \ln E_{it})^2 + u_{it} \tag{22}$$

Assuming that the error term can be decomposed into a component which varies in the cross section across firms and another component which varies across time and firms but is uncorrelated with the regressors, we can estimate this equation using OLS with firm fixed effects. The elasticity of subsitution, γ_s is then derived using the regression coefficients as follows:

$$\gamma_s = 1 + \frac{2\beta_{DE}}{\beta_D \beta_E} \tag{23}$$

4. Characterizing Financial Distortions and Quantifying their Aggregate Implications

We begin our empirical analysis by examining financial misallocation. While the methodology of Hsieh and Klenow (2009) for measuring real-resource misallocation has been widely applied across countries, the approach developed by Whited and Zhao (2021) to assess financial misallocation remains relatively underexplored. In this section, we extend their framework to a broader cross-country context, generating new empirical insights.

The analysis proceeds in two parts. First, we characterize the firm-level heterogeneity in financial distortions, with a particular focus on how age and size shape the distribution of financing costs—two dimensions frequently emphasized in the literature.[1] Second, we examine the aggregate consequences of financial misallocation. Leveraging the direct mapping between financial liabilities and value added implied by the Whited and Zhao (2021) model, we estimate the potential productivity gains from reallocating financial resources efficiently within each country. This exercise provides an upper bound on the aggregate losses due to financial frictions. A more precise estimate is developed later in the manuscript, where we identify the pass-through from financial to real-factor misallocation and quantify its aggregate implications.

4.1. Financial Distortions by Firm Size and Age

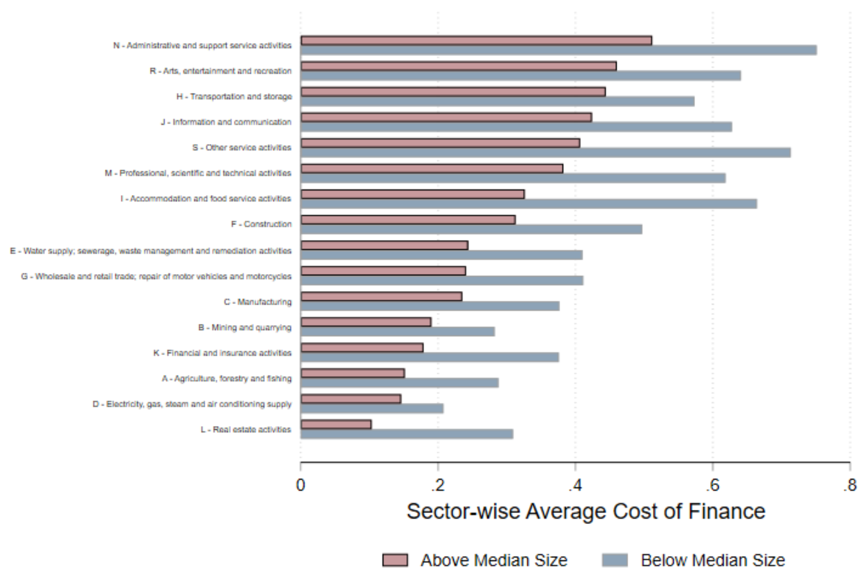
We examine how the average cost of finance varies across firms of different sizes. Within each country-sector, we classify firms as small or large based on whether their asset holdings fall below or above the median. We then compute the model-implied

[1] A long-lasting hypothesis in the macro-finance literature is that the firm's size and age constitute important determinants of a firm's access to finance (Beck et al., 2008). Larger firms can better pledge collateral in contexts where the relevant financial frictions are 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 capital accumulation over time and information availability reduce financial frictions. In this section, we leverage the richness of the data to explore these hypotheses.

average cost of finance separately for small and large firms and average these values across countries to construct a global sector-level measure.

Figure 1 reveals a consistent pattern: in all sectors, smaller firms face higher average financing costs than larger ones. In our framework, a higher cost of finance reflects a higher marginal return to additional funding and indicates a relative scarcity of financial resources. This suggests that finance would tend to flow from larger to smaller firms under a hypothetical reform that liberalizes credit and capital markets. This prediction aligns with recent empirical studies of financial liberalization episodes,[2] although these papers infer reallocation from changes in real input use.

Figure 1: Heterogeneous Costs of Finance: The Role of Size

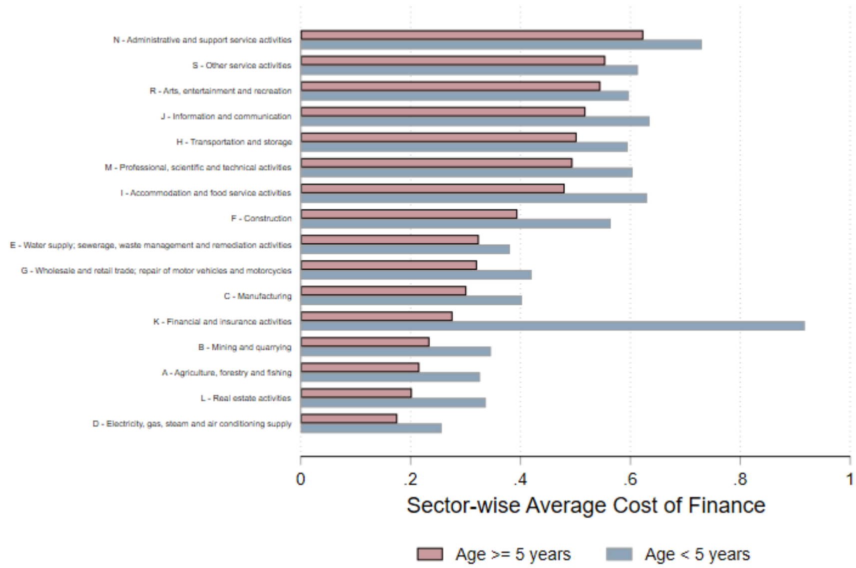


Note: The figure shows the model-based average cost of finance among small (less than the median size of the relevant sector in each country) and large (more than the median size of the relevant sector in each country) firms within each sector classified according to NACE 1.

