Dynamic Inputs and Resource (Mis)Allocation*

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July 26, 2013

Abstract

We investigate the role of dynamic production inputs and their associated adjustment costs in shaping the dispersion of static measures of capital misallocation within industries (and countries). Specifically, across 9 datasets, spanning 40 countries, we find that industries exhibiting greater time-series volatility of productivity have greater cross-sectional dispersion of the marginal revenue product of capital. We use a standard investment model with adjustment costs to show that variation in the volatility of productivity across these industries and economies can explain a large share (80-90%) of the cross-industry (and cross-country) variation in the dispersion of the marginal revenue product of capital.

Keywords: *Misallocation; Adjustment Costs; Dynamic Inputs; Dispersion.*

*JEL Code: D24, D92, O12. An earlier version of this paper was titled: "Productivity Volatility and the Misallocation of Resources in Developing Economies". We would like to thank the Editor and four anonymous referees for excellent comments and suggestions. Furthermore, we thank Dave Backus, Nick Bloom, Gian Luca Clementi, John Fernald, Alessandro Gavazza, Chang-Tai Hsieh, Panle Jia Barwick, Pete Klenow, Marc Melitz, Richard Rogerson, Daniel Xu, Jonathan Fisher, Larry White, and the participants at the NYU Stern Micro Lunch, University of Minnesota, University of Wisconsin, Harvard University, University of Chicago, MIT, CFSP (Financial Systems, Industrial Organization, and Economic Development) Workshop, SITE 2012, NBER Productivity, and NBER EFJK, for their comments. This paper uses restricted data that was analyzed at the U.S. Census Bureau Research Data Center in New York City. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. Financial Assistance from the Center for Global Economy and Business at NYU Stern is greatly appreciated. Contact details: Allan Collard-Wexler, wexler@nyu.edu; John Asker, jasker@stern.nyu.edu; and Jan De Loecker, jdeloeck@princeton.edu. The usual caveat applies.

1 Introduction

It is well documented that firms differ in productivity within even narrowly defined industries.[1] Moreover, across countries, the extent of this dispersion varies considerably, particularly when comparing countries at different stages of economic development. Dispersion is also observed in the marginal revenue products of inputs, particularly capital. Viewed through a standard static model of production and demand, variation in marginal products across firms suggests the existence of frictions that prevent the efficient allocation of resources in an industry, or an economy at large.

A recent literature has tried to identify the degree of misallocation of resources, and its welfare implications, from the variation in marginal products of inputs across producers. For example, Hsieh and Klenow (2009) find that if producers in the manufacturing sectors of India and China had the same degree of misallocation as the manufacturing sector in the United States, output would increase by thirty and sixty percent, respectively. Spurred by this set of facts, a number of recent papers have tried to identify specific mechanisms to explain why productivity differences are not eliminated by market-based resource reallocation.[2]

Underscoring the potential aggregate gains from increased allocative efficiency, studies done at the industry-level have shown that undoing misallocation can have first-order welfare effects. A well-known example is Olley and Pakes (1996)'s study of productivity growth in the telecommunications equipment industry. They find that the reallocation of output to more-productive firms accounts for a large fraction of aggregate productivity growth. Bartelsman, Haltiwanger, and Scarpetta (2013) rely on the reallocation measure introduced by Olley and Pakes (1996), the covariance term between output and productivity, and find that it plays a key role in accounting for aggregate productivity growth across a wide range of countries, while Collard-Wexler and De Loecker (2013) find that the entrance of a new production technology in steel making substantially raised the industry's aggregate productivity by reallocating resources away from the old to the new technology.

This paper investigates the role of dynamically chosen inputs, such as capital, in shaping the dispersion of the marginal product of inputs. Specifically, we consider the dynamic optimization problem faced by firms that must choose capital stocks, which last for multiple periods, subject to adjustment costs. In our model, firms also face a productivity (TFPR) shock in each period that is determined by some known stochastic process.[3] Thus, a capital stock determined in some previous period may no longer appear to be optimal after a productivity shock hits. A literal implication is that resource allocation, while appearing inefficient in a static setting, may well be efficient in a dynamic sense. Our paper then tests the predictions of this model empirically, using rich micro-data for a wide range of firm-level production datasets

[1] We define our measure of productivity, TFPR, below and discuss its measurement in detail. For recent work, see Syverson (2011), Bartelsman and Doms (2000), Bartelsman, Haltiwanger, and Scarpetta (2013) and references therein.

[2] See Restuccia and Rogerson (2008), Hsieh and Klenow (2009), Collard-Wexler (2009), Midrigan and Xu (2013), Moll (2012), Bollard, Klenow, and Sharma (2012), and Peters (2012) for recent work.

[3] Throughout the paper, in discussing our own work, we consider productivity to be TFPR, and use the terms interchangeably.

covering the manufacturing sector of the U.S., and a set of European, Latin American and Asian countries. In addition, we find the same results in a large cross-country firm-level dataset constructed by the World Bank: the World Bank Enterprise Survey (henceforth WBES) database.

Overview of our approach

We begin by writing down a variant of a standard dynamic investment model in which firms: a) face costs when adjusting one factor of production (capital); b) can acquire all inputs in a frictionless spot market and; c) get a firm-specific TFPR shock in each period generated by an AR(1) process. We show that, when firms are making decisions in this setting, dispersion in the marginal revenue product of capital arises naturally.[4]

We then evaluate the empirical value of this model, employing two types of data: The first is country-specific data, which we will refer to as Tier 1 Data, on establishment/firm production in each of the U.S., Chile, France, India, Mexico, Romania, Slovenia, and Spain (all of which have been widely used in the development and productivity literatures). The second data, which we call Tier 2, are the WBES data, which allow us to exploit production data on firms in 33 countries. Each type of data has different strengths: the country-specific data sets have many more observations and tighter data collection protocols, while the WBES data allow us to access a broader set of countries.

Since our approach is founded on a model of an individual firm's investment decisions, the analyst has considerable freedom as to the level of aggregation to apply. Our primary focus is on the level of the industry, inside each of the countries in our Tier 1 data. In these data, we can estimate the TFPR process at the industry-level. Following an extensive investigation at the industry-level, we extend the approach to examing cross-country differences. Here we exploit the WBES data, modeling the TFPR process at the country-level.

The basic reduced-form pattern implied by the model—that as the volatility of TFPR increases, so does the dispersion of marginal product of capital—is strongly supported by both the Tier 1 and Tier 2 data. Furthermore, it is supported both across industries within a country, and across countries.

After documenting this basic reduced-form pattern, we take a more structural approach to see how well the model captures cross-country variation in dispersion. For this exercise, we first estimate capital adjustment costs. These adjustment-cost estimates, along with an (industry-country specific) AR(1) shock process, are used to generate model predictions (that is, we hold all other parameters constant). We then confront the model predictions with the data. We find that the model captures a large share (80-90%) of the cross-industry (and cross-country) variation in the dispersion of the marginal revenue product of capital.

Contributions and implications

We make three specific contributions in this paper: First, we show that the model of dynamic inputs can quantitatively replicate dispersion of the marginal revenue prod-

[4] We focus on the marginal revenue product of capital as this seems the input that is most prone to adjustment costs. This is consistent with data, as we discuss in Section 3.4: we observe more dispersion in the marginal product of capital relative to that of other inputs.

uct of capital that is found in the data. This is true both for the model that uses estimated adjustment costs, and when the only adjustment friction is a one-period time to build. This is important, as it indicates that the model of dynamically chosen inputs provides a natural benchmark for the dispersion of marginal revenue products in an undistorted economy. Indeed the literature on misallocation acknowledges that dispersion of marginal revenue products alone is not evidence of misallocation, and that adjustment costs may play an important role.

Second, we find meaningful differences in the size of TFPR shocks across industries within countries and across countries, of the same relative magnitude as differences in the cross-sectional dispersion the marginal revenue product of capital. Moreover, industries (countries) with the greatest volatility of TFPR also have the greatest dispersion of the marginal revenue product of capital. These results are robust to a wide range of measurement and model specification concerns, such as alternative specifications of the TFPR process and alternative measures of volatility.

Third, holding adjustment costs fixed, the model predicts that larger TFPR shocks will generate differences in the distribution of the marginal revenue product of capital. We show that this model can explain, both qualitatively and quantitatively, much of the cross-industry (country) variation in the dispersion of marginal revenue products of capital. The model performs strongly: when confronted with industry-country data on dispersion in the marginal revenue product of capital it generates a measure of fit equivalent to an uncentered R^2 of around $0.8-0.9$, depending on the specification. Our results indicate that, perhaps surprisingly, the exact level of adjustment costs does not change this measure of fit greatly: whether we rely on the U.S. estimated adjustment costs or a country-specific one, the measure of fit is about the same. The absence of adjustment costs (beyond the one-period time to build), holding all other parts of the model fixed, does lead to a drop in our measure of fit.

In our cross-country data, the WBES, we obtain a measure of fit of around 0.8, suggesting that our mechanism is able to account for a large share of the variation in the dispersion of the marginal revenue product of capital. This suggests a role for volatility, and its subsequent firm-level decisions, in explaining income differences across countries.

Taken as a whole, these results highlight the importance of dynamic inputs in explaining, both in levels and differences, the dispersion of the marginal product of capital. As a corollary, commonly used measures of the efficiency of the allocation of capital, such as the marginal product of capital, may not be informative about distortions impeding reallocation if the process for TFPR shocks differs by industry or country. Whether this process is amenable to policy adjustment is a question we return to in the conclusion.

We purposely rely on a parsimonious model that focuses attention on the role of dynamic inputs in shaping dispersion in performance. In this way we can speak directly to the role of adjustment costs in contributing to the dispersion of firm performance. However, despite its simplicity, we find that our model explains a large share of the dispersion in the marginal revenue product capital in the data. The framework can be extended to accommodate other sources of dispersion such as distortions in input and output markets, or differences in markups, but we would need to include additional data and more importantly rely on extra modeling assumptions.

Furthermore, our analysis suggests that producer-level volatility is an important factor in explaining aggregate welfare. There is an extensive literature documenting differences in the volatility of productivity at the producer level, such as Davis, Haltiwanger, Jarmin, and Miranda (2007)'s finding that volatility has risen for publicly traded U.S. firms, but has fallen for private and publicly held manufacturing firms. While this literature has yet to come to a consensus on the reason behind the differences in the productivity process across firms, we believe that differences in volatility sits well with micro-level studies of the myriad challenges facing firms in developing countries. What we model as the productivity (TFPR) shock process is a reduced-form for a range of time-varying shocks to production, including (but not limited to): demand shocks (Collard-Wexler, 2013); natural disasters, such as floods or landslides (De Mel, McKenzie, and Woodruff, 2012); infrastructure shocks, such as power failures or transportation links being established (Fisher-Vanden, Mansur, and Wang, 2012); variation in the incidence of corruption or nepotism (Fisman and Svensson, 2007); changes in markups due to demand shocks or market-structure changes (De Loecker, Goldberg, Khandelwal, and Pavcnik, 2012) and changes to informational barriers (Bloom, Eifert, Mahajan, McKenzie, and Roberts, 2013). This paper can be viewed as suggesting a channel through which these micro effects can have aggregate implications.

The remainder of the paper is organized as follows: In Section 2, we present our dynamic model of investment. Section 3 discusses the measurement of productivity across several countries and considers reduced-form empirical evidence, and subjects it to a variety of robustness checks. Section 4 confronts the predictions of the dynamic investment model with the data using a structural approach. In Section 5 we consider cross-country variation using the WBES data. Finally, we conclude with a discussion of our findings in Section 6.

2 Theoretical Framework

In this section, we posit a simple model that allows us to consider how the time-series process of productivity (TFPR – which we define precisely below) should affect the cross-sectional dispersion of the (static) marginal revenue product of capital, and other variables. Central to the model is the role of capital adjustment costs, and a one-period time-to-build, in making optimal capital investment decisions. These adjustment frictions create links between the time-series process generating firm-level TFPR shocks and firm-level heterogeneity in the adjustment of capital stocks.

2.1 Modeling preliminaries

We begin by providing an explicit model of TFPR, in the context of a profit-maximizing firm (since we assume that establishments operate as autonomous units, firms and establishments, for our purposes, are synonymous). A firm i, in time t, produces output Q_{it} using the following (industry-specific) constant-returns technology:

$$Q_{it} = A_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M}, \tag{1}$$

where K_{it} is the capital input, L_{it} is the labor input, M_{it} is materials, and we assume constant returns to scale in production so $\alpha_M + \alpha_L + \alpha_K = 1$. This production function is industry-specific; and throughout the paper, the coefficients β (defined below in equation 3) and α are kept country- and industry-specific unless noted otherwise. The demand curve for the firm's product has a constant elasticity:

$$Q_{it} = B_{it} P_{it}^{-\epsilon}. \tag{2}$$

Combining these two equations, we obtain an expression for the sales-generating production function:

$$S_{it} = \Omega_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} M_{it}^{\beta_M}, \tag{3}$$

where $\Omega_{it} = A_{it}^{1-\frac{1}{\epsilon}} B_{it}^{\frac{1}{\epsilon}} b$, and $\beta_X = \alpha_X(1 - \frac{1}{\epsilon})$ for $X \in \{K, L, M\}$. For the purposes of this paper, productivity or TFPR is defined as $\omega_{it} \equiv \ln(\Omega_{it})$.

