The World Bank Economic Review, 00(0), 2020, 1–20
doi: 10.1093/wber/lhaa020
Article

OXFORD

Capital Allocation in Developing Countries

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Abstract

This paper investigates the sources of capital misallocation across a group of developing and developed countries, using the empirical methodology developed in David and Venkateswaran (2019. "The Sources of Capital Misallocation." *American Economic Review* 109 (7): 2531–67). The main findings are: (i) technological frictions—namely, adjustment costs and uncertainty—account for only a modest share of the observed misallocation; (ii) heterogeneity in firm-level technologies potentially explains between one-quarter and one-half, but (iii) dispersion in markups is much smaller; (iv) after accounting for these factors, on average, at least 50 percent of misallocation within each country remains unexplained, suggesting a large role for additional—potentially distortionary—factors. These factors are largely attributable to a component that is correlated with firm size/productivity and one that is essentially permanent to the firm. They exhibit strong negative correlations with income per capita and direct measures of the quality of the business environment from the World Bank Doing Business Report. The paper reports a broad set of moments describing firm-level investment dynamics and detailed parameter estimates on a country-by-country basis with an eye towards future work in this area.

JEL classification: D24, E22, O11, O47

Keywords: productivity, misallocation, investment, adjustment costs, uncertainty

1. Introduction

A large literature in macroeconomics and development explores the "misallocation" of resources across firms, i.e., dispersion in static marginal products of inputs, and the implications for cross-country differences in aggregate productivity and per capita income/output.[1] Because marginal products are not directly observed, the extent of such misallocation is typically inferred from dispersion in the *average* product of

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1 Seminal contributions include Hsieh and Klenow (2009) and Restuccia and Rogerson (2008). Restuccia and Rogerson (2017) and Hopenhayn (2014) provide excellent recent overviews of this line of work.

these inputs (revenue or value-added/input ratios). Under standard assumptions, the dispersion in the two are identical (for example, with common production technologies and demand elasticities). Recently, attention has turned towards examining the role of particular factors in generating the observed misallocation. Examples include technological frictions such as adjustment costs or imperfect information, unobserved heterogeneity at the firm level, for example, in production technologies or markups, as well as firm-specific "distortions" stemming from economic policies or other institutional features.[2] From a policy standpoint, disentangling the roles of these forces is paramount—any prescription for economic reforms aimed at reducing misallocation must be based on a careful understanding of the underlying determinants and nature—e.g., efficient or inefficient—of the observed average product dispersion.

In a recent contribution, David and Venkateswaran (2019) develop an empirical methodology to disentangle a number of sources of *measured* capital misallocation—dispersion in the average (revenue) product of capital (arpk)—using observable data on firm revenues (or value-added) and inputs. The methodology is based on the insight that targeting an appropriately chosen set of moments allows one to jointly estimate the contributions of capital adjustment costs, firm-level uncertainty, and a broad class of other firm-specific factors to observed arpk dispersion. This class includes factors that are correlated with firm fundamentals, e.g., productivity or demand, as well as those orthogonal to fundamentals. The latter can be further broken down into transitory and permanent components. Thus, the specification allows for a rich correlation structure for these factors, both with time as well as with firm characteristics. Further, it is also possible to provide bounds for the roles of two specific factors, namely, firm-level heterogeneity in markups and production technologies.[3]

In this paper, we apply this methodology to data from a number of countries, with a particular focus on developing ones. Specifically, we compile data for 11 countries—9 developing and 2 developed—from various datasets. In the body of the paper, we outline the economic environment underlying the method and describe the main steps in more detail. We report key data moments as well as detailed parameter estimates on a country-by-country basis, along with the contributions of each force to observed arpk dispersion. In addition to furthering our understanding of the sources of capital misallocation, our analysis also aims to provide a broader perspective on firm investment dynamics in these countries, which may help to guide future research.

While there is variation in parameter estimates across countries, there are a number of broad patterns that hold across all the countries in our sample: (i) adjustment costs and informational frictions—although important drivers of investment dynamics—generate only modest arpk dispersion; (ii) correlated, or size-dependent, factors—which implicitly "tax" more productive firms—play a more significant role, especially in developing countries.[4] Indeed, two important cross-country regularities that emerge are that adjustment costs, if anything, are more salient in more developed countries while correlated distortions are more prevalent in less developed ones; (iii) a significant portion of the observed arpk dispersion can be attributed to permanent factors, i.e., firm-level fixed effects; (iv) heterogeneity in production technologies (i.e., firm-level differences in output elasticities of capital and other inputs in the production function) can potentially account for between about one-quarter and one-half of dispersion in arpk. This is an

2 See, e.g., work by Asker, Collard-Wexler, and De Loecker (2014) on adjustment costs, Buera, Kaboski, and Shin (2011), Moll (2014), Gopinath et al. (2017), and Midrigan and Xu (2014) on financial frictions, David, Hopenhayn, and Venkateswaran (2016) on uncertainty, and Peters (2019) on markup dispersion. Following Hsieh and Klenow (2009) and Restuccia and Rogerson (2008), a large number of studies focus on the role of distortions along the lines that we model them here.

3 The data to compute markup dispersion is only available in 4 of the 11 countries, highlighting some of the data hurdles future work along these lines may have to overcome.

4 "Correlated" distortions of this kind have been emphasized in, e.g., Restuccia and Rogerson (2008), Guner, Ventura, and Xu (2008), Bartelsman, Haltiwanger, and Scarpetta (2013), Buera, Moll, and Shin (2013), Buera and Fattal-Jaef (2018), Hsieh and Klenow (2014), and Bento and Restuccia (2017).

important result, as it suggests that a non-negligible portion of observed dispersion may not entail a "misallocation" at all; (v) markup dispersion is generally modest.[5] Taken together, these latter two factors—markup and technology heterogeneity—can explain as much as 50 percent of observed arpk dispersion. But this leaves a substantial unexplained component, which seems to stem from other—potentially distortionary—factors.

Next, we relate our estimates of the magnitude of firm-specific distortions in our sample to survey measures of the business environment in those countries. Specifically, we show that our estimated distortions exhibit a strong negative relationship with the Ease of Doing Business index from the World Bank's Doing Business Report (DBR). This index aims at providing a comprehensive measure of business regulations and their enforcement and is a widely-used indicator of the quality of the institutional framework in a country. Our analysis suggests a tight link between this measure and allocative efficiency.

The DBR also reports a number of subindices, which capture different aspects of the business environment, such as access to credit, effectiveness of the legal system, and bankruptcy laws. These subcomponents allow us to shed further light on their allocative implications. For example, we find that cross-country variation in the ease of enforcing contracts and getting credit is strongly correlated with the magnitude of permanent, uncorrelated factors, which suggests that these distortions have lasting effects on capital allocation. On the other hand, ease of resolving insolvency and undertaking property transactions show a stronger relationship with our estimates of size-dependent factors, indicating that they disproportionately affect larger/more productive firms.

Overall, these findings provide evidence of the significant role played by "distortions" in generating the observed dispersion in firm-level average products. Moreover, by uncovering a link between direct, specific measures of the legal/regulatory framework and capital allocation, they point to a fruitful avenue for future researchers and policy-makers to pursue in isolating and addressing the underlying sources of misallocation.

The remainder of the paper is organized as follows. Section 2 outlines the theoretical economic environment underlying the empirical methodology. Section 3 describes our data sources and reports key moments used in the estimation. Sections 4 and 5 contain our main quantitative results. In Section 6 we relate our estimates to direct measures of the quality of the business environment from the World Bank DBR. Section 7 concludes and discusses some lessons for future work that can be drawn from our analysis.

2. Theoretical Framework

This section lays out the main features of the theoretical environment underlying our empirical exercise.[6] The environment is an extension of the canonical Hsieh and Klenow (2009) framework to include dynamic considerations in firms' investment decisions. Time is discrete and agents are infinitely lived. A representative household inelastically supplies labor and has preferences over consumption of a final good. The household discounts time at rate β. We focus on a stationary equilibrium featuring a rich cross-section of firm-level idiosyncratic risk but no aggregate risk, so that aggregate variables are constant.

Production and Demand

A continuum of firms of fixed measure 1, indexed by i, produce a set of intermediate goods using capital and labor according to a Cobb–Douglas technology:

$$Y_{it} = K_{it}^{\hat{\alpha}_1} N_{it}^{\hat{\alpha}_2}, \quad \hat{\alpha}_1 + \hat{\alpha}_2 \leq 1.$$

5 Note that this refers to dispersion in markups within an industry, not the average level of markups or the dispersion across industries.