We now turn to differences in the average cost of finance across firms of different ages. Within each industry and country, we classify firms as young or old depending on

[2]See, for instance, Larrain and Stumpner (2017) and Bau and Matray (2023).

Figure 2: 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.

whether they are less than or greater than five years old, respectively; firms exactly five years old are grouped with the young. We then compute the model-implied average cost of finance for young and old firms within each country-industry and take the average across countries.

Figure 2 reveals a consistent pattern: young firms face systematically higher shadow costs of finance than their older counterparts. As with firm size, this result implies that younger firms have higher marginal returns to financial resources, suggesting that capital would be reallocated toward them in the absence of financial frictions. This finding is consistent with the empirical literature documenting real-input reallocation following episodes of capital market liberalization.

While Figures 1 and 2 suggest a negative relationship between firm size, firm age, and the average cost of finance, we next assess the statistical significance and quantitative strength of these patterns within a controlled regression framework. To this end, we estimate the following equation:

$$log(TFPR_{i,c,s,t}/\overline{TFPR_{s,t}}) = \beta_1 log(Assets_{i,c,s,t}) + \beta_2 Age_{i,c,s,t}$$
$$+\beta_3 log(TFPQ_{i,c,s,t}/\overline{TFPQ_{s,t}}) + \alpha_i + \alpha_t + \alpha_c * \alpha_t + \alpha_s * \alpha_t + \epsilon_{i,s,t} \qquad (24)$$

Here, subscripts i, c, s, and t index firm, country, sector, and year, respectively. The dependent variable is the logarithm of a firm's model-implied cost of finance relative to the industry-year average in its country. The key explanatory variables are firm size (proxied by assets), age, and relative productivity, measured as the log of the firm's $TFPQ$ relative to the industry-country-year mean, as defined in Equation 20.

The regression includes a rich set of fixed effects to absorb unobserved heterogeneity: firm fixed effects (α_i), year fixed effects (α_t), and interactions between country and year ($\alpha_c \times \alpha_t$) and sector and year ($\alpha_s \times \alpha_t$). This structure controls for time-varying macroeconomic and sectoral conditions and persistent firm-specific factors. In particular, the inclusion of firm fixed effects helps control for unobservable characteristics such as firm-specific risk premia, which, while reflected as financial distortions in our model, may represent warranted price adjustments in a planner's allocation (David et al., 2022).

In addition to isolating the effects of firm age and size on the average cost of finance, the regression framework also aims to assess the productivity dependence of financial distortions. This focus is motivated by a central insight from the real misallocation literature: more productive firms tend to face higher distortions, effectively acting as a tax on efficiency. Prior studies have shown that when idiosyncratic distortions are positively correlated with firm-level productivity, their aggregate consequences are magnified.[3] To examine whether this mechanism extends to financial distortions, we include the relative measure of firm-level productivity, $\log(TFPQ_{i,s,t}/\overline{TFPQ}_{s,t})$, as an explanatory variable—both contemporaneously and, in alternative specifications, with lags. This allows us to test whether higher-productivity firms systematically face higher shadow costs of finance.

Table 2: The Role of Firm Age and Size

	Log TFPR (Finance)			
	(1)	(2)	(3)	(4)
Age of the firm	0.0136***	0.0121***	-0.0024	-0.0368***
	(0.0032)	(0.0032)	(0.0024)	(0.0094)
lnasset	-0.5366***	-0.5435***	-0.5509***	
	(0.0002)	(0.0002)	(0.0002)	
log_TFPQ	0.4028***	0.4044***	0.4221***	
	(0.0001)	(0.0001)	(0.0001)	
L.lnasset				-0.1746***
				(0.0009)
L.log_TFPQ				0.0718***
				(0.0004)
Observations	7,455,583	7,455,583	7,455,583	5,040,069
Time 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 24. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 confirms that older and larger firms face systematically lower costs of finance relative to their younger and smaller counterparts within the same industry and country. Recall that our measure of financing costs is model-based and reflects the shadow price of an additional unit of external finance—both debt and equity—needed

[3] See, for example, Hsieh and Klenow (2014) and Bento and Restuccia (2017).

to rationalize the firm's observed marginal returns. According to the most conservative estimates in Column 3, a 10% increase in firm size is associated with a 5.1% decline in the shadow cost of finance, while each additional year of firm age corresponds to a 0.2% reduction, though the elasticity between age and the firm cost of finance is not statistically significant at the 10% level. Column 4 shows these effects are robust to using lagged firm size and productivity.

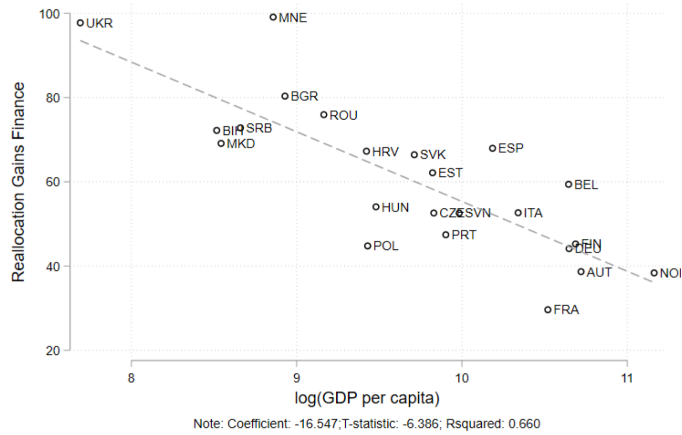
The productivity dependence of financial distortions also emerges clearly. Consistent with findings in the real misallocation literature, financial frictions increase with firm-level physical productivity. Even when controlling for an extensive set of fixed effects and using lagged productivity, the positive relationship between productivity and financial distortions remains statistically significant, though somewhat attenuated.