A fact that we will use repeatedly is that, in a static model with no frictions, profit maximization implies that the marginal revenue product (MRP) of an input should be equal to its unit input cost. For capital, this static marginal revenue product is given by:

$$\frac{\partial S_{it}}{\partial K_{it}} = \beta_K \frac{\Omega_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} M_{it}^{\beta_M}}{K_{it}}. \tag{4}$$

We will frequently refer to the marginal revenue product of capital (MRPK), which we measure in logs:

$$MRPK_{it} = \log(\beta_K) + \log(S_{it}) - \log(K_{it}) = \log(\beta_K) + s_{it} - k_{it}. \tag{5}$$

The marginal revenue products of labor and materials are defined similarly.[5]

Our notion of productivity is a revenue-based productivity measure, or TFPR (as introduced by Foster, Haltiwanger, and Syverson (2008)). As is common in this literature, we do not separately observe prices and quantities at the producer level, and, therefore, we can only directly recover a measure of profitability or sales per input precisely. This implies that all our statements about productivity refer to TFPR, and, therefore, deviations across producers in our measure of productivity, or its covariance with firm size, could reflect many types of distortion, such as adjustment costs, markups or policy distortions, as Hsieh and Klenow (2009) discuss in detail.

2.2 A dynamic investment model

We now articulate a dynamic investment model that allows us to examine the link between TFPR volatility and dispersion in both the static marginal revenue product of capital and other variables of interest. Our model follows, and builds on, a standard model of investment used in the work of Bloom (2009), Cooper and Haltiwanger (2006), Dixit and Pindyck (1994), and Caballero and Pindyck (1996).[6]

[5]Due to the Cobb-Douglas specification the marginal and average products are equivalent in our setup. Hence, in the data we measure the average product and, using the model, interpret it as marginal.

[6]The model used in this paper is a partial equilibrium model, that can be rationalized from a general equilibrium perspective only if there are no aggregate shocks and a continuum of firms. Bloom et al (2012) discuss the implications of putting this type of model into a general equilibrium framework with aggregate shocks, versus using a partial equilibrium model.

Taking the structure in Section 2.1 as given, we begin by assuming that firms can hire labor in each period for a wage p_L and acquire materials in each period at a price p_M. Both of these inputs have no additional adjustment costs. Thus, we can optimize out labor and materials, conditional on Ω_{it} and K_{it}. This leads to a 'period-profit' (ignoring capital costs for the moment) of:

$$\pi(\Omega_{it}, K_{it}) = \lambda \Omega_{it}^{\frac{1}{\beta_K + \epsilon^{-1}}} K_{it}^{\frac{\beta_K}{\beta_K + \epsilon^{-1}}}, \tag{6}$$

where $\lambda = \left(\beta_K + \epsilon^{-1}\right) \left(\frac{\beta_L}{p_L}\right)^{\frac{\beta_L}{\beta_K + \epsilon^{-1}}} \left(\frac{\beta_M}{p_M}\right)^{\frac{\beta_M}{\beta_K + \epsilon^{-1}}}$.

Capital depreciates at rate δ so $K_{it+1} = (1-\delta)K_{it} + I_{it}$ where I_{it} denotes investment. These investment decisions are affected by a one-period time to build and a cost of investment $C(I_{it}, K_{it}, \Omega_{it})$.[7] We employ an adjustment cost function composed of: 1) a fixed disruption cost of investing and 2) a convex adjustment cost expressed as a function of the percent investment rate. Formally:

$$C(I_{it}, K_{it}, \Omega_{it}) = I_{it} + C_K^F \mathbb{I}\{I_{it} \neq 0\} \pi(\Omega_{it}, K_{it}) + C_K^Q K_{it} \left(\frac{I_{it}}{K_{it}}\right)^2. \tag{7}$$

Next, let ω_{it} follow an AR(1) process given by:[8]

$$\omega_{it} = \mu + \rho \omega_{it-1} + \sigma \nu_{it}, \tag{8}$$

where $\nu_{it} \sim \mathcal{N}(0,1)$ is an i.i.d. standard normal random variable. This implicitly defines the transition function of Ω: $\phi\left(\Omega_{it+1} \left| \Omega_{it}, \right.\right)$. When we present results from computing our model, we will vary the volatility and persistence parameters (μ, σ, ρ).

A firm's value function V is given by the Bellman equation:

$$\begin{aligned} V(\Omega_{it}, K_{it}) = \max_{I_{it}} \pi(\Omega_{it}, K_{it}) - C(I_{it}, K_{it}, \Omega_{it}) \\ + \beta \int_{\Omega_{it+1}} V(\Omega_{it+1}, \delta K_{it} + I_{it}) \phi\left(\Omega_{it+1} \left| \Omega_{it}\right.\right) d\Omega_{it+1}, \end{aligned} \tag{9}$$

and, thus, a firm's policy function $I^*(\Omega_{it}, K_{it})$ is just the investment level that maximizes the firm's continuation value less the cost of investment.

Note that since there is neither entry nor exit in this model, there is no truncation of the TFPR distribution.[9] Thus, given the AR(1) structure above, the cross-sectional standard deviation of TFPR is mechanically given by the ergodic distribution of Ω_{it}. Hence,

$$\text{Std.}(\omega_{it}) = \frac{\sigma}{\sqrt{1-\rho^2}}. \tag{10}$$

[7]This time-to-build assumption is, in itself, a friction that we can easily shut down by allowing investment to become productive within a period (equivalent to one month in our implementation). As an indication of the economic effect of adjustment costs, if we set these to zero, then dispersion in the MRPK is reduced by 50 percent in our computational experiments in this section.

[8]Throughout the paper, lower case denotes logs, such that $x = \ln(X)$.

[9]The absence of entry and exit is a consequence of the decreasing returns to scale in the revenue equation (yielded by constant returns to scale in the production function and an elastic demand curve) and the absence of fixed costs, which make it profitable for any firm to operate at a small enough scale. See Midrigan and Xu (2013) for a discussion of the role of entry and exit in a similar model environment.

2.3 Moments of interest

In examining the data through the lens of this model, we will focus on a set of moments that can be generated by the model, three of which warrant explicit definitions. For ease of reference, we provide these definitions here.

The first moment is the dispersion in the (static) marginal revenue product of capital (MRPK, as defined in equation 5). Dispersion in MRPK is defined as: $\mathrm{Std}_{st}\left(MRPK_{it}\right)$, where the st subscript indicates that the standard deviation is taken within industry-country s in year t. This will be our most common specification, although at times we will use different configurations (indicated in the subscript).

We next define the computed volatility in the static marginal revenue product of capital over time as:

$$\mathrm{Std}_{st}\left(\Delta MRPK\right) = \mathrm{Std}_{st}\left[MRPK_{it} - MRPK_{it-1}\right]. \tag{11}$$

Third, the volatility in firms' capital over time is defined as:

$$\mathrm{Std}_{st}\left(\Delta k\right) = \mathrm{Std}_{st}\left[k_{it} - k_{it-1}\right]. \tag{12}$$

It is important to note that the magnitudes of these three moments are unchanged if we adopt an alternate specification of the model in which each firm's TFPR process has a firm-specific fixed effect; that is, if μ is firm-specific. This result is established formally in Theorem 1 in Appendix A. At the heart of the result is the property that a different constant term in the AR(1) results in a level shift in the process, and this generates level shifts in the inputs (K, L, and M) due to the entire problem behaving as if homogeneous of degree 1. These level shifts then get cancelled out when taking differences at the firm level.

2.4 Comparative statics

We analyze the model using computation. Like Bloom (2009), we use a model in which investment decisions are made each month (a period in the model). Modeling decisions at a monthly level is an attractive approach, as the model incorporates the likely time aggregation embedded in annual data.[10] The results we report are in terms of what one would see in annual data — that is, we aggregate up from monthly decision-making to the year.

Figure 1 examines the way $\mathrm{Std}_{st}\left(MRPK\right)$, the dispersion in the static marginal revenue product of capital, changes as σ, the volatility of TFPR, changes. To generate this figure we use parameters estimated using U.S. Census data as described in Section 4. Parameters and details of computation can be found in Appendix C. In the figure there are three lines that correspond to the model with both a one-period time-to-build and adjustment costs, but with different persistence parameters in the AR(1) process. From top to bottom, these lines correspond to ρ equal to 0.94, 0.85, and 0.65

[10] This interpretation requires transforming the AR(1) process–which is quoted to reflect, and empirically estimated off, annual data–into its monthly equivalent. After noting that the sum of normal random variables with the same mean is distributed normally, this reduces to a straightforward algebraic exercise.

respectively.[11] Note that, for any specification and any level of σ, as ρ increases so does dispersion in the static marginal revenue product of capital.

To further understand the pattern in Figure 1, note that this dispersion reflects the optimal investment choices of firms facing different TFPR shocks over time and, hence, different state variables. To make the effect of this clear, note that if all firms had the same capital stock, this graph would contain a series of upward sloping, straight, lines out of the origin. Yet (focusing on the solid black lines) the relationship between $\text{Std}_{st}(MRPK)$ and σ is not linear and has a slope change in the region of $\sigma = 0.5$ for $\rho = 0.94$ and in a (wider) region around $\sigma = 0.6$ for $\rho = 0.85$. There is no readily discernible slope change in this range of σ for $\rho = 0.65$.

To see why this is happening, note that initially, as volatility increases, firms will engage in more investment and disinvestment. Since greater volatility leads to larger changes in TFPR, it is natural that firms respond by altering their capital stock more frequently. However, past a certain point, firms begin to reduce their response to TFPR shocks. This begins as σ approaches 0.5 for $\rho = 0.94$ and 0.6 for $\rho = 0.85$, while for $\rho = 0.65$, the same pattern exists but is much more gradual. At these high levels of volatility, current TFPR is a weaker signal of the future marginal value of capital. Hence, firms respond less to shocks today because those current shocks are more likely to be swamped by future shocks. In the limit, where the TFPR process is an i.i.d. draw, current TFPR provides no information about future profitability. Firms would choose an optimal level of capital and stick to it forever, resulting in no variance in investment across firms. Thus, the slope changes evident in the relationships in Figure 1 reflect a flattening out of capital-adjustments to volatility.

3 Data and Reduced Form Evidence

In this section we introduce our datasets and discuss the measurement approach that we adopt, given our theoretical structure. Using measures of dispersion and volatility, we verify the main predictions of our theoretical framework using a set of reduced form regressions. Finally, we engage in a set of robustness checks.

3.1 Data and Measurement

We begin by describing the data and then discuss how we approach measurement.

3.1.1 Data: Individual Country and Cross Country Data

We employ multiple datasets in our analysis. We classify these datasets into two tiers, shown in Table 1. Tier 1 consists of country-specific high-quality producer-level data from eight countries: the United States, Chile, France, India, Mexico, Romania, Slovenia, and Spain. Each of these data sets has been used extensively in the literature; most commonly in the analysis of productivity.[12]

[11] These three values of ρ represent the 90th percentile, median, and 10th percentile in the U.S. Census data respectively.

[12] See, for instance, Tybout and Westbrook (1995), Roberts (1996), Pavcnik (2002), De Loecker and Konings (2006); De Loecker (2007), Goldberg, Khandelwal, Pavcnik, and Topalova (2009), Bloom, Draca,

The data sets differ in the time period covered, and in how producers are sampled. Table 1 summarizes the main features of the various datasets. Below we briefly discuss the various Tier 1 datasets and defer more details to Appendix B. We describe Tier 2 data, the WBES, in Section 5.

United States

The data for the United States comes from the U.S. Census Bureau's Research Data Center Program. We use data on manufacturing plants from the Census of Manufacturers (henceforth, CMF), and the Annual Survey of Manufacturers (henceforth, ASM) from 1972 to 1997. The CMF sends a questionnaire to all manufacturing plants in the United States with more than 5 employees every five years, while the ASM is a four-year rotating panel with replacement, sent to approximately a third of manufacturing plants, with large plants being over-represented in the sampling scheme. The final dataset contains 735,342 plants over a 26-year period.

An industry is defined as a four digit SIC code. Labor is measured using the total number of employees at the plant. Materials are measured using total cost of parts and raw materials.[13] Capital is constructed in two ways. For the majority of plants, including all plants in the CMF, capital is measured using a question on total assets – be they machines or buildings – at the plant. For the remaining observations, capital is constructed using the perpetual inventory method, using industry-specific depreciation rates and investment deflators from the Bureau of Economic Analysis and the National Bureau of Economic Research. Capital, materials and sales are deflated using the NBER-CES industry-level deflators into 1997 dollars.

Chile

Annual plant-level data on all manufacturing plants with at least ten workers were provided by Chile's Instituto Nacional de Estadistica (INE). These data, which cover the period 1979–1986, include production, employment, investment, intermediate input, and balance-sheet variables. Industries are classified according to their four digit ISIC industry code. The data contain 37,600 plant-year observations.The smallest number of plants observed in any year is 4,205 in 1983.

France, Romania, and Spain

Annual firm-level data on manufacturing firms for France, Romania, and Spain are obtained from Bureau Van Dijck's (BvD) Amadeus dataset and cover firms reporting to the local tax authorities and/or data collection agencies for the period between 1999 and 2007. We selected three relatively large European countries at different stages of economic development. The coverage for all three countries is substantial in that we cover approximately 90 percent of economic activity in each of the three manufacturing sectors. For example for France, in 2000, we record total sales of 739 billion Euros, whereas the OECD reports total sales to be 768 billion Euros. This implies coverage of 96 percent of total economic activity in manufacturing. For Spain we find, using the same coverage calculation, coverage of 88 percent. The collection

and Van Reenen (2011), and Konings and Vandenbussche (2005).