6 For further details and full derivations, see Section 2 of David and Venkateswaran (2019).

A representative final good firm operating in a competitive market bundles these intermediates to produce the single final good using a standard CES aggregator

$$Y_t = \left(\int \hat{A}_{it} Y_{it}^{\frac{\theta-1}{\theta}}\, di\right)^{\frac{\theta}{\theta-1}},$$

where $\theta \in (1, \infty)$ is the elasticity of substitution between intermediate goods and $\hat{A}_{it}$ represents a firm-specific component, which can capture idiosyncratic firm productivity or demand factors. This yields a standard demand function for intermediate good i:

$$Y_{it} = P_{it}^{-\theta} \hat{A}_{it}^{\theta} Y_t \Rightarrow P_{it} = \left(\frac{Y_{it}}{Y_t}\right)^{-\frac{1}{\theta}} \hat{A}_{it},$$

where P_{it} denotes the relative price of good i in terms of the final good. Revenues for firm i at time t are

$$P_{it} Y_{it} = Y_t^{\frac{1}{\theta}} \hat{A}_{it} K_{it}^{\alpha_1} N_{it}^{\alpha_2} \qquad \text{where } \alpha_j = \left(1 - \frac{1}{\theta}\right) \hat{\alpha}_j, \quad j = 1, 2.$$

Input Choices

Firms hire labor on a period-by-period basis under full information at a competitive wage W_t. At the end of each period, firms choose investment in new capital, which becomes available for production in the following period. Investment is subject to quadratic adjustment costs, given by

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

where $\hat{\xi}$ parameterizes the severity of the adjustment cost and δ is the rate of depreciation.[7]

To capture any additional factors that may influence firm investment decisions (in addition to productivity/demand or the level of previously installed capital), we introduce a class of idiosyncratic "wedges" that appear in the firm's optimization problem as proportional taxes on the flow cost of capital. These wedges can arise, for example, from distortionary government policies, additional unmodeled market frictions (e.g., financial frictions), or unobserved heterogeneity in markups/production technologies. We denote these wedges by T_{it}^K.

After optimizing over the static labor decision, the firm's problem in a stationary equilibrium can be written in recursive form as (we suppress the time subscript on all aggregate variables)[8]

$$\begin{aligned}\mathcal{V}(K_{it}, \mathcal{I}_{it}) = \max_{K_{it+1}} \mathbb{E}_{it}\left[G A_{it} K_{it}^{\alpha} - T_{it}^K K_{it+1}(1 - \beta(1-\delta)) - \Phi(K_{it+1}, K_{it})\right] \\ + \mathbb{E}_{it} \beta \left[\mathcal{V}(K_{it+1}, \mathcal{I}_{it+1})\right],\end{aligned} \tag{1}$$

where $\mathbb{E}_{it}[\cdot]$ denotes the firm's expectations conditional on $\mathcal{I}_{it}$, the information set of the firm at the time of making its period t investment choice. We describe this set explicitly below. The term $1 - \beta(1-\delta)$ is the user cost per unit of capital. The constant G is given by $G \equiv (1-\alpha_2)(\frac{\alpha_2}{W})^{\frac{\alpha_2}{1-\alpha_2}} Y^{\frac{1}{\theta}\frac{1}{1-\alpha_2}}$, $A_{it} \equiv \hat{A}_{it}^{\frac{1}{1-\alpha_2}}$ is a simple transformation of idiosyncratic productivity/demand, and $\alpha \equiv \frac{\alpha_1}{1-\alpha_2}$ is the curvature of operating profits (revenues net of wages). From here on, we simply refer to A_{it} as firm-level productivity.

7 This is a standard formulation in the investment literature; see, e.g., Cooper and Haltiwanger (2006), Bloom (2009), and Asker, Collard-Wexler, and De Loecker (2014).

8 The effects of the labor choice (and any other static inputs) are subsumed into the value of α, i.e., they affect the effective curvature in the firm's problem, but otherwise do not play a role in the investment decision. An alternative assumption is that labor is chosen under the same frictions and distortions as capital—in this case, we can show that the problem takes exactly the same form as expression (2), but with a different degree of curvature, specifically $\alpha = 1 - \frac{1}{\theta}$.

Equilibrium

A *stationary equilibrium* in this economy is defined as (i) a set of value and policy functions for the firm, $\mathcal{V}(K_{it}, \mathcal{I}_{it})$, $N_{it}(K_{it}, \mathcal{I}_{it})$, and $K_{it+1}(K_{it}, \mathcal{I}_{it})$, (ii) a wage W, and (iii) a joint distribution over $(K_{it}, \mathcal{I}_{it})$ such that (a) taking as given wages and the law of motion for $\mathcal{I}_{it}$, the value and policy functions solve the firm's optimization problem, (b) the labor market clears, and (c) the joint distribution remains constant through time.

Characterization

We use perturbation methods to characterize the equilibrium. In particular, we log-linearize the firm's optimality conditions and laws of motion around $A_{it} = \bar{A}$ (the unconditional average level of productivity) and $T^K_{it} = 1$ (i.e., no distortions), which yields the following log-linearized Euler equation:

$$k_{it+1}((1+\beta)\xi + 1 - \alpha) = \mathbb{E}_{it}[a_{it+1} + \tau_{it}] + \beta\xi\mathbb{E}_{it}[k_{it+2}] + \xi k_{it},$$

where we use lower case to denote natural logs. The parameter ξ is a composite parameter that captures the degree of adjustment costs and τ_{it} summarizes the effect of T^K_{it} on the firm's investment decision.[9]

Stochastic Processes

We assume that firm productivity A_{it} follows an AR(1) process in logs with normally distributed i.i.d. innovations, i.e.,

$$a_{it} = \rho a_{it-1} + \mu_{it}, \quad \mu_{it} \sim \mathcal{N}\left(0, \sigma^2_\mu\right), \tag{2}$$

where ρ is the persistence and σ^2_μ the variance of the innovations.

We adopt a specification for the distortion τ_{it}, that allows for a rich correlation structure, both with time as well as with firm-level productivity. Specifically, τ_{it} takes the form

$$\tau_{it} = \gamma a_{it+1} + \varepsilon_{it} + \chi_i, \quad \varepsilon_{it} \sim \mathcal{N}\left(0, \sigma^2_\varepsilon\right), \quad \chi_i \sim \mathcal{N}\left(0, \sigma^2_\chi\right),$$

where the parameter γ controls the extent to which τ_{it} comoves with productivity.[10] If $\gamma < 0$, the wedge discourages (encourages) investment by firms with higher (lower) productivity—arguably, the empirically relevant case. The opposite is true if $\gamma > 0$. The remaining components of τ_{it} are both uncorrelated with a_{it}, but differ in their time-series properties. The term χ_i is permanent while ε_{it} is i.i.d. over time. The variances of these two components are denoted σ^2_χ and σ^2_ε. Thus, the severity of factors other than adjustment/information frictions is summarized by three parameters: γ, σ^2_χ, and σ^2_ε.

Information

We introduce uncertainty in the choice of K_{it+1} along the lines of David, Hopenhayn, and Venkateswaran (2016) by assuming that in addition to realized productivity a_{it}, the firm also observes a noisy signal of the following period's innovation:

$$s_{it+1} = \mu_{it+1} + e_{it+1}, \quad e_{it+1} \sim \mathcal{N}\left(0, \sigma^2_e\right),$$

where e_{it+1} is an i.i.d., mean-zero, and normally distributed noise term. This is in essence an idiosyncratic "news shock," since it contains information about future productivity. Finally, firms also perfectly observe the uncorrelated transitory component of distortions ε_{it} (as well as the fixed component χ_i) at the time

9 Specifically,

$$\xi = \frac{\hat{\xi}}{1-\beta(1-\delta)+\hat{\xi}\delta\left(1-\beta\left(1-\frac{\delta}{2}\right)\right)} \quad \text{and} \quad \tau_{it} = -\frac{1-\beta(1-\delta)}{1-\beta(1-\delta)+\hat{\xi}\delta\left(1-\beta\left(1-\frac{\delta}{2}\right)\right)}\log T^K_{it}$$

.

10 In particular, γ is the elasticity of the distortion τ_{it}, with respect to productivity a_{it}.

of choosing period t investment. They do not see the correlated component but are aware of its structure, i.e., they know γ.