In summary, this section provides empirical support for the widely held view that younger and smaller firms face tighter financial constraints. Using a novel framework that infers financial distortions from the observed distribution of liabilities across firms, and leveraging a rich cross-country firm-level dataset, we document that older and larger firms benefit from significantly lower shadow financing costs. Furthermore, we show that more productive firms systematically face higher financial distortions than would be optimal, suggesting a misallocation of finance away from the most efficient producers.

4.2. Aggregate Implications of Financial Distortions

We now turn to quantifying the aggregate implications of the financial distortions identified in the data. Following standard practice in the misallocation literature, we conduct a thought experiment in which all financial distortions are removed and debt and equity are reallocated across firms within each industry to equalize their marginal returns—achieving an efficient allocation. The main quantitative output of this exercise is the potential TFP gain each country could realize from such a

Figure 3: 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.

reallocation.

It is important to emphasize that, given the assumptions underlying the financial misallocation framework, this counterfactual represents an upper bound on the true aggregate impact of financial distortions. In the Whited and Zhao (2021) methodology, debt and equity are assumed to contribute directly to value added, abstracting from alternative reasons firms may have for holding financial liabilities, such as liquidity management under uncertainty. Because the model does not account for these motives, any dispersion in the marginal revenue product of debt and equity is interpreted as inefficient and output-reducing. The next section refines this assessment by isolating the component of financial misallocation that translates into distortions in allocating real factors—labor and capital, which are the proximate drivers of aggregate productivity losses.

Figure 3 plots the aggregate productivity gains from removing financial distortions against the log of GDP per capita, which we use as a proxy for the degree of economic development. The figure reveals a strong negative relationship between financial misallocation and economic development: countries with lower GDP per capita stand to gain significantly more from eliminating financial distortions. At the lower end of the income distribution, the conditional TFP gains from efficiently reallocating financial liabilities (dotted line in Figure 3) approach 75%, nearly twice the size of the gains observed for richer countries. As a benchmark, Whited and Zhao (2021) estimates gains of roughly 11–12% for the U.S. and 70–80% for China. These reference points reinforce the plausibility of our estimates and suggest that the countries in our sample span a wide range of financial development, falling between the two polar cases of the U.S. and China.

The correlation between firm productivity and financial distortions plays a key role in shaping the aggregate effects of financial frictions. Several mechanisms can lead to credit market distortions that systematically favor less productive firms over their more productive counterparts. For example, government policies often subsidize credit to micro and small enterprises, which tend to be less productive. In addition, young but capable entrepreneurs may face elevated financing costs due to limited commitment or informational asymmetries. These policy- and market-driven distortions are not unique to financial allocation: the literature on real misallocation has also established a strong link between firm productivity and the severity of output and factor market distortions. Accounting for this productivity-dependence has proven important in explaining cross-country variation in firm-level outcomes such as size distributions and life-cycle dynamics.[4]

As shown in Table 2, financial distortions in our data exhibit a strong and statistically significant elasticity with respect to firm-level productivity. To explore whether this productivity-dependence varies with the level of development, we estimate this elasticity separately for each country and year. Following a standard approach in the

[4]See, for instance, Hsieh and Klenow (2014) and Fattal-Jaef (2022).

real misallocation literature, we regress financial distortions on firms' physical productivity. Physical productivity ($TFPQ$), defined in equation 20, captures a firm's efficiency in turning financial resources into value added. The elasticity is obtained from the following regression:

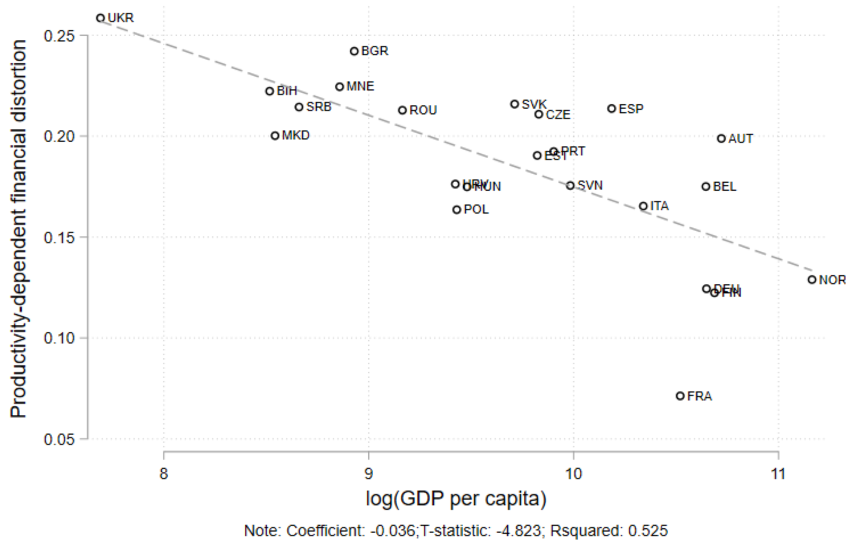
$$\log\left(\frac{TFPR^{fin}_{i,c,s,t}}{\overline{TFPR}^{fin}_{s,t}}\right) = \beta_{c,t}\log\left(\frac{Z_{i,c,s,t}}{\overline{Z}_{s,t}}\right) + \epsilon_{i,c,s,t} \tag{25}$$

Here, $\log(TFPR^{fin}_{i,c,s,t}/\overline{TFPR}^{fin}_{s,t})$ denotes the firm's idiosyncratic financial distortion relative to the industry average in its country and year, and $\log(Z_{i,c,s,t}/\overline{Z}_{s,t})$ is the firm's relative physical productivity. A positive coefficient $\beta_{c,t}$ implies that more productive firms face higher financial distortions, indicating a misallocation of credit away from productive firms. We estimate this regression separately for each country-year and report the average elasticity per country against log GDP per capita in Figure 4.