[13]We also ran robustness checks where we defined labor as total plant hours, and defining materials as including contract work, fuels, and electricity spending. Neither of these robustness checks has an appreciable effect on our results.

protocol of BvD is consistent across countries. We focus on the manufacturing sector to facilitate the measurement of TFPR. Industries are classified according to the two digit NACE Rev 1.1. code for all three countries. Our data covers firms that are primarily active in sectors NACE Rev 1.1. 15 to 36. This leaves us with 391,422, 174,435, and 457,934 firm-year observations for France, Romania, and Spain, respectively. The data include standard production data, including production, employment, investment, intermediate input and other balance-sheet variables.[14]

India

Annual firm-level data on manufacturing firms were provided by Prowess, and are collected by the Centre for Monitoring the Indian Economy (CMIE). Prowess is a panel that tracks firms over time for the period 1989–2003. The data contain mainly medium and large Indian firms. Industries are classified according to the 4 digit PNIC (the Indian industrial classification code). These data include various production, employment, investment, intermediate input, and balance-sheet variables.[15] The final data set comprises 30,709 firm-year observations.

Mexico

Annual plant-level data on manufacturing plants are recorded by Mexico's Annual Industrial Survey and are provided by Mexico's Secretary of Commerce and Industrial Development (SEC-OFI). These data, which cover the period 1984–1990, include production, employment, investment, intermediate input, and balance-sheet variables. The sample of plants represents approximately eight percent of total output, where the excluded plants are the smallest ones. Industries are classified according to the Mexican Industrial Classification (a four digit industrial classification system). The final data contain 21,180 plant-year observations.The minimum number of observed firms in a year is 2,958 in 1989.

Slovenia

The data are taken from the Slovenian Central Statistical Office and are the full company accounts of firms operating in the manufacturing sector between 1994 and 2000. We have information on 7,915 firms: an unbalanced panel with information on production, employment, investment, intermediate input, and balance-sheet variables. Industries are classified according to the two digit NACE Rev 1.1. code.

3.1.2 Measurement

To guide the measurement of TFPR, we build on the model in Section 2.1 and, in particular, rely on the sales-generating production function in equation (3). In order to recover a measure of TFPR, ω_{it}, we need to compute the value of β_L, β_M and β_K by industry-country. Profit maximization implies that for each input facing no adjustment costs, the revenue production function coefficient equals the share of the input's expenditure in sales, or formally:

[14] This data is known to slightly under-represent small firms. In our robustness analysis we verify whether our results are invariant to imposing a common threshold across all our datasets.

[15] The Indian data do not report the wagebill separately from the number of workers. We do, however, take care to appropriately deflate the wagebill.

$$\beta_X = \frac{P_{it}^X X_{it}}{S_{it}} \qquad \text{for } X \in \{L, M\}. \tag{13}$$

As mentioned before, we allow β_X to vary at the industry level within a country, thereby allowing the production function to vary across industries and countries. Thus, our approach to measuring TFPR is to compute, for each individual firm in a given industry-country pair:

$$\omega_{it} = s_{it} - \beta_K k_{it} - \beta_L l_{it} - \beta_M m_{it} \tag{14}$$

In practice, in order to obtain a robust measure of these shares, we rely on the median of the expenditure share for labor and intermediate inputs, in a given industry-country (sc), or

$$\beta_X^{sc} = median\left(\left\{\frac{P_{it}^X X_{it}}{S_{it}}\right\}\right) \qquad \text{for } X \in \{L, M\}, i \in sc. \tag{15}$$

To recover the coefficient on capital, β_K, we use our assumption of constant returns to scale in production– i.e., $\sum_x \alpha_x = 1$, such that:

$$\beta_K = \frac{\epsilon - 1}{\epsilon} - \beta_L - \beta_K. \tag{16}$$

In order to compute β_K we need to assign a value to the elasticity parameter, ϵ. We follow Bloom (2009) and set it equal to four. However, all the findings presented in this paper are invariant to choosing different values for the elasticity of demand in the range $[4, 8]$. Finally, to compute TFPR, we simply plug in the coefficients obtained above into equation (14).

For a small fraction of the industry-country pairs for which the sum of the labor and material coefficients exceeds 0.75, and thus would imply a negative capital coefficient, we proceed by using the relevant country's average coefficient. For the one country, Slovenia, for which the average material coefficient is above 0.75, we rely on OLS production function coefficients, effectively using the average output elasticities.[16] Importantly, this approach in inferring β_K allows capital to have adjustment costs, since it does not rely on a static first-order condition for capital.[17]

To measure the sales generating production function coefficients, and subsequently TFPR (ω_{it}), we require a measure of firm-level sales (S_{it}), employment (L_{it}), material use (M_{it}) and the capital stock (K_{it}). We refer to Bartelsman, Haltiwanger, and Scarpetta (2013) for an overview of the measurement of TFPR using data sources comparable to those we use. In particular, we follow standard practice in handling each individual datasets and use data on sales, number of full-time equivalent workers, total intermediate input use, and the value of the capital stock. For the latter we either construct the capital series from the investment data, or we directly observe the book

[16] Alternatively, we could estimate the output elasticity directly from production data. We follow the standard in this literature and rely on cost shares to compute TFPR and thereby avoid the issues surrounding identification of output elasticities (in our case, across many industries and countries). For the U.S. Census data, we have run the reduced-form specifications in this section using the OLS procedure used for Slovenia, and find similar results.

[17] See De Loecker and Warzynski (2012) for more discussion. Similarly, we could use a value-added, rather than gross output approach to measurement. Doing so does not change the results.

value of a producer's tangible fixed assets. We deflate all output and input data with the relevant country-industry specific producer price deflators.

We provide summary statistics describing our datasets in Table 2. In the left panel we report the median number of workers, and median sales and TFPR growth. The right panel lists the various standard deviations that are of direct interest for our analysis: dispersion in MRPK, dispersion in capital and TFPR, and a simple measure of volatility given by $\mathrm{Std}(\omega_{it} - \omega_{it-1})$.

As expected, the median size varies substantially across the various datasets due to different data collection protocols. In Table B.1 in the appendix we verify the robustness of our results to using a common size threshold. Productivity growth varies across countries, and it is no surprise that Slovenia and India are the fastest growing economies. The dispersion in MRPK ranges from 0.81 in the U.S. to 1.56 in Slovenia, while volatility also varies significantly (0.28 versus 0.40). This table suggests, if anything, a positive association between a country's level of dispersion in MRPK and the volatility faced by producers. The next section examines this relationship, a central implication of our model, in more detail.

3.2 Reduced-form evidence on dispersion and volatility

We begin our analysis by plotting, in Figure 2, the relationship between the dispersion in MRPK and volatility of TFPR for the U.S. Census data, with each dot on the graph representing a specific four digit SIC code. We start with the U.S. Census data, since this is the richest data source we have access to and the dataset in which issues of measurement and sampling frame are plausibly the least important. We find a striking positive relationship between volatility of TFPR and MRPK dispersion. This is the relationship that the discussion of the model in Section 2 prepared us for.

To see if the relationship between MRPK dispersion and volatility of TFPR hold up more generally, Table 3 presents, for each of our high-quality (Tier 1) data sets, regressions of the dispersion in $MRPK$, on TFPR volatility, controlling for industry fixed effects. The focus of Table 3 is the set of country-specific regressions, where the unit of observation is the industry-year. The last two regressions pool the data, such that the unit of observation is the industry-country-year.

For each of the countries, there is a positive, and significant, coefficient. Notably, in the U.S. Census, we see a coefficient of 0.76 (using plant-level data) and 0.68 (using firm-level data), both of which are significant at the 1% level. Since we observe no economically significant difference between plant- and firm-level data using the U.S. census, from this point on, we use plant-level data in computing U.S. numbers.

These country-specific regressions are consistent with the model prediction that dispersion in the static marginal revenue product of capital, at the country-industry level, should be positively correlated with the volatility of TFPR shocks.

Pooling across countries, we see the same pattern. The reported coefficients are 0.55, when the data is pooled in an unweighted way, and 0.74, when the weighting matrix accounts for the number of industry-year observations in a country.

An important element in these regressions is the measurement of volatility. In Table 3 we measure volatility by $\mathrm{Std}_{st}(\omega_{it} - \omega_{it-1})$. This allows the shock process to vary over time, but is not an exact replication of the AR(1) process posited in the model. In what follows we asses the sensitivity of these baseline results to alternative specifications of the TFPR shock process.

3.2.1 Alternative TFPR processes

Using different models to capture the TFPR process will affect the measurement of volatility. In what follows, we confirm that our baseline results reported in Table 3 are robust to using alternate models of the TFPR process. We proceed by showing the correlation among various volatility measures, each generated by a different model, for all countries. Then, we show that our reduced form evidence is unaffected by the use of either an AR(1) process for TFPR, or an AR(1) process including firm-level fixed effects.

Table 4 reports the correlation coefficient between three alternate measures of TFPR volatility. These are: $\text{Std}_s[\omega_{it} - \omega_{it-1}]$, which we refer to in table 4 as 'vol'; an AR(1) measure which is the σ_s term in the following specification: $\omega_{it} = \mu_s + \rho_s \omega_{it-1} + \sigma_s \nu_{it}$; and, finally, an AR(1) specification in which we replace μ_s with a producer-level fixed effects. In Table 4 we refer to this last specification as 'AR(1)FE'.[18] The AR(1) specifications impose the restriction that σ_s is constant over time. To keep our alternative measures comparable, we impose the same restriction on our 'vol' measure.[19]

As Table 4 shows, there is a high correlation among our various alternative approaches to inferring the volatility of the TFPR process. All correlation coefficients are greater than 0.72, and most are above 0.9. Thus, the shock processes are similar across different specifications, and thus our results are robust to alternate measures of volatility.

Table 5 takes these alternate measures of the volatility of the TFPR process and runs country-specific regressions mirroring those presented in Table 3. In all regressions the coefficient on volatility is positive, and in all but two cases – out of 24 – the coefficient is significant at the 10% level or better. In addition, the magnitudes of the coefficients are comparable across all specifications, although the AR(1)FE specification tends to produce coefficients that are somewhat higher than the other two specifications. This is likely due to some of the σ_s variation being absorbed by the producer fixed-effect.[20] Overall, the results support the conclusion that the qualitative reduced-form patterns observed in the baseline specification (Table 3) are robust to alternative specifications of the TFPR process.

[18] Note that the specification for our AR(1) process rules out aggregate-level shocks to TFPR growth. However, a regression of changes in TFPR on country-year dummies in the World Bank data yields an R^2 of only six percent. Similarly, for the eight Tier 1 individual country data sets we find R^2's between 0.001, for Mexico, and 0.023, for Chile, when running TFPR growth against year dummies. Thus, there appears to be only a small aggregate component to TFPR change.

[19] As a consequence, the results in Table 3 (at the country-industry-year level) differ in magnitude from those presented in Table 5 (at the country-industry level) .

[20] All our estimates of volatility, and the subsequent analysis using volatility as an explanatory variable, are robust to using alternative dynamic panel data estimators for the TFPR process with fixed-effects. In particular, we verified the robustness of the estimates of volatility (σ) to the correction suggested by Arellano and Bond (1991).

3.3 Additional Implications

So far we have focussed on the relationship between the dispersion in MRPK and volatility of TFPR. Although, this is the main prediction of our model, there are a number of additional implications, both at the individual producer and aggregate levels. We explore these below.

3.3.1 Individual Producer Implications

An essential prediction of our model is that adjustment costs in capital, coupled with TFPR shocks, lead to differences in MRPK among producers. The model thus implies that once producers install capital, TFPR shocks should manifest themselves in variation in MRPK across producers. In the absence of adjustment costs – including a one-period time-to-build – producers could simply adjust their capital, and this would lead to the equalization of MRPK across producers. To test this mechanism, we run the following regression for each of our Tier 1 countries:

$$\text{MRPK}_{it} = \gamma_0 + \gamma_1 \xi_{it} + \gamma_2 k_{it} + \gamma_3 \omega_{it-1} + \gamma_t + \gamma_s + \nu_{it}, \tag{17}$$

where $\xi_{it} \equiv \omega_{it} - \omega_{it-1}$ is the "shock" in TFPR between t and $t-1$. From our one-period time-to-build assumption, this shock has not been observed when the firm makes its investment decision about capital stock k_{it} at time $t-1$. We also condition on lagged TFPR to make sure we compare two firms with the same TFPR at $t-1$ making the same capital decision, and we ask whether their MRPK is different if they are hit by different TFPR shocks ξ_{it}. Our theory predicts a positive coefficient for γ_1. The null hypothesis, given by the static model, is no meaningful dispersion in MRPK as a function of TFPR shocks between t and $t-1$. Table 6 lists the estimates for γ_1 by country. In every case, in every specification, we observe a significant, positive coefficient on the capital coefficient, γ_1, as predicted.

A further prediction of our framework is that a producer's MRPK should be mean reverting. We run a regression of MRPK at time t on MPRK at time $t-1$, and obtain estimates of the AR(1) coefficient. This coefficient varies by country from 0.73, for Romania, to 0.90, for Chile. The coefficient is significant at the 1% level in all cases. Hence, across all countries we find evidence for mean reversion in the MRPK. That is, in the long run, the restriction of adjustment costs on capital fades, and a firm's capital level reverts to the time invariant mean.[21]

3.3.2 Aggregate Implications

In addition to the aggregate implication that the dispersion in MRPK is strongly related to the volatility of TFPR, our model suggests two additional aggregate implications:

[21] We run $\text{MRPK}_{it} = \mu + \rho\text{MRPK}_{it-1} + \nu_{it}$ by country, and include year and industry fixed effects. The standard errors are clustered at the firm/plant-level to account for serial correlation and heteroskedasticity. All estimates of ρ are significant at the 1 percent level. The ρ estimates, by country are: U.S., 0.83; Chile, 0.90; France, 0.88; India, 0.83; Mexico, 0.87; Romania, 0.73; Slovenia, 0.80; and Spain, 0.88. Note that this specification does not, by itself, rule out some long-run persistence in MRPK, and in the U.S. Census data, we find some small serial correlation in MRPK over a twenty-year period. However, the bulk of MRPK differences between producers are transitory.