Thus, the firm's information set is given by $\mathcal{I}_{it} = (a_{it}, s_{it+1}, \varepsilon_{it}, \chi_i)$. Direct application of Bayes' rule yields the conditional expectation of productivity a_{it+1}:

$$a_{it+1}|\mathcal{I}_{it} \sim N\left(\mathbb{E}_{it}\left[a_{it+1}\right], \mathbb{V}\right) \quad \text{where}$$

$$\mathbb{E}_{it}\left[a_{it+1}\right] = \rho a_{it} + \frac{\mathbb{V}}{\sigma_e^2} s_{it+1}, \quad \mathbb{V} = \left(\frac{1}{\sigma_\mu^2} + \frac{1}{\sigma_e^2}\right)^{-1}.$$

In this Gaussian setting, the posterior variance $\mathbb{V}$ is a sufficient statistic for firm-level uncertainty. Specifically, given the AR(1) assumption on productivity, $\mathbb{V}$ takes on values between 0 and σ_μ^2 and there is a one-to-one mapping between $\mathbb{V}$ and the noisiness of the signal σ_e^2 (given the volatility of productivity σ_μ^2). In the absence of any learning (or "news"), i.e., when σ_e^2 approaches infinity, $\mathbb{V} = \sigma_\mu^2$, that is, all uncertainty regarding the innovation in productivity μ_{it+1}, remains unresolved at the time of investment. In this case, we have a standard one period time-to-build structure with $\mathbb{E}_{it}[a_{it+1}] = \rho a_{it}$. At the other extreme, when σ_e^2 approaches 0, $\mathbb{V} = 0$ and the firm becomes perfectly informed about μ_{it+1} so that $\mathbb{E}_{it}[a_{it+1}] = a_{it+1}$.[11]

Optimal Investment

With this structure, we can explicitly solve for the firm's (log-linearized) optimal investment policy:

$$k_{it+1} = \psi_1 k_{it} + \psi_2 (1+\gamma)\, \mathbb{E}_{it}[a_{it+1}] + \psi_3 \varepsilon_{it} + \psi_4 \chi_i, \tag{3}$$

where

$$\xi\left(\beta\psi_1^2 + 1\right) = \psi_1\left((1+\beta)\xi + 1 - \alpha\right),$$

$$\psi_2 = \frac{\psi_1}{\xi\left(1 - \beta\rho\psi_1\right)}, \quad \psi_3 = \frac{\psi_1}{\xi}, \quad \psi_4 = \frac{1-\psi_1}{1-\alpha}.$$

The coefficients ψ_1 to ψ_4 depend only on production (and preference) parameters, including the adjustment cost, and are independent of assumptions about information and distortions. Note that the coefficient ψ_1 is increasing and ψ_2, ψ_3, ψ_4 decreasing in the severity of adjustment costs ξ. If there are no adjustment costs (i.e., $\xi = 0$), $\psi_1 = 0$ and $\psi_2 = \psi_3 = \psi_4 = \frac{1}{1-\alpha}$. At the other extreme, as ξ tends to infinity, ψ_1 approaches 1 and ψ_2, ψ_3, ψ_4 go to 0. Intuitively, as adjustment costs become large, the firm's choice of capital becomes more autocorrelated and less responsive to productivity and distortions.

Aggregation

Aggregate output in this economy can be expressed as

$$\log Y \equiv y = a + \hat{\alpha}_1 k + \hat{\alpha}_2 n,$$

where k and n denote the (logs of the) aggregate capital stock and labor inputs, respectively. Aggregate total factor productivity (TFP), denoted by a, is given by

$$a = a^* - \frac{(\theta\hat{\alpha}_1 + \hat{\alpha}_2)\,\hat{\alpha}_1}{2}\sigma^2(\text{arpk}), \qquad \frac{da}{d\sigma^2(\text{arpk})} = -\frac{(\theta\hat{\alpha}_1 + \hat{\alpha}_2)\,\hat{\alpha}_1}{2}, \tag{4}$$

where a^* is aggregate TFP if static average (revenue) products of capital (in logs, $\text{arpk}_{it} = p_{it}y_{it} - k_{it}$) are equalized across firms and $\sigma^2(\text{arpk})$ is the cross-sectional dispersion in arpk_{it}. Thus, aggregate TFP is monotonically decreasing in the extent of arpk dispersion, summarized in this log-normal world by

11 In what follows we report values for $\frac{\mathbb{V}}{\sigma_\mu^2}$, which denotes the posterior uncertainty as a percentage of the prior (values of $\mathbb{V}$ are easily calculated by multiplying by σ_μ^2 as reported in table 1). This statistic takes on values between 0 and 1 and is increasing in the extent of uncertainty.

σ^2(arpk). The effect of σ^2(arpk) on aggregate TFP depends on the elasticity of substitution θ, and the relative shares of capital and labor in production. The higher is θ, that is, the closer we are to perfect substitutability, the more severe the losses from variation in value-added/capital ratios. Similarly, fixing the degree of overall returns to scale in production, for a larger capital share $\hat{\alpha}_1$, a given degree of dispersion has larger effects on aggregate outcomes.

With perfect information and no adjustment costs and distortions, it is straightforward to show that expression (3) collapses to $k_{it+1} = \frac{1}{1-\alpha} a_{it+1}$ and the average product of capital is constant across firms. In contrast, in the richer environment here, each of these forces will lead to arpk dispersion. Intuitively, our empirical strategy can be thought of as estimating the coefficients in (3) and using those estimates to infer the structural parameters governing the severity of each friction and its contribution to σ^2(arpk). With these results in hand, we can apply expression (4) to map those contributions to their aggregate implications.

3. The Data

Data Sources

We use data compiled from a number of different sources. First, we use the Bureau van Dijk's Orbis database. Orbis contains firm-level data (including both public and private firms) for a number of countries.[12] We focus mainly on developing countries (and Japan) and use countries that have sufficient data on revenues, capital, and a measure of labor input (the minimum requirements for the analysis).[13] We use only firms in the manufacturing sector and, given our focus on within-industry moments, use only country–year–industry cells with at least 10 firms. The data cover the period 2002–2010. There are seven countries in our Orbis sample: Argentina (ARG), Brazil (BRA), Japan (JPN), Malaysia (MYS), Taiwan (TWN), Thailand (THA), and Turkey (TUR).

We supplement this sample with data on four additional countries. First, we use data on US publicly traded firms from Compustat. Second, we use data on Chinese manufacturing firms from the Annual Surveys of Industrial Production conducted by the China National Bureau of Statistics. Next, we use data in Colombia (at the establishment level) from the Colombian Annual Manufacturers Survey and lastly, data in Mexico (also at the establishment level) from the Mexican Annual Industrial Survey.[14] Throughout the paper, we report results first for the seven Orbis countries (in alphabetical order) and then for the four additional countries (again in alphabetical order).

Table S1.1 in the supplementary online appendix, available with this article at *The World Bank Economic Review* website, reports detailed summary statistics from our final sample in each country. Our use of multiple data sources has the advantage of yielding a wider set of countries on which we can perform our analysis—nine developing and two developed. One important disadvantage is that direct cross-country comparisons become more difficult, given differences in coverage, sample sizes, the set of firms included, etc.[15] For example, the Orbis samples are likely composed of the largest firms in the economy and may tend to under-represent small and medium firms. This is even more the case with the US Compustat data, which includes only publicly traded firms. Further, sample sizes range from close to comprehensive coverage of manufacturing firms (above a certain size) in China to about 550 in Malaysia. However, with this important caveat in mind, we will show that despite these differences, our study leads

12 For a comprehensive description of the Orbis database, see Kalemli-Ozcan et al. (2019). Gopinath et al. (2017) also use the Orbis data in a misallocation context, albeit for a developed country, Spain.

13 The measure of labor varies depending on reporting within each country. For Malaysia and Taiwan, we have measures of the wage bill. For the remaining countries, we have numbers of employees.

14 For a more detailed description of these datasets see, e.g., David and Venkateswaran (2019) and the references therein.

15 It turns out that these issues crop up even using a single cross-country database. For example, table S1.1 shows that the coverage differs widely even within the Orbis database alone.

to a number of robust patterns with respect to the sources of observed misallocation both within and across countries. For example, Section 4 reveals that the relative contributions of various factors to arpk dispersion are broadly consistent across countries and Sections 4 and 6 show that our cross-country estimates of distortions are strongly correlated with income per capita as well as multiple measures of the quality of the business environment.

Investment Moments

The key input into our estimation procedure is a set of carefully chosen moments from firm-level data on capital and revenues, both of which are directly available in our data. Since we are interested in capital allocation across firms within an industry, we extract the firm-level idiosyncratic components of each data series by regressing the measured values on industry-by-year fixed effects and working with the residuals. We trim the 3 percent tails of each series. Industries are defined at the four-digit SIC code level.