Two salient features emerge from Figure 4. Firstly, all countries exhibit a positive elasticity between financial distortions and physical productivity. Secondly, such elasticity is lower in more developed economies, suggesting these countries' more developed financial systems allow for a more efficient allocation of financial resources.

To conclude this section, we decompose the contribution of the level of financial liabilities versus the composition (i.e., the debt-to-equity ratio) in explaining the overall degree of financial misallocation. We do this by comparing our baseline estimates—derived under sector-specific elasticities of substitution between debt and equity—to those obtained under an alternative scenario that assumes perfect substitutability. Under perfect substitution, the composition of liabilities is irrelevant for real value added; thus, the productivity gains in this scenario reflect only the benefits from reallocating the total amount of finance across firms. The difference between the

Figure 4: Productivity Dependence of Financial Distortions



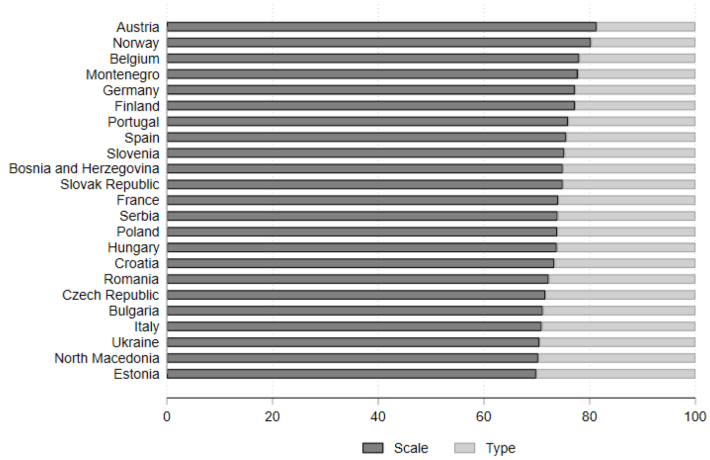
Note: The figure shows the elasticity between the log of $TFPR_{si}$ and log of A_{si} of each country and the log of real GDP per capita. Each dot represents each country's average regression coefficient resulting from estimating equation 25. The dotted line provides a general tendency in the association between financial distortions and the log real GDP per capita.

gains under the baseline and under perfect substitution quantifies the contribution of debt-to-equity ratios in accounting for the aggregate effects of financial misallocation.

Figure 5 reveals that the bulk of aggregate productivity gains arise from achieving the efficient level of finance across firms, rather than optimizing the composition of liabilities. Specifically, even when keeping debt-to-equity ratios fixed, reallocating financial resources from low to high marginal return firms would deliver over 70% of every country's total productivity gains. This result is remarkably consistent across the sample and aligns closely with the findings of Whited and Zhao (2021), who report a 79%–83% contribution from levels in the case of China.

In sum, this section has examined the macroeconomic implications of financial misallocation using a novel measurement strategy applied to firm-level data across a wide range of countries. The analysis revealed a robust inverse relationship between a country's level of development and the severity of financial misallocation. Further-

Figure 5: 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 were eliminated, both under the baseline estimation of the elasticity of substitution between debt and equity, and under the alternative scenario of perfect substitutability. Gains under perfect substitution are shown in light grey (type), and the incremental contribution of optimal debt-to-equity composition is shown in dark grey (scale).

more, the cross-country decomposition supports the conclusion, previously established for China, that the level of finance, rather than its composition, accounts for the lion's share of misallocation-induced productivity losses.

5. Establishing the Link between Financial and Real (Mis)allocation

The previous section showed that the aggregate gains from removing financial distortions are potentially large. However, these gains represent an upper bound: they assume that every unit of finance directly contributes to value added. In practice, firms may issue debt or equity for a range of purposes, such as financing intangible investments or maintaining liquidity buffers, that do not necessarily translate into higher measured output. As a result, the true extent of finance-induced misallocation of real inputs may be smaller than what the financial distortion framework alone suggests.

This section bridges the two strands of the misallocation literature by linking financial distortions to real factor misallocation. We adopt a regression-based approach to quantify the extent to which our finance-based measure of misallocation, derived from Whited and Zhao (2021), explains the real-based measure of misallocation developed by Hsieh and Klenow (2009). Concretely, we estimate the following equation:

$$
\begin{aligned}
\log(\text{TFPR}_{i,c,s,t}/\overline{\text{TFPR}_{s,t}}) = {} & \beta_1 \log(\text{Assets}_{i,c,s,t}) + \beta_2 \text{Age}_{i,c,s,t} \\
& + \beta_3 \log(\text{TFPQ Finance}_{i,c,s,t}/\overline{\text{TFPQ Finance}_{s,t}}) \\
& + \beta_4 \log(\text{TFPR Finance}_{i,c,s,t}/\overline{\text{TFPR Finance}_{s,t}}) \\
& + \alpha_i + \alpha_c * \alpha_t + \alpha_s * \alpha_t + \epsilon_{i,s,t}
\end{aligned} \tag{26}
$$

This empirical framework isolates the contribution of financial distortions, measured as $\log(\text{TFPR}^{\text{Finance}} i, c, s, t/\overline{\text{TFPR}^{\text{Finance}} s, t})$, to real distortions, captured by $\log(\text{TFPR} i, c, s, t/\overline{\text{TFPR} s, t})$, while controlling for a rich set of confounding factors. In addition to firm, sector-year, and country-year fixed effects, the specification explicitly controls for $TFPQ^{\text{Finance}}$, a finance-based measure of physical productivity. As shown in Table 2, this variable is strongly correlated with financial distortions and captures the efficiency with which firms convert financial resources into value added.[5] Including this control helps disentangle distortions in access to finance—measured by $\text{TFPR}^{\text{Finance}}$—from differences in firms' ability to use finance efficiently.

Table 3 reports the estimates from the proposed regression. We find a positive and statistically significant coefficient of 0.373 for the elasticity between financial and real distortions (β_4, Table 3, Column 4). This estimate implies that, on average, a 10% increase in a firm's idiosyncratic cost of finance—measured relative to its industry-

[5] Just as managerial ability affects a firm's capacity to transform labor and capital into output, heterogeneity in financial management affects firms' ability to turn finance into value added.