The following moments, at the industry-year level, are all correlated with volatility: a) the dispersion in the change in MRPK; and, b) dispersion in the change in capital.[22] We pool across all our Tier 1 countries, and run reduced-form regressions for both these aggregate variables, measured at the industry-year-country level, on volatility. We include year and country fixed effects, and cluster standard errors by country. The regression results are shown in Table 7.

We begin with the dispersion in the change in MRPK, $\mathrm{Std}_{st}(\Delta MRPK)$. Model simulations (as described in Section 2.4) indicate that the dispersion in the change in MRPK should be positively correlated with volatility.[23] In Table 7, we observe a positive and significant correlation between volatility and the dispersion in the change in MRPK both within the U.S. data, and within the pooled data across all Tier 1 countries (both excluding and including the U.S.). While the degree of correlation should vary with the persistence of the AR(1) process present in each country, the positive correlation in the pooled sample is consistent with the model prediction.

The second moment, the dispersion in the change in capital $[\mathrm{Std}_{st}(\Delta k)]$ has a strongly non-linear relationship to volatility. Figure 3 shows the relationship predicted by the model using the same simulation procedure as in Section 2, where panel (a) presents this relationship for the adjustment costs we will estimate for the U.S. in the next section, and panel (b) also includes the case without any adjustment cost, but preserving the assumption of a one-period time-to-build. The reader should note the difference in the vertical scale for these two panels.

Figure 3 reflects the mechanism described in Section 2.4. That is, the flattening of the change in capital-adjustments as volatility increases is due to the changing trade-off in determining the value of investment today, as between the size of shocks experienced today and the likelihood that they will be swamped by future shocks. The same qualitative pattern is observed when adjustment costs are equal to zero, where the only friction is the one-period time-to-build (the dashed lines in panel (b)).

To examine this in a reduced form, we take, for each sample shown in Table 7, the median volatility within industry-countries and interact the volatility coefficient with a dummy for high volatility if the volatility associated with that industry-year-country observation is higher than the median for that industry-country. The model prediction is that the coefficient on this interaction is (weakly) negative. As can be seen in Table 7, this coefficient is always negative and, in the case of the U.S. and the all-country sample, significant.

3.4 Adjustment Costs in Other Inputs

Our model makes the stark assumption that capital is the only input that faces adjustment costs, and our empirical approach builds on this assumption. This is clearly

[22]A related literature explores the responsiveness of productivity dispersion to the business cycle. Bachmann and Moscarini (2012), Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), and Kehrig (2011) all find that productivity volatility increases in recessions. We find no economically significant impact of recessions on the dispersion of MRPK, although, like Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012), we see sales volatility increase. Given that MRPK is the sales to capital ratio, this suggests that capital input adjustments offset any effect coming via changes in sales.

[23]See Figure D.1 in the Online Appendix. The lines describing the relationship is essentially straight.

a simplification of the data-generating process. This raises the question of whether adjustment costs for other inputs are likely to be of the same order of magnitude as that for capital, and whether this substantively affects the work presented here. That is, to what extent is focusing on capital adjustment costs a reasonable resolution to the trade-off between model parsimony and model realism?

At the highest level of abstraction, the existence of adjustment costs for other inputs only underpins the central thesis of this paper: that the dynamic nature of inputs is relevant to understanding the nature of cross-sectional dispersion in marginal revenue products. As argued previously, this, in turn, colors the way to think about the policy implications of these dispersions. At a more granular level, this issue becomes one of appropriate measurement, and it is to the evaluation of that feature that we now turn.

Our approach is based on the assumption that, across the span of countries and industries examined in this paper, capital adjustment costs are first-order as compared to the adjustment costs of other inputs. A simple way to evaluate this claim is to examine the (log) dispersion in the marginal revenue products of capital, labor, and intermediate inputs ($k, l,$ and m). To do this we compute $\text{Std}_{st}\left(\ln(\beta_X) + s_{it} - X_{it}\right)$ for $X \in \{k, l, m\}$ for each country. Table 8 shows the results.

Across all countries, dispersion in the marginal revenue product of capital is greater than that for any other input. Further, the order of dispersion is in line with what one might expect: $MRPK > MRPL > MRPM$.[24] Given these results we proceed with the maintained assumption that capital adjustment costs are the most important component of the adjustment costs likely facing many firms in making input decisions.[25]

4 Structural Model

In this section we evaluate the ability of the model to capture the magnitude of the degree of dispersion in the marginal product of capital at the industry level, across our Tier 1 country datasets. We begin by evaluating a baseline specification of our model, in which we assume all industry-countries have the same production technology and the same adjustment costs (we use the U.S. mean production coefficients, with the adjustment costs estimated from the U.S. data). In this simple version, the only thing that varies over industries in the structural model is the AR(1) process governing TFPR shocks. This specification is intended to highlight the extent to which, on its own, the TFPR shock process can capture dispersion in marginal products.

Following this baseline specification, we explore the extent to which using industry-specific production functions and different adjustment cost specifications allow us to

[24] Moreover, we also find that the relationship of dispersion in MRPK and volatility holds up in every dataset (including the Tier 1 and Tier 2), while for the MPRL and MRPM this is far from the case. In fact we could not find any particular pattern (either positive or negative relationship) between volatility and the dispersion measures for L and M.

[25] Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) estimate a structural model of adjustment costs in both labor and capital using Compustat data on U.S. firms. While the model of Bloom (2009) is suggestive of an similar extension in our setting, given that we encompass 9 countries in our Tier 1 data, and 33 in our Tier 2 dataset, we have chosen to use a more parsimonious model. In our data environment, it seems to strike an appropriate balance between realism, insight, and feasibility.

capture additional richness. Before getting to these results, we first set out the elements in the structural estimation of the model.[26]

4.1 Estimation

We briefly discuss the estimation of the crucial parameters of our structural model, those that vary by industry – i.e., the TFPR process, and how we recover the estimates of the adjustment cost parameters.

4.1.1 The TFPR process

The AR(1) TFPR process is specified as: $\omega_{it} = \mu_{sc} + \rho_{sc}\omega_{it-1} + \sigma_{sc}\nu_{it}$. Note that the coefficients are country-industry specific. Estimation follows the procedure described in Section 3.2.1 and relies on standard maximum likelihood estimation techniques to recover the parameters.

4.1.2 Estimation of Adjustment Costs

Recall that the adjustment cost specification is given by:

$$C(I_{it}, K_{it}, \Omega_{it}) = I_{it} + C_K^F \mathbb{I}\{I_{it} \neq 0\}\pi(\Omega_{it}, K_{it}) + C_K^Q K_{it} \left(\frac{I_{it}}{K_{it}}\right)^2. \tag{18}$$

We estimate $\theta = \{C_K^F, C_K^Q\}$ using a minimum-distance procedure very similar to that in Cooper and Haltiwanger (2006). That is, we seek parameters that minimize the distance between the moments predicted by the model, and those that are found in the data. The moments we use are: the proportion of firms with less than a 5 percent year-on-year change in capital; the proportion of firms with more than a 20 percent year-on-year change in capital; and the standard deviation of the year-on-year change in log capital.[27]

Denote the predicted moments from the model for an industry s in country c as $\mathbf{\Psi}_{cs}(\theta)$, found by solving for the firms' optimal policies and simulating the model forward for 1000 months for 10,000 firms, and computing moments based on the last two years of the simulated data set.[28] These predictions may differ across industries,

[26] We take care in converting the measured production coefficients from an annual to a monthly level to reflect a period in our structural model.

[27] Notice that according to the results of Theorem 1, stated in the appendix, these moments are invariant to differences in the mean μ of the TFPR process, and thus we do not need to take a stand on the presence of a firm fixed-effect in the estimation procedure. However, we have also looked at the model's predictions using estimates of the AR(1) process that include a producer fixed-effect for the United States, and we find comparable results (contained in the Online Appendix).

[28] We employ a very fine grid for capital stock (of 3 percent), since fixed costs are identified from the absence of small changes in capital. With a coarser grid for capital stock, it is difficult to identify small fixed costs. This comes at the expense of computational time, and solving the value function takes over a half-hour. The total computation time required for a single 3GHz processor to complete the estimation and simulations reported in this section is 2,286,000 minutes (1,587 days). The computational burden was significantly reduced via parallel computation on a large computing cluster at NYU. For further details regarding computation, see the appendix.

depending on production function coefficients β_l, β_m, and β_k, as well as the TFPR process estimated in the previous subsection. We then aggregate the industry prediction to the country level by taking a weighted average of the industry-level prediction; i.e., $\mathbf{\Psi}_c(\theta) = \frac{1}{\sum_s N_{sc}} \sum_s N_{sc} \mathbf{\Psi}_{cs}(\theta)$, where N_{sc} denotes the number of producers in industry s for country c. Thus, the country-level predictions are matched to country-level moments on changes in capital, where the moments from the data are denoted $\hat{\mathbf{\Psi}}$.

We estimate the model's adjustment costs using minimum distance with a criterion function given by the usual quadratic form, with weighting matrix $\mathbf{W}$:

$$\mathcal{Q}(\theta) = \left(\hat{\mathbf{\Psi}} - \mathbf{\Psi}(\theta)\right)' \mathbf{W} \left(\hat{\mathbf{\Psi}} - \mathbf{\Psi}(\theta)\right). \tag{19}$$

As the moments in the data are similarly scaled, we pick the identity matrix as a weighting matrix ($\mathbf{W} = \mathbf{I}$). We find the minimized value of the criterion using a grid search.

Table 9 presents estimates of the adjustment costs by country, along with the moments used to estimate the model. Three aspects of the table are noteworthy.

First, the moments on the year-to-year change in capital differ substantially between countries. For the United States, over 39% of plants do not change their capital by more 5%, while this number is 20% for Spain, and 8% for Romania.[29] Likewise, the share of plants that vary their capital by more than 20% is 21% for the U.S., 28% for Chile, but 76% for Slovenia. These differences in the variation of capital translate into differences in the estimated adjustment costs by country, with the U.S. having relatively high convex and fixed adjustment costs, and Mexico having convex adjustment costs that are at least five times smaller.

The large differences in moments on changes in capital are striking. Beyond differences in adjustment costs, they also reflect differences in patterns of aggregate growth for each of these countries, and differences in the data collection protocols for Tier 1 data. For instance, Slovenia experienced a rapid increase in output over the time period we study (1994-2000), but this is not the case for the U.S. manufacturing sector from 1963 to 1997.[30] As well, for some datasets, changes in capital are computed from the change in the reported book value of assets, while for other datasets, these are inferred from investment and depreciation. Presumably, these differences in the reporting protocol will also lead to differences in the measurement in the change in capital.

Second, for several countries—France, Mexico, Romania—we estimate no fixed costs of adjustment (beyond the one-period time-to-build, which is in itself a form of adjustment friction). In these countries, even with no fixed cost of adjustment, the model predicts that fewer firms would change their capital by less than 5% than what we find in the data. Conversely, a zero convex cost of adjustment is strongly rejected. As the convex adjustment costs get closer to zero, the volatility of capital rises sharply. Given the data, this allows us to conclusively reject the absence of any costs of adjusting a firm's capital stock.

[29] Note that Spain and Romania are firm-level data.

[30] Since the standard approach to estimating adjustment costs which we use, such as found in Cooper and Haltiwanger (2006) or Bloom (2009), matches moments from the steady-state distribution, this type of model has difficulty dealing with aggregate shocks.

Third, focusing on the U.S., we obtain the following estimates: fixed adjustment costs (C_K^F), 0.09; convex adjustment cost (C_K^Q), 8.8. The fixed cost of adjustment is equivalent to 1.5 months of output, while the convex adjustment costs are such that when a firm doubles its capital in a month, this component of cost is equal to 8.8 times the value of its investment.[31]

4.2 Evaluating model fit

To assess the fit of the model, we compute the sum of squared errors, scaled by the sum of the squared 'dependent' variable (data). That is, if the data are a vector $\mathbf{x}$ that is predicted by a variable $\hat{\mathbf{x}}$, then we compute

$$S^2 = 1 - \frac{(\mathbf{x} - \hat{\mathbf{x}})' (\mathbf{x} - \hat{\mathbf{x}})}{\mathbf{x}'\mathbf{x}} \tag{20}$$

as our measure of fit. This measure of fit is closely related to the uncentered R^2 measure of fit familiar from regression analysis. However, because our model's prediction does not come from a regression, but from a parameterized model, nothing in the structure restricts S^2 to lie in $[0, 1]$, though, by definition, it must be less than or equal to one. That being said, to map our measure of fit into a context equivalent to the R^2, it is correct to interpret S^2 as the proportion of the observed data captured by the model's prediction, with the caveat that it is possible for this number to be negative.

4.3 Baseline specification

As noted above, our baseline specification assumes that all industries in all countries have the same adjustment costs and the same production technology. We take both from the U.S. data: we use the mean U.S. production coefficients and U.S. adjustment costs.[32] Our objective in evaluating this specification is to highlight the extent to which (just) differences in the AR(1) process can capture dispersion in the marginal revenue product of capital, at the industry level, across a variety of data sets (equivalently, countries).

Table 10 shows the S^2 measure of fit, comparing the model prediction of the dispersion in the MRPK to that observed in our various Tier 1 data sets. Pooling across all industry-countries, the S^2 is 0.674, while, if the U.S. is excluded, the S^2 is 0.879. This suggests that the model does a good job of capturing the observed dispersion. It also highlights the curious fact that the performance of this baseline model is worst on the U.S. data, despite being based on U.S. numbers.