We report a number of moments for each of the countries in table 1, grouped into four categories. The first group describes the stochastic process of firm-level productivity.[16] Under our assumptions of a Cobb–Douglas production function and constant elasticity of substitution demand, firm-level productivity can be inferred from revenues and capital as $a_{it} = y_{it} - \alpha k_{it}$, where α is defined in expression (1). For simplicity, we use a common value of α across countries and set it equal to 0.62.[17] We estimate the parameters ρ and

Table 1. Moments of Investment Dynamics

		Productivity		Investment		Investment growth			Avg. prod. of capital	
	Num. obs.	ρ	σ_μ^2	$\rho(i, i_{-1})$	$\sigma^2(i)$	$\rho(\Delta i, \Delta a_{-1})$	$\rho(\Delta i, \Delta i_{-1})$	$\sigma^2 \Delta i)$	$\rho(\text{arpk}, a)$	$\sigma^2(\text{arpk})$
ARG	993	0.89	0.05	0.19	0.04	0.31	−0.36	0.06	0.58	0.54
BRA	1389	0.90	0.08	0.13	0.05	0.35	−0.39	0.09	0.60	0.65
CHN	797,047	0.91	0.14	0.04	0.08	0.25	−0.36	0.14	0.68	0.92
COL	44,909	0.95	0.09	0.13	0.04	0.28	−0.35	0.07	0.61	0.98
MEX	3208	0.93	0.07	0.17	0.01	0.17	−0.39	0.02	0.69	0.79
MYS	548	0.95	0.06	0.31	0.02	0.18	−0.29	0.03	0.86	0.73
TWN	2076	0.96	0.04	0.34	0.03	0.21	−0.36	0.04	0.66	0.57
THA	4025	0.95	0.07	0.26	0.06	0.27	−0.32	0.08	0.57	0.88
TUR	830	0.89	0.08	0.11	0.05	0.37	−0.38	0.09	0.57	0.56
JPN	60,720	0.98	0.03	0.13	0.02	0.17	−0.40	0.03	0.48	0.43
USA	34,260	0.93	0.08	0.25	0.04	0.13	−0.30	0.06	0.55	0.45

Source: Authors' calculations based on firm-level data from Orbis (Argentina, Brazil, Japan, Malaysia, Taiwan, Thailand, and Turkey), Annual Surveys of Industrial Production (China), Annual Manufacturers Survey (Colombia), Annual Industrial Survey (Mexico), and Compustat (United States).

Note: This table reports moments in firm-level investment dynamics across 11 countries. The first panel reports the persistence and the variance of the innovations in the firm-level productivity process, ρ and σ_μ^2, respectively. The second panel reports the serial correlation and volatility of investment rates, $\rho(i, i_{-1})$ and $\sigma^2(i)$. The third panel reports the correlation of investment growth rates with lagged innovations in productivity $\rho(\Delta i, \Delta a_{-1})$, and the serial correlation and volatility of investment growth, $\rho(\Delta i, \Delta i_{-1})$ and $\sigma^2(\Delta i)$. The last panel reports the correlation of the average revenue product of capital with productivity $\rho(\text{arpk}, a)$ and the variance of the average revenue product of capital $\sigma^2(\text{arpk})$. All series are regressed on industry-by-year fixed effects to extract the firm-level variation within an industry, where industries are defined at the four-digit SIC code level.

16 As is well known, in standard models of misallocation/firm dynamics, measures of productivity can also be interpreted as idiosyncratic demand factors.

17 Estimating α using an indirect inference approach in the United States (specifically, finding the value of α so that the coefficient from an ordinary least squares regression of revenue on capital using model-simulated data matches its counterpart from the same regression in the true data) yields $\alpha = 0.62$. Using this estimate along with the value of labor's share of GDP reported by the Bureau of Economic Analysis (0.56) implies an elasticity of substitution, θ, equal to 6 (for details of the mapping, see Supplementary Online Appendix S1). We have also performed the estimation using country-specific labor shares and estimates of α and report the results in table S1.4 in Supplementary Online Appendix S1. The results on the decomposition of $\sigma^2(\text{arpk})$ are similar (note that α also affects the TFP losses from arpk dispersion; intuitively, the higher is α, the greater the losses for a given $\sigma^2(\text{arpk})$).

σ_μ^2, which capture the persistence and volatility of firm-level productivity, as a standard autoregression as defined by (2).

In the second panel of the table, we report two commonly used moments of firm-level investment: the serial correlation $\rho(i, i_{-1})$ and the variance $\sigma^2(i)$. We measure net investment as the period-over-period percentage change in the firm's capital stock, i.e., $i_{it} = k_{it+1} - k_{it}$ (reported capital stocks in the data are year-end, which we map to k_{it+1}). The third panel of the table reports these two moments for investment growth rates (denoted Δi) along with the correlation of investment growth with lagged productivity growth (denoted Δa_{-1}).

Finally, the last panel of table 1 reports moments related to the average (revenue) product of capital, i.e., (in logs) $\text{arpk}_{it} = y_{it} - k_{it}$. The table reports the correlation of the arpk with productivity, denoted ρ(arpk, a), and its cross-sectional dispersion σ^2(arpk), a standard indicator of misallocation, which represents the key object of interest.

Table 1 uncovers a number of noteworthy patterns. First, across all countries, firm-level productivity is very persistent and volatile, especially when compared to the variability of investment.[18] The serial correlation of investment is relatively modest. These patterns also hold for investment growth rates, which also show low variability and a low serial correlation (indeed, the latter are significantly negative). Turning to the last panel, the average product of capital tends to be significantly correlated with productivity—in other words, high (low) productivity firms tend to have less (more) capital than would seem to be dictated by their fundamentals. This correlation is especially strong in the developing countries. Finally, the dispersion in the average product of capital is everywhere positive and significant (and again, is largest in the developing countries), suggesting a substantial degree of "misallocation" in all countries, but especially developing ones. In the next section, we use the moments in table 1 to shed light on the underlying drivers of this dispersion in the arpk. In the following section, we add additional data on other inputs into production (i.e., labor and intermediate inputs, where available) to further explore the extent to which σ^2(arpk) reflects a true misallocation—i.e., dispersion in *marginal* products—or whether unobserved heterogeneity across firms confounds the mapping from the former to the latter.

4. The Sources of Misallocation

Estimation Overview

What are the sources of variation in the arpk? In this environment, five distinct forces all contribute to this dispersion: adjustment costs, uncertainty, and the three components of the wedge, parameterized by ξ, $\mathbb{V}$, γ, σ_χ^2, and σ_ε^2. The main contribution of David and Venkateswaran (2019) is an empirical strategy that combines the information contained in the moments reported in table 1 to estimate these five parameters from firm-level data on revenues and capital. Specifically, they develop a simulated method-of-moments estimator targeting the following five moments from table 1: the variability and serial correlation of investment growth, the correlation of investment growth with lagged changes in a, the correlation of arpk with a, and the cross-sectional dispersion in arpk. Using this method, it is possible to *simultaneously* measure the contributions of (i) adjustment frictions, (ii) information frictions, and (iii) other firm-specific factors influencing investment decisions. We follow their approach and report the resulting parameter estimates in table 2.[19] The implications for arpk dispersion and aggregate productivity are presented in table 3 and discussed in detail there.

18 As a benchmark, without adjustment costs or other distortions, capital is given by $k_{it} = \frac{1}{1-\alpha} a_{it}$, so the variability of investment should be $\left(\frac{1}{1-\alpha}\right)^2 = \frac{1}{0.38^2} = 6.92$ times as volatile as productivity growth.

19 We report 95 percent confidence intervals for the parameter estimates in Supplementary Online Appendix S1, table S1.3. The estimation also uses standard values for other parameters governing production and demand. We report the values for these parameters in table S1.2 in Supplementary Online Appendix S1.