Table 3: The bridge between real and finance misallocation

	Log TFPR (Real)			
	(1)	(2)	(3)	(4)
Age of the firm	-0.0067***	0.0263***	0.0256***	0.0214***
	(0.0000)	(0.0064)	(0.0065)	(0.0065)
lnasset	0.0110***	0.0674***	0.0845***	0.0843***
	(0.0002)	(0.0010)	(0.0010)	(0.0012)
log_TFPQ	0.0221***	0.0718***	0.0631***	0.0654***
	(0.0002)	(0.0006)	(0.0006)	(0.0008)
Log TFPR	0.2569***	0.3538***	0.3764***	0.3726***
	(0.0005)	(0.0013)	(0.0014)	(0.0019)
Observations	7,455,583	7,455,583	7,455,583	7,455,583
Time fixed effects	N	Y	N	N
Firm fixed effects	N	Y	Y	Y
Industry-time fixed effects	N	N	Y	Y
Country-time fixed effects	N	N	N	Y

Note: Standard errors in parentheses. This table presents the results obtained using equation 26. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

year average—is associated with a 3.62% increase in the firm's TFPR, relative to its sectoral mean. In other words, higher financing costs are systematically linked to a higher degree of real factor misallocation.

We use the estimated elasticity to construct firm-level predicted values of real distortions based solely on observed financial distortions. Specifically, we compute:

$$\log\left(\frac{\widehat{TFPR}_{i,c,s,t}}{\overline{TFPR}_{c,s,t}}\right) = \beta_4 \log\left(\frac{TFPR^{\text{Finance}}i, c, s, t}{\overline{TFPR^{\text{Finance}}c, s, t}}\right) \tag{27}$$

This expression isolates the component of $TFPR$ variation that can be explained by firm-level variation in financial distortions, holding other sources of misallocation constant.

Our next step is to feed the predicted values of real distortions into an otherwise undistorted version of the model introduced in Section 2.1. Recall from expression 9 that $TFPR$ captures the combined effect of two idiosyncratic distortions: one affecting the overall scale of the firm ($\tau_{Y_{si}}$), and another distorting the capital-to-output ratio ($\tau_{k_{si}}$). Since our regression estimates only the composite distortion embodied in $TFPR$, we cannot separately identify $\tau_{Y_{si}}$ and $\tau_{k_{si}}$. To proceed, we attribute the entire effect of financial distortions on real outcomes to an output distortion, $\tau_{Y_{si}}$. This simplifying assumption allows us to map the predicted $TFPR$ directly into a corresponding output wedge, which is recoverable from the following relationship:

$$\widehat{1-\tau_{Y_{si}}} = \left[\widehat{TFPR}_{si}\right]^{-1} \tag{28}$$

Once predicted values of the output wedge have been generated, aggregate TFP in each sector in the counterfactual distorted economy can be computed as:

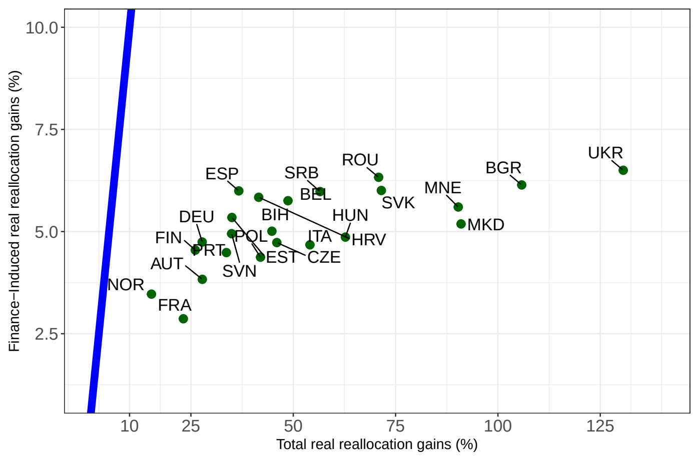
$$\widehat{TFP_s} = \left[\sum_{i=1}^{M_s}\left[A_{si}(\widehat{1-\tau_{Y si}})\right]^{\sigma-1}\right]^{\frac{\sigma}{\sigma-1}} \Bigg/ \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1}(\widehat{1-\tau_{Y si}})^{\sigma}\right) \tag{29}$$

The $TFPQ$ of the firms, A_{si}, remains the same as computed from the data using equation 16.

Figure 6 illustrates the results from a hypothetical reform that eliminates all finance-induced distortions and achieves the efficient allocation. As a benchmark, we illustrate these gains relative to the gains from removing the overall degree of misallocation of factors of production as in Hsieh and Klenow (2009). We also add a 45-degree line to facilitate the comparison.

Figure 6 shows that there are sizable productivity gains from eliminating finance-induced misallocation, ranging from almost 3% in France to nearly 7% in Ukraine.

Figure 6: Relevance of financial frictions for real misallocation



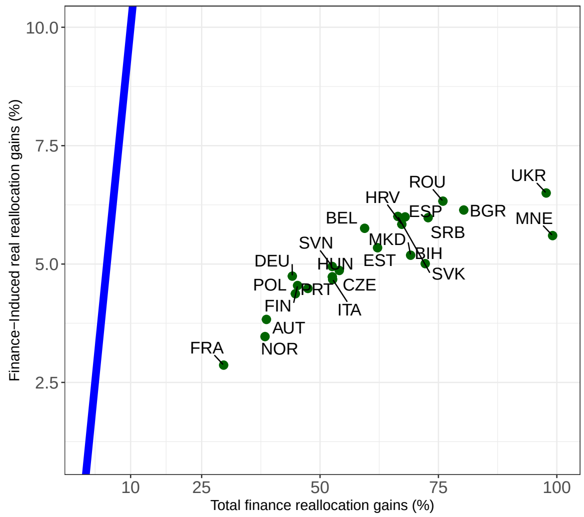
Note: The figure plots the aggregate TFP gains from reversing overall resource misallocation, following Hsieh and Klenow (2009), on the horizontal axis, against the TFP gains from removing only the real distortions attributable to financial frictions on the vertical axis. A 45-degree line is added for reference.