The U.S. S^2 is 0.223, as compared to 0.879 for all non-U.S. countries. The reason for this is that the U.S. data employs a far finer industry definition than do our other data sets. In the U.S. data firms are allocated to one of 188 industry classifications, whereas

[31] These parameters can be compared to those found in Bloom (2009) (Table 3, column 2) who, using a sample of (only) large publicly listed firms in Compustat, obtains fixed adjustment costs of 0.01 and convex adjustment costs of 1.00.

[32] Mean production coefficients are computed by taking the mean of the industry labor and materials coefficients and then using these to compute the capital coefficient.

in the other data the numbers of industries varies from 8 (Chile) to 52 (Mexico).[33] This means that, when we impose mean production coefficients, we do so on industry definitions which incorporate differing levels of aggregation. In the U.S., where the industries are finely defined, this means that some industries will have firms that all use production technologies that differ markedly from the standard firm in the economy. As a result, the baseline model can have a hard time capturing the investment patterns observed in these industries when it has to use the production coefficients from a 'standard' firm.

The impact of industry heterogeneity in the U.S. data is illustrated by comparing specification (2) to specification (1) for the U.S.[34] Specification (2) adds industry specific production coefficients to the model. Once industries are allowed to vary in their production technology the U.S., S^2 increases from 0.223 to 0.806, reflecting the model's increased capacity to captures investment patterns across a much wider range of industries.

4.4 Extensions: Industry-specific production coefficients and alternate adjustment costs

As illustrated by the discussion of the baseline results, adding more flexibility to the model can increase the extent to which the dispersion in the data can be captured. To this end, we depart from the baseline model and allow each country to have its own adjustment costs (from Table 9), and allow each country-industry to have its own production function coefficients (specification (2) in Table 10). Following that we investigate the sensitivity of this expanded model to changes in the adjustment costs: we impose U.S. adjustment costs, twice the U.S. adjustment costs, and zero adjustment costs (aside from the one-period time-to-build) on all countries (specifications (3), (4), and (5) respectively, in Table 10).

Prior to discussing results, we outline some measurement issues: Recall that we assume $\sum_x \beta_x = 0.75$ (given constant returns in the production function, and a demand elasticity of -4). Given this, we handle the data as described in Section 3.1.2, with one exception: In the Slovenian data, the material coefficient is greater than 0.75 on average. As a result a strict application of our procedure would imply negative capital coefficients for all Slovenian manufacturing sectors, which we think is not plausible. To avoid having to omit Slovenia, an interesting country in its own right, we use the mean U.S. coefficients to generate all Slovenian results in this section.[35]

[33] After accounting for disclosure, and basic data integrity (i.e. missing data etc.), the numbers of industries by country (data-set) are: Chile 8, France 21, India 20, Mexico 52, Romania 21, Slovenia 18, and Spain 22. The U.S. has 188. This merely reflects that the detail of industrial activity reporting varies across datasets. For example for the French data we observe the principal activity of the firm, a 2 digit industry code, while we also observe its (potentially) multiple 4 digit industry codes. However, we do not see the output and input data broken down at this level of aggregation, which is standard in these data.

[34] In Table 10, specifications (2) and (3) are equivalent for the U.S.

[35] Slovenia is interesting due to the volatility introduced by the transition process it experienced during our sample time period. Using U.S. production coefficients keeps the specification consistent with the structural model, albeit in a way that restricts us to examining how Slovenian firms would behave if they had the production technology of U.S. firms. A computationally feasible alternative would be to use estimated

Across specifications (2), (3), (4), and (5) there is little qualitative difference in the capacity for the model to capture dispersion. This reflects the good fit of the baseline model. That is, there is not a great deal of scope for improvement in many cases. Perhaps most interestingly, the model's performance in capturing dispersion in MRPK is not dramatically altered by changing the level of adjustment costs. A zero adjustment cost reduces fit in most countries somewhat, but imposing twice the U.S. adjustment cost does not have an economically meaningful impact. This suggests that the presence of some capital adjustment friction is important, but that the extent of the friction is not crucial, at least as far as dispersion in MRPK is concerned.[36]

5 Extension: A cross-country analysis

The main source of variation that we have relied on thus far is cross-industry variation within a country. Although our results suggest a positive correlation between dispersion and volatility in cross country settings, drawing a stronger inference is limited by only having a sample of eight countries, each with different data collection protocols. In this section, in order to provide auxiliary evidence that speaks to such a conclusion, we exploit a larger-cross section of developing countries for which we only observe a sample of firms for, at most, three consecutive periods. To this end, we rely on the WBES data. These data trade off greater cross-country variation, at the expense of stricter data collection protocols and a much larger, within-country, sample of firms. As before, we apply our reduced form and structural analysis (as carried out in Section 3 and 4, respectively) on a large cross-section of countries. We briefly introduce the data before we present our results.

5.1 The WBES Data

The WBES data were collected by the World Bank across 41 developing countries and many different industries between 2002 and 2006. Standard output and input measures are reported in a harmonized fashion. In particular, the data report sales, intermediate inputs, various measures of capital, and employment, for a three-year period, which allows us to compute changes in TFPR and capital. Out of the 41 countries in the data, 33 have usable firm-level observations. This is primarily because, for many years and countries, the World Bank did not collect multi-year data on capital stock.

To construct data on both TFPR and the change in TFPR we need two years of information on sales, assets, intermediate inputs, and employment. 5,558 firms across our 33 countries meet this criterion.[37] The firms in the final data are almost certainly not representative of firms in their economies; for instance, the mean number of workers is 248. Thus, for instance, the data tend to oversample larger firms. In

production coefficients as in Section 3. However, this would violate the maintained assumptions of the structural model. Nonetheless, doing so produces qualitatively similar results.

[36]For other moments, notably the dispersion in the change in capital, the level of the adjustment can make a significant difference. See Table D.1 in the Online Appendix, and in particular column (5) corresponding to the case of no adjustment costs.

[37]We also drop countries with fewer than 25 observations. This has little effect on our results.

the data appendix we provide further details on sample construction and compare the firms in our sample with the universe of sampled firms.

5.2 Cross-Country Reduced-Form Results

We start by establishing the relationship between static misallocation and volatility across countries, using a similar method to what we used at the industry-level. Figure 4 plots the volatility of TFPR against the dispersion of MRPK for our 33 countries in the WBES data. We find the same striking positive relationship as we presented in Figure 2 in Section 3 using U.S. Census data.

Table 11 presents regressions of static misallocation, $MRPK$, on TFPR volatility, as defined before. Panel A performs this regression at country-level, while panel B uses data at the country-industry level.[38]

The coefficients in each specification of Panel A (at the country-level) of Table 11 are 0.67, 0.75, 0.64, and 0.63, respectively. All coefficients are statistically significant. Moreover, the R^2 is 0.31 in specification I, where no other controls are included. This increases to 0.36 when industry fixed-effects and log assets are included as controls. Thus, a substantial fraction of cross-country differences in misallocation can be attributed to differences in country-specific TFPR volatility. This reproduces the empirical evidence from our individual country datasets in Section 3, and shows the link between the volatility of TFPR in a country and the extent of (static) capital misallocation in that economy.

In Panel B we reproduce the same exercise as in Panel A, but at the country-industry level. This is similar in spirit to the industry-level variation we utilized in Section 3, with the notable difference that we pool industry-level data across the 33 countries. These coefficients are all statistically significant and positive, regardless of whether we include no controls (Column V), TFPR and capital (Column VI), or country and industry fixed effects (Column VII). The coefficients are 0.43, 0.42, and 0.28, respectively.

5.3 Structural analysis

We now perform a structural analysis of the World Bank data, in the same spirit as that conducted in Section 4. We apply the same model, with two alterations. We estimate a AR(1) process for TFPR at the country-level; and we use the adjustment costs estimated for the U.S. reported in Table 9. We use U.S. adjustment costs since we found in the analysis of the Tier 1 country datasets that the precise level of adjustment costs appears to have little influence on the ability of the model to capture the dispersion

[38] We have performed multiple robustness checks on these results, which are reported in the Online Appendix. Tables D.5 and D.6 in the Online Appendix investigate the measurement of TFPR in more detail, by relating TFPR to investment. We find that firms with higher TFPR have both higher investment rates, and are more likely to invest in the first place. Moreover, the coefficients in Table 11 are qualitatively robust across a number of specifications: only larger firms, only the manufacturing sector, dropping firms with extreme factor input ratios, as well as measuring productivity using an OLS regression, plant-level input shares used to estimated production function coefficients, different assumptions on the elasticity of demand, and using the interquartile range rather than the standard deviation as a measure of dispersion.

in the MRPK.[39] Hence, we examine the capacity of the model to capture dispersion using this simple specification.

To obtain country-level predictions, we aggregate predictions at the industry-level, using the number of producers in an industry as weights. Moreover, since dispersion in MRPK at the country-level includes both variation in MRPK within an industry, as well as between industries, we need to account for both these sources of variation when aggregating MRPK.

The results are depicted in Figure 5. The countries in the World Bank data are shown using unfilled circles, while, for comparison, the Tier 1 countries are shown using filled circles.[40] The horizontal axis measures the model's prediction, while the vertical axis measures the dispersion in MRPK present in the data.

The model does quite well. The S^2 for the WBES countries is 0.802. This is comparable to the model performance reported in Table 10 for the industry-level data from Tier 1 countries. When we treat the Tier 1 country data in the same way as the WBES data, we get an S^2 of 0.906 . Also, if anything, the model has a tendency to over-predict the dispersion in MRPK, suggesting that the dispersion observed in data is less than what might be expected to be generated by firms operating in the U.S., facing U.S. adjustment costs, but otherwise equivalent AR(1) and technological environments.

5.4 Volatility and external measures

So far, our strategy has been to estimate volatility of TFPR and see how this measure of volatility is linked to the dispersion in various economic variables. We have shown that volatility varies across industries within countries, as well as across countries. Although it is beyond the scope of this paper to develop a theory of volatility to explain why volatility varies across different economic environments, it is only natural to ask whether our measures of differences in volatility across countries are related to features of these economies.

To this end we match the World Bank Doing Business Dataset (henceforth the WBDB data) with the WBES data and check whether volatility is correlated with some of the survey questions in the WBDB data. In particular we examine whether countries with greater volatility also face more frictions in contract enforcement—a measure that would plausibly affect the uncertainty faced by producers. The advantage of this survey question is that the variable is directly comparable across countries and is plausibly related to the predictability of doing business. It should therefore show up as variation in volatility.

Table 12 presents regressions of our estimates of the volatility of TFPR on measures of the ease of enforcing contracts, political stability, and natural disasters. More information on the construction of these variables is provided in Section B.9 of the Appendix.

[39] Similarly, using alternative adjustment costs to model MRPK dispersion in the WBES data makes little quantitative difference.

[40] The Tier 1 country data is aggregated in the same way as the World Bank data, and we use a country-specific AR(1) process in in the model simulation.

When we run volatility against this cost of contract enforcement in Column (1) we find a significant—at the ten percent level—and positive coefficient of 0.003, and an R^2 of 7%. This suggest that countries that exhibit larger volatility are also characterized by higher contracting costs. In Columns (2) and (3) we run volatility against political stability and an index of natural disasters. As discussed before, our measure of volatility is based on firm-level sales per input and are therefore subject to a wide range of shocks. We inspect whether our measure of volatility, at the country level, is at all related to measures of political stability and the extent to which a country is subjected to disasters. While the F-statistic—significant at the 10% level—in Column (3) suggests that natural disasters explain some of the variation in volatility, the coefficient on natural disasters itself is only statistically significant at a 10% level, which is unsurprising given the limited number of countries for which we have measures of volatility. In Column (4), we run a regression with all of our measures of the economic environment in a country against volatility and find, as before, that the cost of contract enforcement is associated with significantly higher volatility. Moreover, the F-stat is significant at the 10% level, indicating that the combination of contract enforcement, political instability, and natural disasters does explain some component of the cross-country differences we observe in volatility. In particular this simple linear cross-sectional regression leads to a R^2 of more than 14 percent.

Note that none of these "external" measures should be the sole explanatory variable for volatility. An issue with any of these measures is whether they accurately reflect volatility or, instead, persistence, or even adjustment costs. We merely provide some descriptive evidence for the link between volatility and external measures. That said, these regressions suggest that there may be linkages between volatility and features of a country's operating environment that are worth investigating further.

6 Conclusion

The primary contribution of this paper is to establish the link between the dynamic process governing TFPR changes over time, and cross-sectional measures of (static) capital misallocation. We have shown that a parsimonious model of the TFPR process coupled with capital adjustment costs explains both the level and variation of the dispersion in the static marginal revenue product of capital across industries within countries, and across countries. We do this by examining eight large-scale high quality country-level data sets, including the U.S. Census, and then extend the analysis with data from the World Bank on a further 33 developing countries.

These findings suggest that producers in industries (countries) that experience larger 'uncertainty' in the future operating environment (i.e., higher volatility in TFPR) make different investment decisions than those producers active in less volatile environments. This leads to different levels of capital and output and, moreover, means that the welfare gains from policies inducing reallocation of factors of production are likely to be lower than otherwise implied by static models, at least to the extent that the TFPR process is exogenous. Indeed, if one has the view that the productivity process is an exogenous, or primitive, feature of the model, then our findings suggest that, in an aggregate sense, the firms in the countries we studied are acting much as the social planner in our model would have them act (assuming that the social planner takes the capital adjustment costs as given). This suggests that there are few welfare implications for differences in cross-sectional measures of (static) capital misallocation across industries or countries. On the other hand, if government policy can affect the productivity process, then there may be significant welfare dividends to policy interventions aimed at moving toward some socially-optimal productivity process. However, characterization of what this optimal process is likely requires a more subtle modeling approach than that offered here.