Table 2. Parameter Estimates

	Adjustment costs	Uncertainty	Other factors		
			Correlated	Permanent	Transitory
	ξ	$\mathbb{V}/\sigma^2_\mu$	γ	σ^2_χ	σ^2_ε
ARG	0.19	0.67	−0.79	0.36	0.00
BRA	0.12	0.71	−0.67	0.42	0.00
CHN	0.16	0.63	−0.63	0.51	0.00
COL	0.54	0.61	−0.55	0.60	0.01
MEX	0.13	0.58	−0.82	0.42	0.00
MYS	0.83	0.49	−0.94	0.18	0.00
TWN	0.20	0.58	−0.65	0.32	0.00
THA	0.29	0.61	−0.58	0.59	0.00
TUR	0.15	0.72	−0.61	0.37	0.00
JPN	2.05	0.49	−0.35	0.32	0.06
USA	1.38	0.42	−0.33	0.29	0.03

Source: Authors' calculations based on firm-level data from Orbis (Argentina, Brazil, Japan, Malaysia, Taiwan, Thailand, and Turkey), Annual Surveys of Industrial Production (China), Annual Manufacturers Survey (Colombia), Annual Industrial Survey (Mexico), and Compustat (United States).
Note: This table reports estimated parameter values capturing adjustment costs, uncertainty, and other factors (correlated with productivity, permanent and transitory) across 11 countries.

Parameter Estimates

There are a number of takeaways from table 2. First, we find evidence of economically meaningful adjustment costs in all countries. Our estimates for the United States are within the range, albeit towards the lower end, of previous values found in the literature.[20] They are higher in the two developed countries in our sample, Japan and the United States, as compared to the developing ones. Second, the estimates suggest that firms make investment decisions under considerable uncertainty. This information friction tends to be more severe in the developing countries. For example, the posterior uncertainty as a share of the prior ranges from lows of 42 percent in the United States and 49 percent in Japan to as high as 72 percent in Turkey. Finally, the last three columns show the estimates for factors other than adjustment/information frictions. Turning first to the correlated component, the negative values of γ suggest that, across all countries, these factors act to disincentivize investment by more productive firms. The estimates of γ are more negative in the developing countries, suggesting the magnitude of these factors is larger in those countries. The estimates of the fixed component of the distortion are quite substantial across the board, while the transitory component appears to be negligible in most of the countries.

Which features of the data lead us to these estimates? David and Venkateswaran (2019) develop a formal identification argument; here, we restrict ourselves to the key intuition. First, as we saw in table 1, the volatility of investment is relatively low. By itself, this would suggest a significant role for adjustment frictions. However, quadratic adjustment costs tend to induce strong serial correlation in investment, since they create incentives to smooth capital accumulation over time. But, as we saw, the autocorrelation of investment is relatively low, which translates to relatively modest estimates for adjustment costs.[21] The low volatility of investment along with the high correlation between the arpk and productivity together point to large negative values for γ, which acts to dampen the responsiveness of investment to shocks without

20 Our estimate is smaller than that in Asker, Collard-Wexler, and De Loecker (2014) and closer to (and slightly higher than) those in Cooper and Haltiwanger (2006) and Bloom (2009) (although it should be noted that each of these papers uses different data and considers different additional elements in their specification of these costs, making direct comparisons difficult).

21 An obvious concern with this argument is the possibility for non-convex (e.g., fixed) costs of adjustment. David and Venkateswaran (2019) extend their baseline model to allow for such costs, but find that they are quite small in the Chinese and US samples.

Table 3. The Sources of Misallocation

			Other factors					
			In isolation			With interactions		
	Adjustment costs	Uncertainty	Correlated	Permanent	Transitory	Correlated	Permanent	Transitory
ARG								
Effect on σ^2(arpk)	0.00	0.03	0.16	0.36	0.00	0.14	0.36	0.00
% of total σ^2(arpk)	(1)	(6)	(29)	(67)	(0)	(25)	(67)	(0)
Effect on TFP	0.00	0.01	0.07	0.16	0.00	0.06	0.16	0.00
BRA								
Effect on σ^2(arpk)	0.00	0.05	0.19	0.42	0.00	0.17	0.42	0.00
% of total σ^2(arpk)	(1)	(8)	(29)	(64)	(0)	(26)	(64)	(0)
Effect on TFP	0.00	0.02	0.08	0.18	0.00	0.07	0.18	0.00
CHN								
Effect on σ^2(arpk)	0.01	0.09	0.33	0.51	0.00	0.31	0.51	0.00
% of total σ^2(arpk)	(1)	(9)	(36)	(55)	(0)	(33)	(55)	(0)
Effect on TFP	0.00	0.04	0.14	0.22	0.00	0.13	0.22	0.00
COL								
Effect on σ^2(arpk)	0.02	0.05	0.30	0.60	0.01	0.30	0.60	0.00
% of total σ^2(arpk)	(3)	(6)	(31)	(61)	(1)	(31)	(61)	(0)
Effect on TFP	0.01	0.02	0.13	0.26	0.00	0.13	0.26	0.00
MEX								
Effect on σ^2(arpk)	0.00	0.04	0.36	0.42	0.00	0.33	0.43	0.00
% of total σ^2(arpk)	(1)	(5)	(45)	(53)	(0)	(41)	(54)	(0)
Effect on TFP	0.00	0.02	0.16	0.18	0.00	0.14	0.19	0.00
MYS								
Effect on σ^2(arpk)	0.02	0.03	0.54	0.18	0.00	0.50	0.18	0.00
% of total σ^2(arpk)	(3)	(4)	(73)	(25)	(0)	(68)	(25)	(0)
Effect on TFP	0.01	0.01	0.23	0.08	0.00	0.22	0.08	0.00
TWN								
Effect on σ^2(arpk)	0.00	0.02	0.23	0.32	0.00	0.22	0.32	0.00
% of total σ^2(arpk)	(1)	(4)	(40)	(56)	(0)	(39)	(56)	(0)
Effect on TFP	0.00	0.01	0.10	0.14	0.00	0.10	0.14	0.00
THA								
Effect on σ^2(arpk)	0.01	0.05	0.24	0.59	0.00	0.24	0.59	0.00
% of total σ^2(arpk)	(1)	(5)	(28)	(67)	(0)	(27)	(67)	(0)
Effect on TFP	0.00	0.02	0.11	0.26	0.00	0.10	0.26	0.00
TUR								
Effect on σ^2(arpk)	0.01	0.05	0.14	0.37	0.00	0.12	0.37	0.00
% of total σ^2(arpk)	(1)	(10)	(25)	(67)	(0)	(22)	(67)	(0)
Effect on TFP	0.00	0.02	0.06	0.16	0.00	0.05	0.16	0.00
JPN								
Effect on σ^2(arpk)	0.02	0.01	0.07	0.32	0.06	0.08	0.32	0.00
% of total σ^2(arpk)	(5)	(3)	(16)	(73)	(14)	(18)	(73)	(0)
Effect on TFP	0.01	0.01	0.03	0.14	0.03	0.03	0.14	0.00
USA								
Effect on σ^2(arpk)	0.05	0.03	0.06	0.29	0.03	0.08	0.29	0.00
% of total σ^2(arpk)	(11)	(7)	(14)	(65)	(6)	(17)	(65)	(0)
Effect on TFP	0.02	0.01	0.03	0.13	0.01	0.03	0.13	0.00

Source: Authors' calculations based on firm-level data from Orbis (Argentina, Brazil, Japan, Malaysia, Taiwan, Thailand, and Turkey), Annual Surveys of Industrial Production (China), Annual Manufacturers Survey (Colombia), Annual Industrial Survey (Mexico), and Compustat (United States).

Note: For each country, the first row reports the effect of each force on σ^2(arpk); the second row expresses these effects as a percentage of the observed σ^2(arpk); the third row calculates the implied total factor productivity (TFP) losses. The contribution of adjustment costs is calculated under the assumption that they are the only source of dispersion in arpk, i.e., with all other factors set to zero. The contribution of uncertainty is computed under the same assumption. The contributions from other factors are calculated in two ways. The first (columns "In isolation") assumes that all other forces are set to zero while the second (columns "With interactions") holds adjustment costs/uncertainty at their estimated values.

unduly raising the serial correlation. The non-trivial correlation of current investment decisions with lagged productivity changes—in other words, that firms do not seem to respond immediately to shocks—suggests learning and therefore, the degree of uncertainty. Finally, given all of these factors, matching the observed degree of cross-firm dispersion in arpk requires substantial variation in the fixed effect χ_i.