These gains amount to about 10% of the overall gains from reversing all sources of capital and labor misallocation, suggesting a significant contribution from the financial channel.

Figure 7 benchmarks the finance-induced real allocative gains against those achieved from removing all of the financial distortions. Whited and Zhao (2021) found sizable TFP gains from reversing financial frictions in China, a finding that we validate in a broader sample of countries, as reported on the horizontal axis of Figure 7. However, we establish that once the mapping of the identified financial frictions into real-factor distortion is properly identified, the resulting TFP gains from undoing the resource misallocation attributable to financial friction are still notable, yet smaller than those resulting from removing these frictions directly in the framework of Whited and Zhao (2021).

Our quantitative findings regarding the aggregate implications of finance-induced real-factor misallocation align with the range of values documented in the macroeco-

Figure 7: Relationship between finance misallocation and real misallocation attributable to finance



Note: The figure plots the aggregate TFP gains from reversing overall finance misallocation, following Whited and Zhao (2021), on the horizontal axis, against the TFP gains from removing only the real distortions attributable to financial frictions on the vertical axis. A 45 degree line is added for reference.

nomic development literature on financial frictions. These studies postulate a specific financial friction—typically collateral constraints—within general equilibrium models of firm dynamics, and quantify the productivity gains that would result from alleviating those frictions. Midrigan and Xu (2014), a prominent study in this literature, reports productivity losses in the range of 5% to 10% due to the misallocation of labor and capital across firms within a sector caused by credit market frictions. Similarly, Moll (2014) finds comparable magnitudes under plausible calibration of persistence in idiosyncratic productivity shocks. Buera et al. (2011) obtains larger gains when incorporating additional mechanisms, such as the impact of financial frictions on the adoption of superior technologies, a mechanism that is absent in our work. We interpret the similarity between our results and those of alternative quantification approaches as reassuring evidence for the validity of our empirical strategy.

To conclude, we examine the relationship between the estimated pass-through from financial to real distortions and the magnitude of the aggregate TFP gains from eliminating these distortions. While the estimated pass-through from financial to real markets was substantial, at 40%, the aggregate productivity gains associated with this channel are more modest, amounting to only about 10% of the total gains from addressing financial frictions (as reported in Figure 7).

To uncover non-linearities in the mapping from finance to real distortion elasticities and aggregate gains, we quantify aggregate reallocation gains under alternative finance-to-real pass-through. As in the baseline, the alternative scenarios are generated from equation 27, assuming $\beta_4 = 1$ and $\beta_4 = 0.7$, respectively, and then attributing the implied real distortion entirely as an output wedge, according to equation 28.[6]

Figure 8 reveals a non-linear mapping of the pass-through from finance into real distortions and the resulting aggregate efficiency gains from reallocation. As shown in the figure, the aggregate gains are virtually identical in the real and financial contexts when there is full pass-through. However, these decrease abruptly when the pass-through decreases to 70%, and then to the estimated 40%.

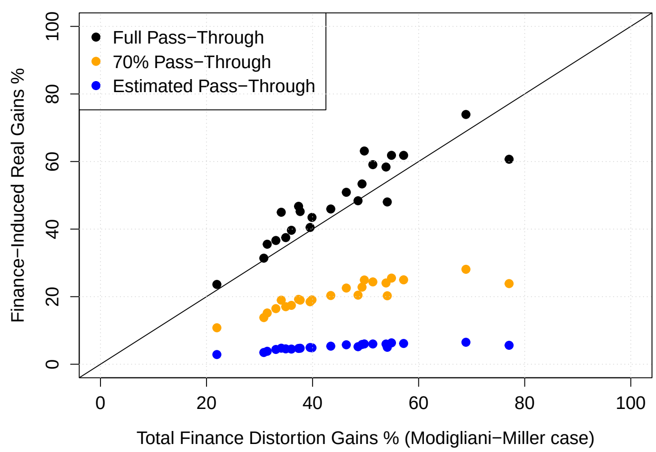
6. Conclusion

Financial frictions are a central source of aggregate inefficiency. In this paper, we provide new cross-country evidence on the magnitude and consequences of financial misallocation, and show that distortions in access to external finance translate systematically into misallocation of real resources across firms.

Using firm-level data from the ORBIS database, we characterize patterns of financial misallocation in a diverse set of economies. We document that financial dis-

[6]Since our counterfactual analysis of reallocation gains from removing the finance-induced real distortions attributes all the distortion to the output wedge, abstracting from capital to labor ratio distortions, we compare these gains against the removal of all financial distortions in the version of the Whited and Zhao (2021) model assuming the Modigliani-Miller benchmark, which abstracts from debt-to-equity ratio distortions.

Figure 8: Real Reallocation Gains Under Varying Degrees of Finance to Real Distortion Pass-Through



Note: The figure plots the aggregate TFP gains from reversing finance-induced real distortions, imposing varying elasticities of real to finance distortions. The points labeled "estimated Pass-Through" refer to a finance to real elasticity estimated in equation 26, whereas the points corresponding to Full Pass-Through and 70% Pass-Through refer to artificial real distortions generated assuming elasticities of 1 and 0.7 from $log(TFPR^{finance})$ to $log(TFPR)$. The horizontal axis reports the reallocation gains in the Modigliani-Miller benchmark of Whited and Zhao (2021).

tortions—measured using the approach introduced by Whited and Zhao (2021)—are strongly correlated with income levels: firms in low-income countries face misallocation levels twice as high as those in high-income countries. We also confirm that small and young firms face disproportionately high financial frictions, and find that these distortions systematically reallocate credit away from the most productive firms and toward the least productive ones.