Nonetheless, an alternative suite of policy options, aimed at making the TFPR process more benign, may be attractive as a complement to the redistributive measures featured in the counterfactuals considered in other studies. These redistributive measures are usually framed as the outcome of the elimination of static distortions arising from, for instance, ill-considered regulation. Nothing in this paper contradicts the value of removing such distortions. It is likely that at least some component of the stochastic process of TFPR is influenced by government policy. In fact, we present some descriptive evidence that suggests volatility differences across countries are linked to contract enforcement (presumably one aspect of the implementation of the rule of law) and general political stability. To the extent that this is true, our findings suggest that if government policies can provide a more predictable business environment then this may benefit the economy and help producers allocate resources in more-productive ways.

This raises the important issue of the specific sources of adjustment costs and TFPR volatility, a topic on which we provide some suggestive evidence, but otherwise leave open for future research. In particular, TFPR is not just technological in nature. Our measure of TFPR volatility will capture changes in managerial and physical technology. It will also capture year-on-year variation in the intensity of corruption (and the implicit tax therein); other aspects of the application of the rule of law relevant to business (such as erratic contract enforceability); changing regulatory frictions; environmental factors (e.g., floods and other natural disasters) and the efficacy of infrastructure used to cope with them; and year-on-year variation in markups and product market competition. Many of these elements of measured productivity volatility may be effectively influenced by appropriate policy aimed at providing a stable business environment.

From a methodological perspective, we have focused on capital adjustment costs, coupled with TFPR shock processes, to interpret the observed cross-country differences in the dispersion in the marginal revenue product of capital. In doing so, we shut down many other economically relevant features of a firm's environment that could lead to differences in the measured marginal revenue product of inputs, including, for instance, differences in the factor prices for inputs, differences in the size of adjustment costs, and heterogeneity in market power. This keeps our model parsimonious and makes the approach in this paper directly comparable with the approach taken in the existing literature on cross-country productivity differences. However, the dynamic model of misallocation proposed in this paper is clearly compatible with additional sources of heterogeneity between producers. A natural alternative starting point would be to include additional heterogeneity in market power and interpret the differences in marginal revenue product differently—i.e., as a reflection of differences in market power that vary over time. We note this to underscore the fact that observed productivity and MRPK differences can have many underlying drivers. We have focused on just one.

References

Arellano, M., and S. Bond (1991): "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations," *The Review of Economic Studies*, 58(2), 277.

Bachmann, R., and G. Moscarini (2012): "Business cycles and endogenous uncertainty," Discussion paper, Yale University.

Bartelsman, E., and M. Doms (2000): "Understanding productivity: Lessons from longitudinal microdata," *Journal of Economic Literature*, 38(3), 569–594.

Bartelsman, E., J. Haltiwanger, and S. Scarpetta (2013): "Cross-country differences in productivity: the role of allocation and selection," *American Economic Review*, 103(1), 305–334.

Bloom, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77(3), 623–685.

Bloom, N., M. Draca, and J. Van Reenen (2011): "Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity," Discussion paper, National Bureau of Economic Research.

Bloom, N., B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts (2013): "Does management matter? Evidence from India," *Quarterly Journal of Economics*, 128(1), 1–51.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2012): "Really Uncertain Business Cycles," Working Paper 18245, National Bureau of Economic Research.

Bollard, A., P. J. Klenow, and G. Sharma (2012): "India's Mysterious Manufacturing Miracle," *Review of Economic Dynamics*, 16(1), 59–85.

Caballero, R., and R. Pindyck (1996): "Uncertainty, investment, and industry evolution," *International Economic Review*, 37(3), 641–662.

Collard-Wexler, A. (2009): "Productivity Dispersion and Plant Selection in the Ready-Mix Concrete Industry," *Working Paper, New York University.*

——— (2013): "Demand Fluctuations in the Ready-Mix Concrete Industry," *Econometrica*, 81(3), 1003–1037.

Collard-Wexler, A., and J. De Loecker (2013): "Reallocation and Technology: Evidence from the U.S. Steel Industry," Discussion paper, National Bureau of Economic Research.

Cooper, R., and J. Haltiwanger (2006): “On the nature of capital adjustment costs,” *Review of Economic Studies*, 73(3), 611–633.

Davis, S., J. Haltiwanger, R. Jarmin, and J. Miranda (2007): “Volatility and dispersion in business growth rates: Publicly traded versus privately held firms,” in *NBER Macroeconomics Annual 2006, Volume 21*, pp. 107–180. MIT Press.

De Loecker, J. (2007): “Do exports generate higher productivity? Evidence from Slovenia,” *Journal of International Economics*, 73(1), 69–98.

De Loecker, J., P. Goldberg, A. Khandelwal, and N. Pavcnik (2012): “Prices, Markups and Trade Reform,” NBER Working Paper.

De Loecker, J., and J. Konings (2006): “Job reallocation and productivity growth in an emerging economy. Evidence from Slovenian manufacturing,” *European Journal of Political Economy*, 22(2006), 388–408.

De Loecker, J., and F. Warzynski (2012): “Markups and firm-level export status,” *American Economic Review*, 102(6), 2437–2471.

De Mel, S., D. McKenzie, and C. Woodruff (2012): “Enterprise Recovery Following Natural Disasters,” *The Economic Journal*, 122(559), 64–91.

Dixit, A., and R. Pindyck (1994): *Investment Under Uncertainty*. Princeton University Press.

Fisher-Vanden, K., E. Mansur, and Q. Wang (2012): “Costly Blackouts? Measuring Productivity and Environmental Effects of Electricity Shortages,” Discussion paper, National Bureau of Economic Research.

Fisman, R., and J. Svensson (2007): “Are corruption and taxation really harmful to growth? Firm level evidence,” *Journal of Development Economics*, 83(1), 63–75.

Foster, L., J. Haltiwanger, and C. Syverson (2008): “Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?,” *American Economic Review*, 98(1), 394–425.

Goldberg, P., A. Khandelwal, N. Pavcnik, and P. Topalova (2009): “Trade liberalization and new imported inputs,” *American Economic Review*, 99(2), 494–500.

Hsieh, C.-T., and P. J. Klenow (2009): “Misallocation and Manufacturing TFP in China and India,” *Quarterly Journal of Economics*, 124(4), 1403–1448.

Kehrig, M. (2011): “The cyclicality of productivity dispersion,” *US Census Bureau Center for Economic Studies Paper No. CES-WP-11-15*.

Konings, J., and H. Vandenbussche (2005): “Antidumping protection and markups of domestic firms,” *Journal of International Economics*, 65(1), 151–165.

MIDRIGAN, V., AND D. Y. XU (2013): "Finance and Misallocation: Evidence from Plant-Level Data," *American Economic Review*, (forthcoming).

MOLL, B. (2012): "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?," Discussion paper, Princeton University.

OLLEY, G. S., AND A. PAKES (1996): "The dynamics of productivity in the telecommunications equipment industry," *Econometrica*, 64(6), 1263–1297.

PAVCNIK, N. (2002): "Trade liberalization, exit, and productivity improvements: Evidence from Chilean plants," *Review of Economic Studies*, pp. 245–276.

PETERS, M. (2012): "Heterogeneous mark-ups and endogenous misallocation," Discussion paper, London School of Economics.

RANKIN, N., M. SÖDERBOM, AND F. TEAL (2006): "Exporting from manufacturing firms in sub-Saharan Africa," *Journal of African Economies*, 15(4), 671–687.

RESTUCCIA, D., AND R. ROGERSON (2008): "Policy distortions and aggregate productivity with heterogeneous establishments," *Review of Economic Dynamics*, 11(4), 707 – 720.

ROBERTS, M. (1996): "Colombia, 1977-1985: Producer Turnover, Margins, and Trade Exposure," in *Industrial evolution in developing countries: micro patterns of turnover, productivity and market structure*, ed. by M. Roberts, and J. Tybout, chap. 10, pp. 227–259. Oxford University press, New York.

SYVERSON, C. (2011): "What Determines Productivity," *Journal of Economic Literature, forthcoming*, 49(2), 326–65.

TAUCHEN, G. (1986): "Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions," *Economics Letters*, 20(2), 177–81.

TYBOUT, J., AND M. WESTBROOK (1995): "Trade liberalization and the dimensions of efficiency change in Mexican manufacturing industries," *Journal of International Economics*, 39(1), 53–78.

VAN BIESEBROECK, J. (2005): "Firm size matters: Growth and productivity growth in African manufacturing," *Economic Development and Cultural Change*, 53(3), 545–583.

Tables and Figures

Table 1: Data sources, type and tier classification

Country	Plant	Firm	Provider – Survey Type	Size Threshold
		TIER 1		
United States	X	X	U.S. RDC - Census	More than 5 workers
France		X	BvD Amadeus – Tax Records	No
Romania		X	BvD Amadeus – Tax Records	No
Slovenia	X		Statistical Office – Census	No
Spain		X	BvD Amadeus – Tax Records	No
Chile	X		INE – Census	More than 10 workers
Mexico	X		SEC-OFI – Sample	Medium/Big Plants
India		X	CMIE (Prowess) – Balance Sheet	Large Firms
		TIER 2		
WBES		X	WB Doing Business Survey	Yes

Note: The X refers to which unit of observation the specific data records. Datasets can comprise both firm- and plant-level data if the plant-level data contains firm identifiers. Unless specified thresholds vary across datasets and are based on multiple characteristics of producers and/or dependent on reporting taxes. We verify the robustness of our results using a common threshold on firm/plant size.

Table 2: Summary Statistics Across Datasets

	Medians			Standard Deviations			
Country	Workers	Δs	$\Delta\omega$	Disp MRPK	Disp. k	Disp. ω	Volatility
U.S.	111	0.01	0.00	0.98	1.78	0.63	0.35
Chile	19	0.02	0.00	1.22	1.92	0.54	0.29
France	8	0.02	0.02	1.28	2.04	0.61	0.19
India	n.a.	0.06	0.04	1.13	1.61	0.67	0.29
Mexico	141	0.02	0.02	1.40	2.13	0.86	0.39
Romania	5	0.01	0.01	1.38	2.05	0.70	0.39
Slovenia	4	0.07	0.03	1.56	2.51	0.59	0.40
Spain	8	0.03	0.01	1.48	2.00	0.46	0.23
World Bank	55	0.08	0.02	1.10	2.10	0.80	0.40

Note: Dispersion MRPK is given by Std($MRPK_{it}$), and volatility is Std($\omega_{it} - \omega_{it-1}$) – i.e., we compute dispersion across the entire dataset. For the World Bank Data, we compute the relevant statistic across all countries.

Table 3: Dispersion MRPK and volatility

Country	Coefficient	R^2	Industry-Year Obs.
U.S. [Plants]	0.76***	0.47	4,037
	(0.04)		
U.S. [Firms]	0.68***	0.44	4,037
	(0.07)		
Chile	0.54*	0.13	55
	(0.29)		
France	1.03***	0.28	167
	(0.33)		
Mexico	0.19**	0.07	296
	(0.07)		
India	0.61**	0.28	279
	(0.17)		
Romania	0.44***	0.21	126
	(0.13)		
Slovenia	0.53**	0.09	108
	(0.21)		
Spain	0.56*	0.35	181
	(0.33)		
All I	0.55***	0.67	5,326
(unweighted)	(0.15)		
All II	0.74***	0.50	5,326
(weighted)	(0.03)		

Note: We report the coefficient of a regression of $\mathrm{Std}_{st}\,(MRPK)$ against volatility, defined as $\mathrm{Std}_{st}(\omega_{it}-\omega_{it-1})$, including year dummies. Standard errors are clustered at the industry level. *,**, and *** denote significance at the 10%, 5% and 1% levels respectively. 'All I' refers to the unweighted regression, whereas 'All II" refers to a weighted regression with the weights the number of producers in a country-industry-year observation. These cross-country regressions include year and country dummies, and report standard errors clustered at the country level.

Table 4: Correlation among volatility measures

Country	vol, AR(1)	vol, AR(1)FE	AR(1), AR(1)FE
U.S.	0.82	0.80	0.93
Chile	0.97	0.84	0.76
France	0.99	0.96	0.97
India	0.98	0.73	0.78
Mexico	0.99	0.94	0.95
Romania	0.99	0.85	0.91
Slovenia	0.93	0.85	0.92
Spain	0.99	0.80	0.77

Note: We report the correlation coefficient between the various measures of volatility: our reduced form measure of volatility ($vol = \text{Std}_s[\omega_{it} - \omega_{it-1}]$), and those obtained from the structural process for TFPR using either an $AR(1)$, and an $AR(1)$ with producer fixed effects.

Table 5: Dispersion of MRPK and volatility of TFPR: robustness

	Volatility measure		
Country	$\text{Std}_s[\omega_{it} - \omega_{it-1}]$	AR(1)	AR(1)FE
U.S.	0.82***	0.86***	1.24***
	(0.04)	(0.07)	(0.11)
Chile	1.48*	2.10***	0.33
	(0.65)	(0.65)	(1.48)
France	1.73***	1.75***	2.55***
	(0.41)	(0.41)	(0.61)
India	1.31***	1.75***	2.75***
	(0.33)	(0.39)	(0.55)
Mexico	0.39*	0.41**	0.33
	(0.17)	(0.17)	(0.25)
Romania	0.76***	0.94***	1.38*
	(0.23)	(0.36)	(0.72)
Slovenia	2.73***	2.47***	3.47***
	(0.41)	(0.41)	(0.69)
Spain	1.24***	1.46***	2.55***
	(0.34)	(0.44)	(0.59)

Note: We report the coefficient of a regression of $\text{Std}_{st}(MRPK)$ against alternative measures of volatility, defined in the text. Standard errors are clustered at the industry level. *,**, and *** denote significance at the 10%, 5% and 1% levels respectively.