Implications

With these parameter estimates in hand, we compute their implications for measured misallocation and the resulting effects on measures of aggregate TFP. We report these calculations in table 3. Each horizontal panel contains the results for a single country. The top row of each panel displays the contribution of each of the factors to arpk dispersion. First, we calculate these values under the assumption that only the factor of interest is operational, i.e., in the absence of the others, so that the contribution of each one is measured relative to a frictionless benchmark. Second, we recalculate the contributions of the non-technological factors, i.e., the components of the distortion, holding the technological frictions, i.e., adjustment/information, fixed at their estimated values. This second calculation takes into account interaction effects between the factors, whereas the first does not. The columns labeled “In isolation” display the contributions of distortions on their own; the columns labeled “With interactions” their contributions (or the decrease in arpk dispersion that would arise from eliminating them) in the presence of adjustment/information frictions. The second row of each panel expresses these contributions as a percentage of the total arpk dispersion measured in the data. The last row uses expression (4) to translate these values into implied losses in aggregate TFP; in other words, by how much would aggregate productivity improve if one could eliminate the various factors.

The results show that adjustment costs and information frictions play a relatively modest role in generating the observed dispersion in arpk. Together, these two forces account for between about 5 percent (Taiwan) and about 20 percent (the United States) of total σ^2(arpk). The resulting TFP losses are also modest—at their highest, they lead to losses of about 4 percent (China). Our finding of a limited role for adjustment costs comes mainly from the facts that investment flows are small and exhibit only modest serial correlation—together, these observations imply only a moderate contribution to arpk dispersion from these types of costs.[22] Additionally, adjustment costs on their own struggle to generate the significant correlation between arpk and productivity that we observe in the data, particularly in developing countries (ρ(arpk, a) in table 1).[23]

In contrast, other firm-specific factors account for a large portion of the observed dispersion, everywhere upwards of about 80 percent. These effects are essentially entirely driven by the correlated and fixed components of the distortion, though there is some variation across countries in their relative importance. In other words, the main drivers of observed arpk dispersion manifest themselves in firm-level data by (i) disproportionately reducing (increasing) the investment of high (low) productivity firms relative to what their fundamentals would dictate and (ii) as an extremely persistent firm-level effect.[24]

22 To see why both moments are necessary, consider an extreme scenario with very large adjustment costs. This would induce both small investment flows and a large amount of arpk dispersion. Crucially, however, it would also imply a very high serial correlation of investment, contrary to what we see in the data. See also the discussion in David and Venkateswaran (2019), who elaborate on this intuition more extensively.

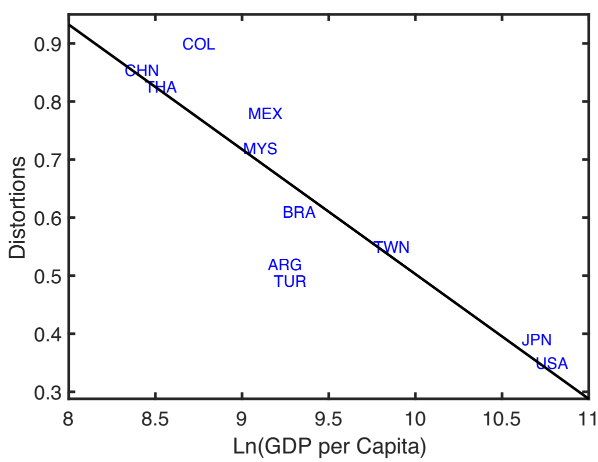
23 To see this, we calculated the covariance between arpk_{it} and a_{it} assuming adjustment costs were the only friction affecting the capital choice (and setting the parameter ξ to its baseline level in each country) and compared the implied covariance to the covariance observed in the data. The covariances induced by adjustment costs alone were less than 10 percent of the covariance in the data for the developing countries in our sample (the fraction was highest for Japan (about 20 percent), where the estimated adjustment costs are more salient). A related result is in Bento and Restuccia (2020), who also find that adjustment frictions alone struggle to generate a significant correlation between arpk and a (see Online Appendix B of that paper).

24 As recently emphasized in Bils, Klenow, and Ruane (2020), another potential source of observed arpk dispersion is measurement error in revenues or inputs. In an important advance, those authors propose a method to estimate the

It is also instructive to compare the characteristics of the developed countries in the sample to the developing ones. First, as shown in table 1, the total amount of $\sigma^2(\text{arpk})$ is smaller in the developed countries, suggesting a priori a lower degree of overall misallocation. Correspondingly, the magnitude of each of the factors in absolute terms also tends to be smaller in the developed countries. Table 3 reveals that as a *share* of total dispersion, adjustment/information frictions tend to have a larger role in more developed countries, particularly in the United States. Another key difference is the magnitude of correlated factors: as shown in table 2, the estimate of γ is smallest (in absolute value) in the developed countries, indicating that productivity or size-dependent distortions are relatively less important there. For example, these factors account for 14 percent and 16 percent of $\sigma^2(\text{arpk})$ in Japan and the United States, respectively. In contrast, the corresponding figures are substantially higher in the developing countries, where correlated factors explain from 25 percent (Turkey) to 73 percent (Malaysia) of total arpk dispersion. The implied TFP losses in these latter countries are thus substantial, ranging from 6 percent to as high as 23 percent.

Lastly, fig. 1 plots the total dispersion in arpk that stems from distortions (the sum of the dispersion coming from the correlated and permanent components reported in table 3) against income (GDP) per capita.[25] The figure reveals a strong negative relationship (correlation of −0.89). The individual components, i.e., correlated and permanent, also comove negatively with income (correlations of −0.63

Figure 1. Distortions and Income



Source: Authors' calculations based on firm-level data from Orbis (Argentina, Brazil, Japan, Malaysia, Taiwan, Thailand, and Turkey), Annual Surveys of Industrial Production (China), Annual Manufacturers Survey (Colombia), Annual Industrial Survey (Mexico), and Compustat (United States), the World Bank Development Indicators database (GDP for all countries except Taiwan), and the National Statistics, Republic of China (GDP data for Taiwan).
Note: This figure plots estimated distortions against GDP per capita.

role of additive measurement errors. We applied their methodology to our data and found that this type of error can only account for up to 16 percent of the $\sigma^2(\text{arpk})$ across our samples. Notably, if we perform the same calculations on our raw data (before trimming outliers), measurement error can explain as much as 36 percent, i.e., plays a much larger role (although $\sigma^2(\text{arpk})$ is also much larger in the untrimmed data, with the end result that the portion of $\sigma^2(\text{arpk})$ unexplained by measurement error turns out to be larger than $\sigma^2(\text{arpk})$ in our final trimmed samples). Thus, it seems that trimming outliers can do a relatively good job at eliminating this type of error and if anything, may yield conservative estimates of the true dispersion. Of course, it should be pointed out that this method is silent about other forms of measurement error (e.g., multiplicative). We present the detailed results in Supplementary Online Appendix S2.

25 GDP data are from the World Bank World Development Indicators database for all countries except Taiwan, and the National Statistics, Republic of China for Taiwan. All GDP data are for the year 2010 and are expressed in 2010 US dollars.

and −0.62, respectively). In other words, our estimates of "distortions" vary systematically with overall economic development.

5. Heterogeneity in Markups and Technologies

In this section, we dig deeper into the firm-specific factors that seem to generate much of the observed arpk dispersion. In particular, we investigate two potential sources—unobserved heterogeneity in markups and production technologies. In our baseline setup, all firms within an industry (1) had homogeneous production technologies and (2) were monopolistically competitive facing CES demand curves and therefore set identical markups. As a result, any firm-level heterogeneity in technologies and/or markups would show up in our estimates as other firm-specific factors. In what follows, we relax both of these assumptions. To focus on the role of these two forces, the analysis abstracts from adjustment/information frictions in firms' input decisions. This is largely in the interest of simplicity, but is also supported by the relatively modest role played by these dynamic considerations in our baseline estimates.

Markup Dispersion

To explore the potential for markup dispersion, we follow the methodology in De Loecker and Warzynski (2012). We first extend our production function to include raw materials. Under two key assumptions, (i) the materials elasticity in production is common across firms (within an industry) and (ii) the materials choice is a static, otherwise undistorted (besides the markup) decision, we can directly measure these firm-specific markups using the average revenue product of materials, arpm (the inverse of the share of revenues paid to intermediates). This result implies that the cross-sectional dispersion in arpm can be mapped one-for-one into dispersion in markups (for detailed derivations, see Supplementary Online Appendix S3).[26]

Data on intermediate inputs are only available for four of the countries in our sample—China, Colombia, Mexico, and the United States.[27] In the first column of table 4, we report the (within-industry) dispersion in the arpm for these four countries. In the first column of the second panel of the table, we report the dispersion in arpk that arises from markups (this is simply equal to the markup dispersion itself, given by $\sigma^2(\text{arpm})$), and in parentheses, we report the share of observed arpk that the dispersion in markups can explain. The results show that markup dispersion can account for between 4 percent (China) and 18 percent (Colombia) of the observed $\sigma^2(\text{arpk})$. Although the shares are generally significant (except in China), these findings seem to suggest that markup heterogeneity is unlikely to be the primary force behind the unexplained arpk dispersion.