Our most novel contribution is to establish an empirical link between financial misallocation and real-input misallocation, as captured by the widely used TFPR-based measure of Hsieh and Klenow (2009). This connection provides crucial validation for the premise that financial frictions distort firms' ability to acquire efficient levels of labor and capital. Leveraging our regression results and structural model, we construct predicted real distortions from observed financial frictions and quantify their aggregate effects. Our counterfactual simulations show that financial distortions alone can account for 2–7% losses in aggregate TFP—magnitudes that are consistent with existing estimates of the macroeconomic costs of finance-based misallocation, including Midrigan and Xu (2014).

While our approach sheds light on the consequences of financial frictions, it remains agnostic about their origins. Future research can build on our framework by exploiting the rich time and cross-country variation in the data to study the causal impact of financial reforms or shocks. Identifying the mechanisms that generate these distortions will be essential to designing policy interventions that enhance allocative efficiency and productivity growth.

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.

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Appendix A. Supplementary tables

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

Continued on next page

Table A.1 – continued from previous page

Code Value	Description	Industry
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
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. Data Cleaning

Following Bureau van Dijk (2011), Kalemli-Ozcan et al. (2015), Cusolito and Didier (2020), 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.[7]

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

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

Appendix C. 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 database to their corresponding aggregates, in the same manner as Gopinath et al. (2017). Aggregates for employment and gross output are obtained from Eurostat's Structural Business Statistics Database (SBS). Tables C.1 and C.2 show the coverage of our sample by country, separately for non-manufacturing and manufacturing sectors.

Table C.1: Coverage of Final Database Relative to Eurostat (SBS) - Non-Manufacturing

Country	**Employment**							**Turnover**						
	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Austria	19%	21%	28%	32%	26%	31%	26%	16%	18%	34%	42%	36%	39%	36%
Belgium	44%	41%	43%	45%	44%	44%	43%	55%	56%	55%	55%	55%	53%	52%
Bosnia and Herzegovina		72%	34%	66%	65%	53%	60%		73%	40%	70%	63%	59%	62%
Bulgaria	47%	58%	73%	70%	72%	76%	71%	53%	58%	61%	62%	62%	63%	62%
Croatia	53%	57%	59%	60%	60%	61%	63%	66%	67%	74%	76%	72%	72%	75%
Czechia	64%	70%	68%	69%	66%	68%	63%	48%	48%	49%	51%	52%	54%	51%
Estonia	41%	42%	42%	43%	46%	45%	47%	38%	39%	41%	39%	43%	42%	44%
Finland	42%	45%	45%	44%	44%	41%	39%	52%	60%	56%	61%	60%	60%	57%
France	25%	25%	24%	28%	32%	32%	29%	30%	31%	26%	34%	39%	37%	35%
Germany	26%	28%	29%	29%	30%	28%	27%	47%	51%	49%	50%	49%	45%	45%
Hungary	38%	39%	41%	43%	44%	39%	36%	73%	77%	82%	84%	85%	79%	72%
Italy	39%	54%	55%	54%	56%	59%	56%	48%	58%	55%	54%	55%	55%	56%
Montenegro														
North Macedonia			58%	63%	66%	67%	71%			77%	83%	87%	90%	84%
Norway	10%	10%	9%	7%	7%	69%	69%	9%	9%	8%	7%	11%	59%	65%
Poland	19%	18%	13%	7%	6%	4%	12%	21%	20%	14%	7%	7%	6%	15%
Portugal	42%	46%	44%	44%	46%	46%	43%	50%	56%	55%	53%	57%	56%	51%
Romania	43%	47%	49%	51%	54%	58%	58%	56%	63%	69%	71%	72%	81%	82%
Serbia							59%							102%
Slovak Republic	52%	60%	59%	65%	65%	59%	58%	54%	71%	68%	68%	66%	64%	61%
Slovenia	64%	65%	69%	69%	68%	66%	67%	70%	76%	78%	79%	78%	76%	74%
Spain	42%	44%	43%	44%	45%	45%	42%	50%	52%	52%	53%	53%	54%	49%

Note: Blanks correspond to country-year pairs for which the Eurostat's SBS Database does not report information. Montenegro and Ukraine are excluded from this table as the SBS Database does not include information for any of the years in our sample.

Table C.2: Coverage of Final Database Relative to Eurostat (SBS) - Manufacturing

Country	**Employment**							**Turnover**						
	2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Austria	14%	21%	34%	41%	44%	45%	47%	12%	17%	35%	51%	54%	58%	58%
Belgium	63%	64%	64%	65%	67%	67%	66%	78%	76%	76%	72%	74%	79%	76%
Bosnia and Herzegovina		64%	44%	67%	60%	62%	59%		62%	49%	68%	62%	66%	62%
Bulgaria	54%	65%	73%	71%	70%	74%	70%	45%	50%	41%	40%	42%	45%	45%
Croatia	61%	65%	65%	62%	65%	67%	65%	68%	76%	79%	75%	73%	71%	65%
Czechia	74%	77%	76%	77%	75%	79%	72%	50%	52%	53%	55%	53%	62%	60%
Estonia	39%	41%	41%	43%	44%	43%	44%	33%	33%	33%	35%	35%	36%	38%
Finland	47%	52%	53%	54%	49%	48%	48%	45%	50%	52%	49%	46%	46%	49%
France	30%	28%	23%	31%	37%	38%	40%	27%	25%	19%	30%	35%	37%	37%
Germany	32%	34%	34%	34%	35%	34%	33%	46%	49%	48%	48%	50%	50%	49%
Hungary	57%	61%	62%	62%	64%	63%	60%	75%	78%	79%	83%	89%	89%	90%
Italy	47%	59%	59%	62%	63%	65%	64%	54%	61%	59%	62%	61%	61%	62%
North Macedonia			61%	65%	66%	60%	61%			56%	63%	47%	43%	
Norway	32%	36%	40%	28%	25%	68%	75%	31%	35%	31%	27%	26%	64%	73%
Poland	26%	22%	16%	10%	7%	7%	16%	31%	25%	20%	12%	10%	10%	23%
Portugal	61%	65%	66%	68%	68%	69%	68%	62%	64%	65%	67%	56%	59%	56%
Romania	50%	53%	55%	57%	59%	60%	59%	45%	48%	57%	57%	60%	59%	58%
Serbia							65%							87%
Slovak Republic	61%	59%	63%	63%	61%	57%	52%	44%	48%	57%	59%	53%	43%	42%
Slovenia	71%	74%	75%	71%	72%	74%	66%	71%	74%	75%	72%	70%	73%	65%
Spain	52%	54%	54%	57%	59%	59%	56%	46%	46%	43%	49%	47%	49%	47%