Table 6: Additional Predictions: MRPK against shocks to TFPR

Country	Shock	Shock AR1	Shock AR1-FE
U.S.	1.29***	1.26***	1.13***
	(0.00)	(0.00)	(0.01)
Chile	1.42***	1.42***	1.04***
	0.02	0.02	0.02
France	1.37***	1.37***	1.26***
	(0.01)	(0.01)	(0.01)
India	1.32***	1.32***	1.16***
	0.04	0.04	0.04
Mexico	1.07***	1.07***	0.67***
	0.04	0.04	0.05
Romania	1.31***	1.31***	1.12***
	(0.01)	(0.01)	(0.01)
Slovenia	1.65***	1.64***	1.48***
	0.04	0.04	0.04
Spain	1.28***	1.28***	0.69***
	(0.01)	(0.01)	(0.01)

Note: We run, by country, ln(MRPK) against the TFPR shock, capital, lagged TFPR and year and industry fixed effects. The TFPR shock is given by $\xi_{it} \equiv \omega_{it} - E(\omega_{it}|\mathcal{I}_{it-1})$, where $\mathcal{I}_{it-1}$ is the information set of producer i at time $t-1$; depending on the TFPR process we consider this contains lagged TFPR and producer and year fixed effects. We suppress the coefficients on capital and lagged TFPR (they are significant with negative and positive signs, respectively, everywhere) and also suppress the fixed effects on year and industry. The standard errors are clustered at the firm/plant-level to account for serially correlation and heteroskedasticity. *** denotes significance at the 1 percent level.

Table 7: Aggregate Implications

Aggregate Moment	Coefficient	R^2	Obs.
$\text{Std}_{st}(\Delta MRPK)$ [U.S. only]	1.03***	0.63	4,039
	(0.03)		
$\text{Std}_{st}(\Delta MRPK)$ [excl U.S.]	0.56***	0.64	1,289
	(0.07)		
$\text{Std}_{st}(\Delta MRPK)$ [All]	0.89***	0.68	5,326
	(0.04)		
$\text{Std}_{st}(\Delta k)$ [U.S. only]	0.13***	0.31	4,037
	(0.02)		
$\text{Std}_{st}(\Delta k)$ [excl U.S.]	0.07***	0.62	1,182
	(0.02)		
$\text{Std}_{st}(\Delta k)$ [All]	0.12***	0.76	5,219
	(0.02)		
$\text{Std}_{st}(\Delta k)$ [U.S. only]	0.17***	0.31	4,037
	(0.03)		
$\times\{>$Median Vol.$\}$	-0.03**		
	(0.01)		
$\text{Std}_{st}(\Delta k)$ [excl U.S.]	0.19**	0.63	1,182
	(0.09)		
$\times\{>$Median Vol.$\}$	-0.09		
	(0.06)		
$\text{Std}_{st}(\Delta k)$ [All]	0.17***	0.76	5,219
	(0.03)		
$\times\{>$Median Vol.$\}$	-0.04**		
	(0.02)		

Note: The coefficients are obtained by regressing each aggregate moment against volatility using country-industry-year variation, where we include year and country fixed effects. Standard errors are clustered by country when pooled, and by industry when using U.S. data.

Table 8: Comparing dispersion of MRPK to other inputs' MRPs

	Input		
Country	Capital	Labor	Materials
U.S.	0.81	0.63	0.54
Chile	1.22	0.93	0.48
France	1.25	0.79	0.87
India	1.01	0.87	0.55
Mexico	1.19	0.85	0.51
Romania	1.40	1.17	0.67
Slovenia	1.54	0.98	0.54
Spain	1.45	0.93	0.70

Note: We compute the standard deviation of the MRP of each input by industry-year, and we report the average across industry-years by country.

Table 9: Adjustment Cost Estimates and Moments by Country

Country	Adjustment Costs		Data Moments on Change in Log Capital		
	Convex	Fixed	Less than 5%	More than 20%	Standard Deviation
U.S.	8.80	0.09	0.39	0.09	0.21
Chile	4.10	0.07	0.19	0.11	0.28
India	3.46	0.12	0.29	0.19	0.30
France	0.21	0.00	0.13	0.57	0.57
Spain	0.74	0.00	0.20	0.41	0.59
Mexico	1.15	0.22	0.08	0.73	0.66
Romania	0.66	0.03	0.08	0.61	0.72
Slovenia	0.35	0.00	0.15	0.52	0.76

Notes: Standard errors were computed using the usual formula for minimum-distance estimators. However, due to the large size of the datasets we employ, the standard errors are of the order of 1×10^{-3} or smaller and so we do not report them. Adjustment costs for Slovenia are based on a model with production function coefficients set to the mean U.S. coefficients (see the discussion in Section 4.4).

Table 10: Dispersion in MRPK, S^2 measures of model fit by specification

Country	Specification (1)	(2)	(3)	(4)	(5)
United States	0.223	0.806	0.806	0.643	0.820
France	0.892	0.702	0.899	0.944	0.651
Chile	0.994	0.983	0.987	0.963	0.785
India	0.984	0.941	0.964	0.976	0.596
Mexico	0.879	0.813	0.883	0.908	0.634
Romania	0.983	0.923	0.817	0.702	0.846
Slovenia	0.967	0.774	0.967	0.984	0.683
Spain	0.718	0.627	0.600	0.530	0.495
All (ex U.S.)	0.879	0.777	0.820	0.800	0.640
All	0.674	0.786	0.816	0.748	0.696

Note: The unit of observation is the country-industry. Specifications are: (1) All countries have the U.S.'s estimated adjustment costs and production coefficients equal to the U.S. averages across industries; (2) Industry-country specific production coefficients (except for Slovenia see Section 3.1.2), country specific adjustment costs, industry-country specific AR(1); (3) as for (2), but with the U.S.'s estimated adjustment costs for all countries; (4) as for (3), but with twice the U.S.'s estimated adjustment costs for all countries; and, (5) as for (3), but with zero adjustment costs (other than the one period time-to-build) for all countries. In all specifications, the AR(1) is estimated using TFPR computed using the production coefficients used in the model specification.

Table 11: Static misallocation and volatility:
Using the World Bank data (33 countries)

Panel A: Country-level analysis				
Specification	I	II (unweighted)	III	IV
Dependent Var:	Standard Deviation of $MRPK$, by country			
Std.$[\omega_{it} - \omega_{it-1}]$	0.67***	0.75**	0.64***	0.63***
	(0.21)	(0.28)	(0.22)	(0.21)
Log Assets $(t-1)$				0.00
				(0.01)
Industry FE			X	X
Constant	0.78***	0.79***	0.79***	0.77***
	(0.10)	(0.12)	(0.10)	(0.10)
R^2	0.31	0.22	0.36	0.36

Panel B: Country-Industry-level analysis			
Specification	V	VI	VII
Dependent Var:	Standard Deviation of $MRPK$, by country-industry		
Std.$[\omega_{it} - \omega_{it-1}]$	0.43***	0.42***	0.28**
	(0.08)	(0.08)	(0.10)
Incl. k_{it} & ω_{it}		X	
Industry & Country FE's			X
Industry-Countries	249	249	249
R^2	0.12	0.12	0.53

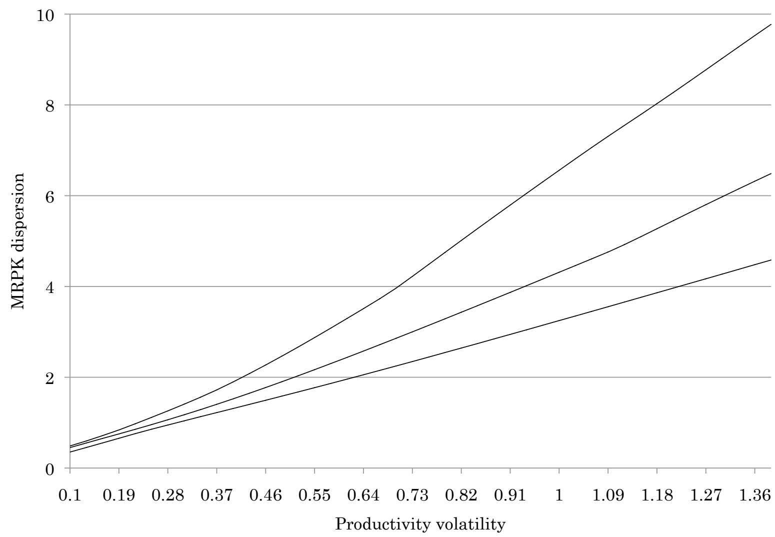
Note: Panel A: Column I and II run regressions on country-level aggregates. Column I runs a weighted OLS with weights equal to the number of firms per country, whereas Column II has equal weights for each country. Columns III and IV run regressions at the firm level (where the dependent variable and Std.$[\omega_{it} - \omega_{it-1}]$ only vary at the country level). The standard errors are clustered at the country level. Panel B: The dispersion in MRPK is computed by industry-country. Standard errors are clustered by industry-country.

Table 12: Correlates of Volatility; Std.$[\omega_{it} - \omega_{it-1}]$

Dependent Var:	TFPR Volatility (Std.$[\omega_{it} - \omega_{it-1}]$)			
	(1)	(2)	(3)	(4)
Cost of Contract Enforcement	0.003*			0.003**
	(0.001)			(0.001)
Time to Enforce Contract	0.000			0.000
	(0.000)			(0.000)
Political Stability Index		-0.030		-0.036
		(0.024)		(0.026)
Natural Disaster Index			0.157*	0.082
			(0.093)	(0.108)
Constant	0.276**	0.607**	0.385**	0.459**
	(0.086)	(0.149)	(0.042)	(0.160)
R-squared	0.074	0.016	0.054	0.143
F-Stat	2.285	1.525	2.843	2.337
Countries	33	33	33	33

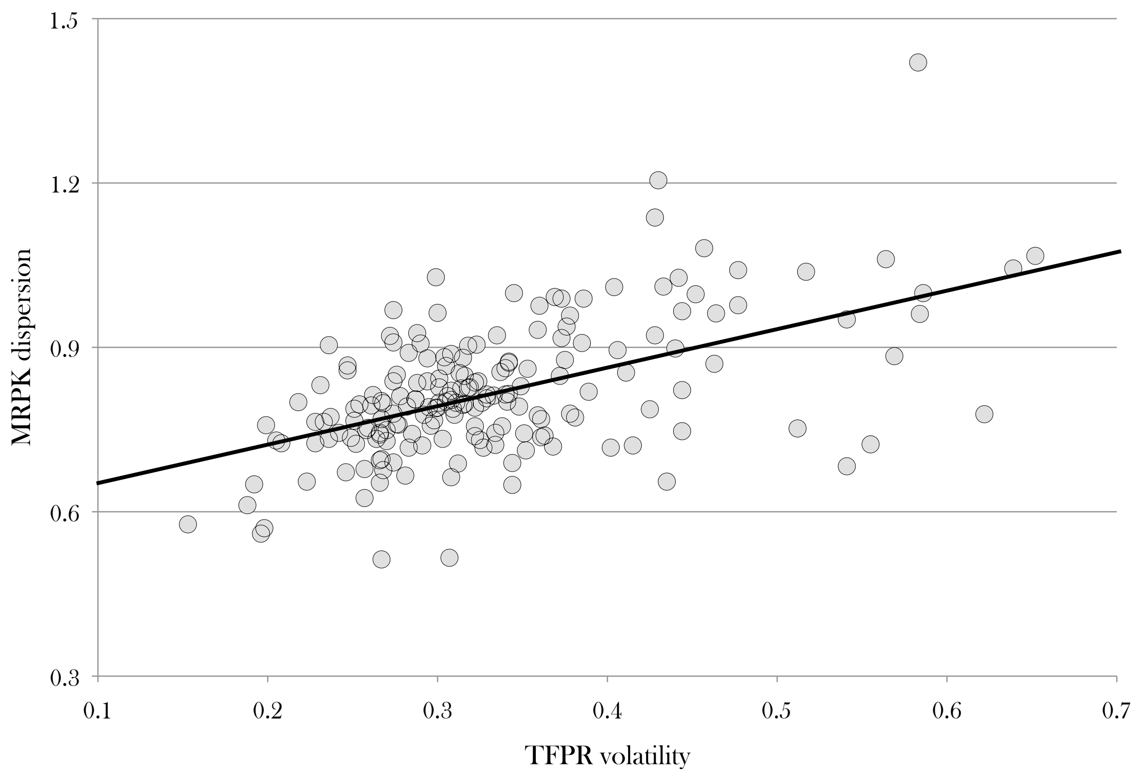
Note: The unit of observation is the country. The specification is an OLS regression. The F-statistic tests for joint significance of all explanatory variables. * $p < 0.10$, ** $p < 0.05$. Cost of Contract Enforcement: Cost is recorded as a percentage of the claim, assumed to be equivalent to 200% of income per capita from the World Bank Doing Business Survey. Time to Enforce Contract: calendar days to enforce a contract, counted from the moment the plaintiff decides to file the lawsuit in court until payment, again from the World Bank Doing Business Survey. Political Stability Index: Economists Intelligence Units measure of political stability and unrest. Natural Disaster Index: count of the number of disasters including natural, meteorological and climatological disasters, from the International Disaster Database. To obtain a meaningful measure we divide the number of disasters by land area.

Figure 1: MRPK dispersion and volatility: Model simulation



Notes: Values used in this simulation are: $\epsilon = -4, \delta = 10\%, \beta = \frac{1}{1+0.065}, \beta_K = 0.12, \beta_M = 0.40, \beta_L = 0.23, C_K^F = 0.09, C_K^Q = 8.8, \lambda = 1, \mu = 0, \rho \in \{0.65, 0.85, 0.94\}$ (corresponding to the lines from bottom (0.65) to top (0.94)), $\sigma \in [0.1, 1.4]$. We use the means in the U.S. Census Data to get our β's and use estimates of adjustment costs for the United States discussed in Section 4.