Can markups help explain the large role of correlated distortions? Although in principle, yes—markups that increase in firm productivity/size would be consistent with our findings—the data show only very modest correlations between firm-level markups (measured using the inverse of materials' share of revenues) and productivity/size. For example, projecting markups on productivity in each of the four countries with sufficient data yields positive, but economically small coefficients, between about 0.002 and 0.006 (the raw correlations range from essentially 0 to about 0.02). Similar results hold using firm size

26 The method remains valid even with unobserved firm-specific variation in the price of intermediate goods, i.e., it does allow for distortions in the market for intermediate inputs so long as they are reflected in prices. In the case of distortions that are not reflected in prices, the mapping between dispersion in the average revenue product of materials (arpm) and markup dispersion is no longer one-for-one and depends on the correlation between distortions and the markup. If markups and distortions are uncorrelated (or positively correlated), our method provides an upper bound for the contribution of markup dispersion. Our method understates the true role of markup dispersion only in the case of a sufficiently strong negative correlation.

27 In the United States, we construct the measure of intermediate expenditures as sales less operating income before depreciation less wage bill. Following, e.g., Keller and Yeaple (2009), the wage bill is imputed as the number of employees multiplied by the average industry wage calculated using data from the NBER-CES Manufacturing Industry Database (available at http://www.nber.org/nberces/).

Table 4. Heterogeneous Markups and Technologies

	Moments				Effect on σ^2(arpk) (% of total σ^2(arpk))	
	σ^2(arpm)	σ^2(arpk)	σ^2(arpn)	cov(arpk, arpn)	Markups	Capital elasticities
ARG	—	0.55	0.31	−0.01	—	0.32
						(58)
BRA	—	0.74	0.52	0.09	—	0.40
						(54)
CHN*	0.05	1.37	0.76	0.41	0.05	0.48
					(4)	(37)
COL*	0.22	1.49	0.87	0.40	0.22	0.59
					(18)	(48)
MEX*	0.13	1.18	0.50	0.31	0.13	0.35
					(12)	(33)
MYS	—	0.93	0.49	0.35	—	0.25
						(27)
TWN	—	0.62	0.30	0.18	—	0.20
						(32)
THA	—	0.95	0.76	0.22	—	0.48
						(51)
TUR	—	0.84	0.47	0.09	—	0.41
						(49)
JPN	—	0.56	0.29	0.08	—	0.24
						(44)
USA*	0.06	0.52	0.35	0.23	0.06	0.16
					(14)	(38)

Source: Authors' calculations based on firm-level data from Orbis (Argentina, Brazil, Japan, Malaysia, Taiwan, Thailand, and Turkey), Annual Surveys of Industrial Production (China), Annual Manufacturers Survey (Colombia), Annual Industrial Survey (Mexico), and Compustat (United States).

Note: This table reports estimates of (within-industry) dispersion in firm-level markups and production technologies. The first panel displays the data moments used for these calculations—dispersion in the average revenue products of materials (arpm), capital (arpk), and labor (arpn), and the covariance of the arpk and arpn. For the countries denoted with an asterisk, the arpk and arpn moments pertain to markup-adjusted average revenue products, calculated by subtracting the firm-specific markup (measured by arpm_{it}) from arpk_{it} and arpn_{it}, as detailed in equations (S3.2) and (S3.3). The second panel of the table displays the contributions of the two forms of heterogeneity to the dispersion in arpk. Values in parentheses express these contributions as percentages of total observed dispersion.

(revenues) rather than productivity. Thus, the data suggest little scope for markups to contribute to correlated distortions.

Technology Heterogeneity

Next, we analyze the contributions of dispersion in production technologies. Specifically, we generalize the production function to allow for firm-specific output elasticities of capital and labor. The key insight that informs our analysis is the observation that, all else equal, with firm-specific elasticities, a high output elasticity of capital would be associated with a low output elasticity of labor. As a result, to the extent this form of heterogeneity is present, it would induce the average revenue products of capital and labor to move in opposite directions—specifically, firms with a high $\hat{\alpha}_{it}$ will, *ceteris paribus*, tend to have a low arpk and a high arpn, and vice versa. We can exploit this implication to derive an upper bound on the potential for this type of heterogeneity based on the observed covariance of arpk and arpn (we derive the bound in Supplementary Online Appendix S3).[28]

28 Markups, on the other hand, are a source of positive comovement between the average revenue products of all inputs—see Supplementary Online Appendix S3 for details. For the countries where we have materials data, we can use it to adjust the observed cov(arpk, arpn) to control for the effect of markups. The numbers reported in table 4 for China, Colombia, Mexico, and USA are after this adjustment (again, see Supplementary Online Appendix S3 for details).

Table 4 reports the results from computing this bound in each country. In the last three columns of the first panel, we show the values of the moments that are used in the bound calculation: $\sigma^2(\text{arpk})$, $\sigma^2(\text{arpn})$, and $\text{cov}(\text{arpk}, \text{arpn})$. The column labeled "Capital elasticities" shows the implied dispersion in arpk arising from heterogeneity in firm-level technologies. With the caveat that these represent upper bounds, they point to a substantial role for this form of heterogeneity: depending on the country, it can explain between about one-quarter and one-half of total arpk dispersion. A promising, if challenging, area for future research would be to further explore this channel by estimating firm-level production functions. This would likely require data with a significant panel dimension.

6. The Doing Business Report

In this section, we relate our estimates to country-level measures of institutional quality obtained from the World Bank DBR. The DBR provides standardized quantitative measures of business regulation and enforcement affecting domestic firms across 10 categories—ease of starting a business, dealing with construction permits, getting electricity, registering property, getting credit, protecting minority investors, paying taxes, trading across borders, enforcing contracts, and resolving insolvency. The detailed definitions of each category are provided in Supplementary Online Appendix S1. The DBR also reports a composite "Ease of Doing Business" index, which is an aggregate across the 10 categories. Higher scores are given "where governments have managed to create rules that facilitate interactions in the marketplace without needlessly hindering the development of the private sector," for example, for better-functioning institutions, simplified ways of applying regulation that reduce compliance costs for firms and using regulation to address social and environmental concerns.[29] The data are obtained via surveys of local experts, including lawyers, business consultants, accountants, freight forwarders, government officials, and other relevant professionals.

In table 5, we report the correlation of our estimates of the dispersion in arpk that stems from correlated and permanent firm-specific distortions from table 3 with the composite "Ease of Doing Business"

Table 5. Estimated Distortions and Doing Business Indices

Measure	Total distortions	Correlated	Permanent
Ease of Doing Business index	−0.46	−0.23	−0.43
Categories:			
Starting a business	−0.29	−0.13	−0.29
Dealing with construction permits	−0.41	−0.33	−0.24
Getting electricity	−0.50	−0.26	−0.46
Registering property	−0.26	−0.61	0.28
Getting credit	−0.37	0.16	−0.71
Protecting minority investors	0.07	0.18	−0.08
Paying taxes	−0.26	0.11	−0.50
Trading across borders	−0.19	0.11	−0.40
Enforcing contracts	−0.46	−0.21	−0.45
Resolving insolvency	−0.44	−0.50	−0.10

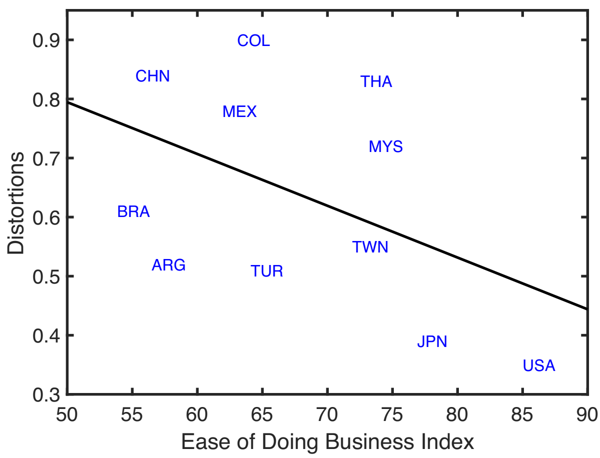
Source: Authors' calculations based on firm-level data from Orbis (Argentina, Brazil, Japan, Malaysia, Taiwan, Thailand, and Turkey), Annual Surveys of Industrial Production (China), Annual Manufacturers Survey (Colombia), Annual Industrial Survey (Mexico), and Compustat (United States), and the World Bank Doing Business Report.