Note: Blanks correspond to country-year pairs for which the Eurostat's SBS Database does not report information. Montenegro and Ukraine are excluded from this table as the SBS Database does not include information for any of the years in our sample.

References

Natalie Bau and Adrien Matray. Misallocation and capital market integration: Evidence from india. *Econometrica*, 91(1):67–106, 2023.

Thorsten Beck, Asli Demirgüç-Kunt, Luc Laeven, and Ross Levine. Finance, Firm Size, and Growth. *Journal of Money, Credit & Banking*, 40(7):1379–1405, 2008.

Pedro Bento and Diego Restuccia. Misallocation, Establishment Size, and Productivity. *American Economic Journal: Macroeconomics*, 9(3):267–303, 7 2017. ISSN 1945-7707. doi: 10.1257/mac.20150281. URL https://pubs.aeaweb.org/doi/10.1257/mac.20150281.

Francisco J. Buera, Joseph P. Kaboski, and Yongseok Shin. Finance and development: A tale of two sectors. *American Economic Review*, 101(5):1964–2002, 2011. ISSN 00028282. doi: 10.1257/aer.101.5.1964.

Bureau van Dijk. Orbis - User Guide, 2011.

Tiago V. Cavalcanti, Joseph P. Kaboski, Bruno S. Martins, and Cezar Santos. Dispersion in Financing Costs and Development. NBER Working Papers 28635, National Bureau of Economic Research, Inc, April 2021. URL https://ideas.repec.org/p/nbr/nberwo/28635.html.

Ana Paula Cusolito and Tatiana Didier. Methodology, sql, and stata codes to create a clean financial firm-level data using orbis raw files. Working paper, World Bank, Washington, DC, US, 2020.

Joel M David, Lukas Schmid, and David Zeke. Risk-adjusted capital allocation and misallocation. *Journal of Financial Economics*, 145(3):684–705, 2022.

Roberto N. Fattal-Jaef. Entry barriers, idiosyncratic distortions, and the firm size distribution. *American Economic Journal: Macroeconomics*, 14(2):416–68, April 2022.

doi: 10.1257/mac.20200234. URL https://www.aeaweb.org/articles?id=10.1257/mac.20200234.

Gita Gopinath, Sebnem Kalemli-Ozcan, Loukas Karabarbounis, and Carolina Villegas-Sanchez. Capital allocation and productivity in south europe. *Quarterly Journal of Economics*, 132(4):1915–1967, 2017. ISSN 15314650. doi: 10.1093/qje/qjx024.

Jeremy Greenwood, Juan M. Sanchez, and Cheng Wang. Financing development: The role of information costs. *American Economic Review*, 100(4):1875–91, September 2010. doi: 10.1257/aer.100.4.1875. URL https://www.aeaweb.org/articles?id=10.1257/aer.100.4.1875.

Chang-Tai Hsieh and Peter J. Klenow. Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics*, 124(4):1403–1448, 2009. doi: 10.1093/qje/qjs020.Advance.

Chang-Tai Hsieh and Peter J. Klenow. The life cycle of plants in India and Mexico. *Quarterly Journal of Economics*, 129(3):1057–1106, 2014. doi: 10.1093/qje/qjs020.Advance.

Sebnem Kalemli-Ozcan, Bent Sorensen, Carolina Villegas-Sanchez, Vadym Volosovych, and Sevcan Yesiltas. How to Construct Nationally Representative Firm Level Data from the Orbis Global Database: New Facts and Aggregate Implications. NBER Working Papers 21558, National Bureau of Economic Research, Sep 2015. URL https://ideas.repec.org/p/nbr/nberwo/21558.html.

Sebnem Kalemli-Ozcan, Bent Sorensen, Carolina Villegas-Sanchez, Vadym Volosovych, and Sevcan Yesiltas. How to construct nationally representative firm level data from the Orbis global database: New facts on SMEs and aggregate implications. *American Economic Journal: Macroeconomics*, (Forthcoming):–, 2023. ISSN 1945-7707.

Jan Kmenta. On estimation of the ces production function. *International Economic Review*, 8(2):180–189, 1967.

Mauricio Larrain and Sebastian Stumpner. Capital Account Liberalization and Aggregate Productivity: The Role of Firm Capital Allocation. *Journal of Finance*, 72(4):1825–1858, 2017. ISSN 15406261. doi: 10.1111/jofi.12497.

Virgiliu Midrigan and Daniel Yi Xu. Finance and misallocation: Evidence from plant-level data. *American Economic Review*, 104(2):422–458, 2 2014. ISSN 00028282. doi: 10.1257/aer.104.2.422.

Benjamin Moll. Productivity losses from financial frictions: Can self-financing undo capital misallocation? *American Economic Review*, 104(10):3186–3221, 2014. ISSN 00028282. doi: 10.1257/aer.104.10.3186.

Toni M. Whited and Jake Zhao. The Misallocation of Finance. *The Journal of Finance*, 76(5):2359–2407, 10 2021. ISSN 0022-1082. doi: 10.1111/jofi.13031. URL https://onlinelibrary.wiley.com/doi/10.1111/jofi.13031.