Note: This table reports cross-country correlations between the estimated distortions and various indices from the World Bank Doing Business Report.

29 For full details on the DBR, see http://doingbusiness.org. Note that the economies that rank highest are not necessarily those with the least regulation (some of the indicators give a higher score for more regulation), but rather where regulation best satisfies the criterion quoted in the text.

index, as well as each of the subindices (the underlying data for each country are reported in Supplementary Online Appendix S1, table S1.5). The top row of table 5 displays the correlation of the three measures of distortions (correlated, permanent, and total) with the composite "Ease of Doing Business" index. The results show that the estimates of distortions are inversely related to the quality of the business environment captured by the composite DBR index. The relationship is particularly strong for total distortions and the permanent component. We illustrate these findings in fig. 2, which plots the measure of total distortions against the composite DBR index. These results are suggestive evidence that a poor institutional framework also worsens allocative efficiency: in other words, the burden of distortionary regulations and weak enforcement does not fall uniformly on all firms. The patterns in the table suggest that they have long-lasting effects, inducing persistent wedges that are relatively uncorrelated with size/productivity into firms' capital decisions.

Figure 2. Distortions and Ease of Doing Business



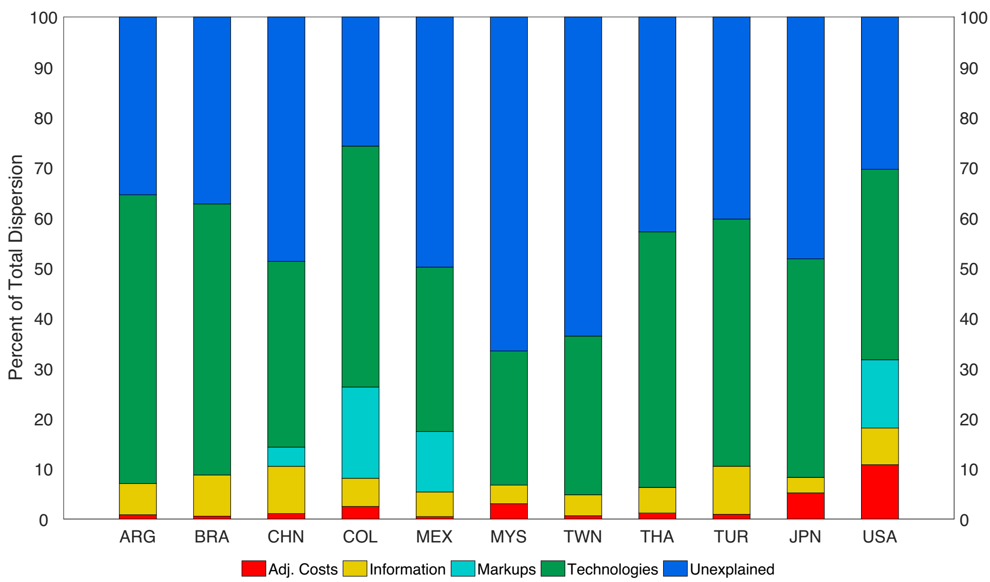
Source: Authors' calculations based on firm-level data from Orbis (Argentina, Brazil, Japan, Malaysia, Taiwan, Thailand, and Turkey), Annual Surveys of Industrial Production (China), Annual Manufacturers Survey (Colombia), Annual Industrial Survey (Mexico), and Compustat (United States), and the World Bank Doing Business Report (Ease of Doing Business index).
Note: This figure plots estimated distortions against the World Bank Ease of Doing Business index.

The remaining rows of table 5 display correlations with each of the subcategories of the composite DBR index. It shows a fair amount of heterogeneity in how various frictions in the business environment are related to the estimated distortions. A number of key patterns emerge: first, financial frictions (proxied by the getting credit subindex) and the effectiveness of the legal system (the enforcing contracts subindex) show a clear association with estimated distortions. Neither of these frictions are new to the misallocation literature—see, e.g., Midrigan and Xu (2014) and Moll (2014) for financial frictions and Boehm and Oberfield (2018) and Iacovone, Maloney, and Tsivanidis (2019) for contract enforceability. By connecting quantitative estimates of distortions from firm-level data to survey data from local experts, our analysis provides additional evidence in support of the role of these frictions. It also uncovers new patterns that can help guide future work. Both the getting credit and enforcing contract indices covary strongly with estimates of permanent, uncorrelated distortions and less so with correlated distortions. This is also the case for the complexity of the tax system (the ease of paying taxes) and ease of getting electricity. On the other hand, property rights (measured by the ease of registering property subindex) and the efficacy of bankruptcy laws (ease of resolving insolvency) are more closely related to correlated distortions, suggesting that default and the costs associated with it are a potential driver of these distortions (see, e.g., Gilchrist, Sim, and Zakrajšek (2013) for an example of how default can affect costs of capital and so measured misallocation). Needless to say, these conclusions are tentative, but they do point to the value of linking the direct measures of institutional quality from survey/other data and quantitative models of misallocation estimated to match firm-level micro-data. This is likely to be a productive path forwards, both for the academic literature as well as policy-makers.

7. Conclusion

This paper has explored the determinants of capital allocations—in particular, the sources of dispersion in the average revenue product of capital, a standard indicator of capital misallocation—across a number of developing and developed countries. Figure 3 summarizes the main findings. Our results suggest that much of the observed dispersion stems not from technological and informational frictions but, rather, from other firm-specific factors, both those systematically correlated with firm productivity/size and those that are relatively persistent. The former is particularly important in the developing countries in our sample. Unobserved heterogeneity in demand and production technologies can potentially account for a significant portion of the observed arpk dispersion. Perhaps most promisingly, we also find that measured distortions correlate strongly with a number of indicators of the business environment from the World Bank DBR.

Figure 3. The Sources of Misallocation



Source: Authors' calculations based on firm-level data from Orbis (Argentina, Brazil, Japan, Malaysia, Taiwan, Thailand, and Turkey), Annual Surveys of Industrial Production (China), Annual Manufacturers Survey (Colombia), Annual Industrial Survey (Mexico), and Compustat (United States).

Note: This figure plots the contribution of each force—adjustment costs, uncertainty, heterogeneity in markups and technologies, and the remainder—as a share of total dispersion in arpk.

The obvious next step in this research agenda is to explore specific candidates for the sizable firm-specific factors our estimation uncovers, along the lines of our analyses in Sections 5 and 6. Our results will hopefully prove useful both in identifying suitable candidates and in guiding the empirical strategy to measure their impact. For example, policies and/or frictions which induce transitory wedges that are unrelated to firm size seem relatively less promising. On the empirical front, our analysis could help researchers investigate particular forces while controlling for others in a tractable, albeit reduced-form, way. A recent example is David, Schmid, and Zeke (2018), who propose a theory based on heterogeneity in firm-level risk premia that delivers a fixed wedge in firms' capital choices of exactly the type our results ascribe a large role to. To quantify this mechanism, they adopt an approach that is robust to the presence of other distortions, modeled along the lines we have outlined here.

Given that capital typically exhibits larger dispersion in average products than other inputs (see, e.g., table 4), our study focused primarily on capital allocations, but an important extension would be to use similar methods to study the dynamics and allocation of labor and/or other inputs. Such an analysis is promising, both for understanding the role of various forces in driving the dynamics of firm-level labor choices and dispersion in labor products and further, in narrowing the list of candidate factors driving input allocations more broadly. As illustrated in Section 5, combining data on multiple inputs can be very informative about the nature of distortionary factors.

Finally, our findings have implications beyond static arpk dispersion. A number of recent papers have emphasized the dynamic effects of distortions on entry/exit, firm life-cycles and the productivity distribution itself, e.g., Midrigan and Xu (2014), Hsieh and Klenow (2014), Bento and Restuccia (2017) and Da-Rocha, Tavares, and Restuccia (2017). An important insight from these papers is that the exact nature of the underlying distortions (e.g., their correlation with firm productivity or demand) is key to understanding their dynamic implications. Given that we find patterns in this correlation that look very different in developing vs. developed countries, an ambitious next step would be to use an empirical strategy like the one in this paper to analyze richer environments featuring some of these elements. Ultimately, how these forces simultaneously shape the distribution of resources across firms of different productivity (in a static sense) and the distribution of productivity across firms itself (in a dynamic sense) may reveal much about what drives differences in income and standards of living across countries.

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