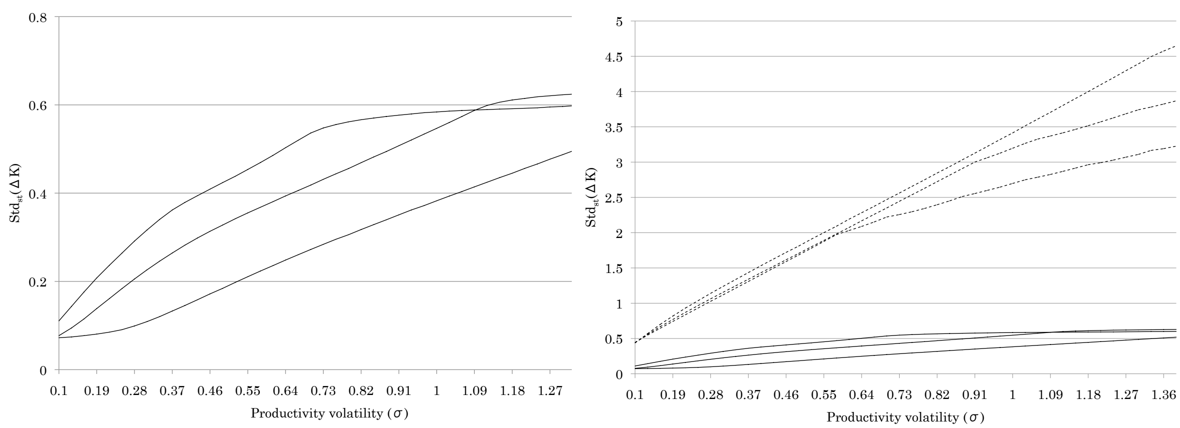
Figure 2: Volatility and the dispersion in MRPK: U.S. plant data 1972-97



Notes: The unit of observation is the industry. The line is generated by an OLS regression, in which the estimated slope is 0.69 (0.10) and the $R^2 = 0.3$. There are 187 observations.

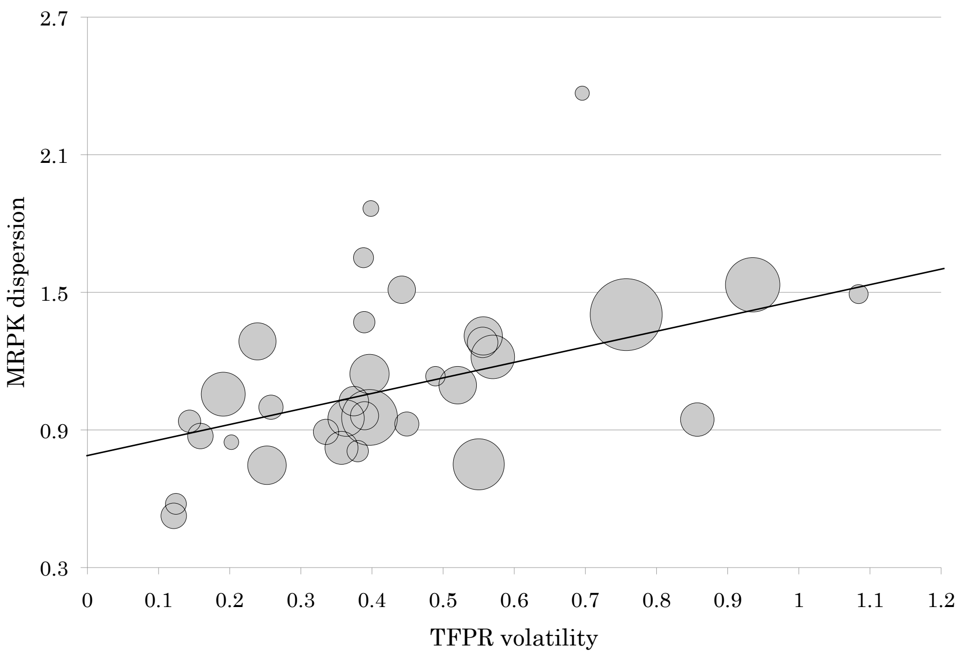
Figure 3: Model Simulation: Dispersion in the change in Capital and Volatility

(a) Adj. costs: $(C_K^F, C_K^Q) = (0.09, 8.8)$ (b) Adj. costs: $(C_K^F, C_K^Q) = (0.09, 8.8)$ and $(0, 0)$



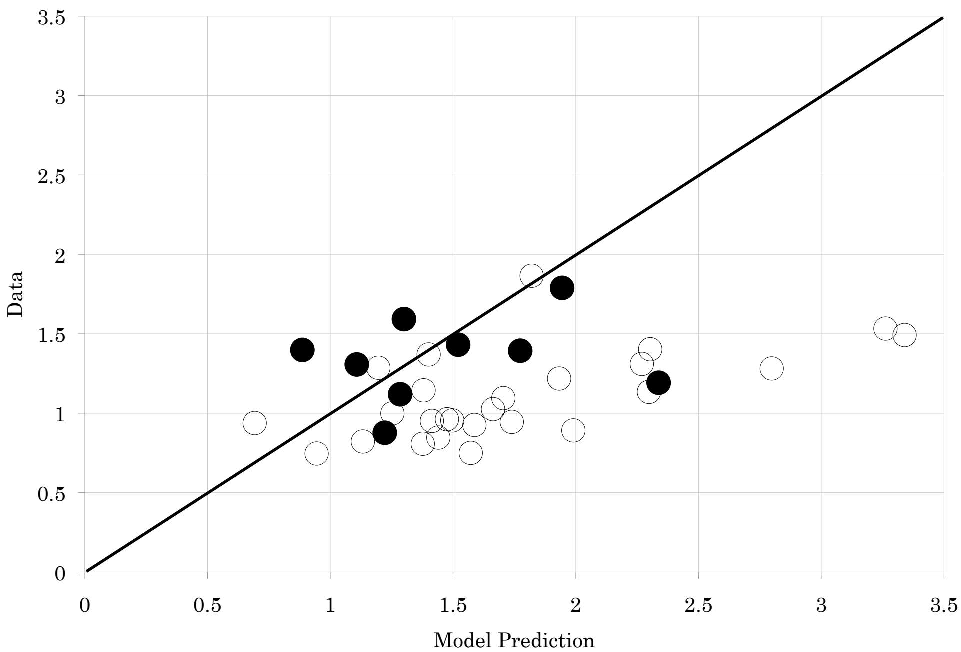
Notes: Parameters are as for Figure 1. $\rho \in \{0.65, 0.85, 0.94\}$ (corresponding to the lines from bottom (0.65) to top (0.94), when $\sigma = 0.3$)

Figure 4: Country-level Static misallocation and TFPR volatility



Note: Circles indicate countries, where circle size is increasing in the number of firms per country. The bold straight line is the line–of–best–fit for the World Bank data (computed using OLS with a constant term, as per specification I in Table 11). The horizontal axis indicates the value of the standard deviation of $[\omega_{it} - \omega_{it-1}]$. The vertical axis indicates the standard deviation in $MRPK$).

Figure 5: Country-level MRPK dispersion: Data vs model simulation



Notes: The vertical axis is data, while the horizontal axis is the model prediction. The unit of observation is the country. Predictions are computed at the industry-country level and then aggregated to the country level. Black dots are tier 1 countries. Unfilled circles are countries in the WBES data. All predictions use industry-country specific production coefficients, a country-level AR(1) process and the adjustments costs estimated for the U.S. in Section 4. The S^2 for the World Bank countries is 0.802 and is 0.906 for the Tier 1 countries. The solid line is the 45° line.

Appendix

A Proof of Invariance to Fixed Effects in Productivity Process

Theorem 1 *Consider the dynamic optimization problem described by the Bellman equation:*

$$\begin{aligned} V(\Omega, K) = \max_{I,M,L} & S(\Omega, K, L, M) - p_L L - p_M M - C(I, K, L, M, \Omega) \\ & + \beta \int_{\Omega'} V(\Omega', \delta K + I) f(d\Omega'|\Omega). \end{aligned} \tag{21}$$

Let $f(\Omega'|\Omega)$ be described by one of the following processes:
(A) $\omega_{it+1} = \mu_i + \rho\omega_{it} + \sigma\epsilon_{it}$; and
(B) $\tilde{\omega}_{it+1} = \tilde{\mu}_i + \rho\tilde{\omega}_{it} + \sigma\epsilon_{it}$.
Then, for any μ_i and $\tilde{\mu}_i$,

i. $(s_{it} - x_{it}|\mu_i) = (s_{it} - x_{it}|\tilde{\mu}_i)$; and

ii. $(x_{it} - x_{it-1}|\mu_i) = (x_{it} - x_{it-1}|\tilde{\mu}_i)$, where $x \in \{l, m, k\}$.

Proof. The proof proceeds by: First, showing that changing the constant in the AR(1) amounts to a level shift in the AR(1) process; then, Second, showing that the entire problem is homogenous of degree 1; then, Third, using this to show that changing the AR(1) constant results in a level shift in the inputs; Lastly, we note that these level shifts get cancelled out when computing differences at the firm level. We use a series of lemmas to develop this reasoning.[41]

Lemma 1 *Consider two processes (A) and (B), above. Process (B) is a level shift of process (A). That is, conditional on initial conditions and the history of ϵ_{it}, $\tilde{\omega}_{it} = \omega_{it} + \log\Lambda$ where $(1-\rho)\log\Lambda = \tilde{\mu}_i - \mu_i$.*

Proof. Starting with process (A), increase ω_{it} by $\log\Lambda$. Now, consider the evolution of process (B) from $\omega_{it} + \log\Lambda$:

$$\begin{aligned} \tilde{\omega}_{it+1} &= \tilde{\mu}_i + \rho(\omega_{it} + \log\Lambda) + \sigma\epsilon_{it} \\ &= \mu_i + (1-\rho)\log\Lambda + \rho(\omega_{it} + \log\Lambda) + \sigma\epsilon_{it} \\ &= \mu_i + \log\Lambda + \rho\omega_{it} + \sigma\epsilon_{it} \\ &= \omega_{it+1} + \log\Lambda \end{aligned}$$

Hence, process (B) is a level shift of process (A). ■

Lemma 2 *A process determining the evolution of $\tilde{\Omega}$, where $\log\tilde{\Omega} = \tilde{\omega}$, described by (B) is isomorphic, in terms of realizations of random variables, to a process determining $\Lambda\Omega$ where the process describing the evolution of Ω is (A).*

Proof. This is a corollary of Lemma 1. ■

The rest of the proof employs a transformation of the problem.[42] Let

[41]In both the theorem and proof, unless noted otherwise, variable definitions and notation follows that used in the paper.

[42]Bloom (2009) employs a similar transformation (at footnote 25).

$$G_{it}^{1-a-b-c} = \Omega_{it}, \text{ and } (1-a-b-c)\, g_{it} = \omega_{it}$$

.
since this is a bijective mapping, we can rewrite the TFPR process as

$$(1-a-b-c)\, g_{it+1} = \mu_i + \rho\,(1-a-b-c)\, g_{it} + \sigma\epsilon_{it} \tag{22}$$

and the sales function as

$$S_{it} = G_{it}^{1-a-b-c} K_{it}^{a} L_{it}^{b} M_{it}^{c}$$

This transformation will allow us to exploit homogeneity properties in a transparent manner. To keep notation consistent, but distinct, let $\lambda^{1-a-b-c} = \Lambda$. Note that:

Lemma 3 (Sales) $\lambda S_{it}\,(G_{it}, K_{it}, L_{it}, M_{it}) = S_{it}\,(\lambda G_{it}, \lambda K_{it}, \lambda L_{it}, \lambda M_{it})$

Before proceeding to the homogeneity of the value function, it is helpful to establish that the static inputs, L and M, under processes (A) and (B) are (multiplicative) level shifts of each other. This makes it easier to state subsequent Lemmas and manipulate the value function.

Lemma 4 *If L_{it}^* and M_{it}^* are solutions to the system of first order conditions of static inputs, given G_{it} and K_{it}; then, given λG_{it} and λK_{it}, λL_{it}^* and λM_{it}^* are solutions.*

Proof. It is sufficient to show that this is true for labor. As established in the paper, the first order condition is

$$\frac{b S_{it}\,(G_{it}, K_{it}, L_{it}^*, M_{it}^*)}{L_{it}^*} = p_L \tag{23}$$

Now, we need to show that, given λG_{it} and λK_{it}, λL_{it}^* and λM_{it}^* solve the first order condition.

$$\begin{aligned}
\frac{b S_{it}\,(\lambda G_{it}, \lambda K_{it}, \lambda L_{it}^*, \lambda M_{it}^*)}{\lambda L_{it}^*} &= \frac{b \lambda S\,(G_{it}, K_{it}, L_{it}^*, M_{it}^*)}{\lambda L*} \\
&= \frac{b S_{it}\,(G_{it}, K_{it}, L_{it}^*, M_{it}^*)}{L*} \\
&= p_L
\end{aligned}$$

where the first equality follows from Lemma 3, and the last from equation (23) . Hence, λL_{it}^* and λM_{it}^* solve the first order condition. ■

Lemma 4 allows us to express everything that follows as functions of G and K (and I), noting that, where relevant, a proportional increase in both leads to a equivalent proportional increase in L and M. Note, in particular, that we can re-write the Bellman equation as

$$V(G,K) = \max_I \pi(G,K) - C(G,K,I) + \beta \int_{G'} V(G', \delta K + I)\phi(dG'|G). \tag{24}$$

We now turn to establishing the homogeneity properties of the various components of the Bellman equation, stated in Theorem 1.

Lemma 5 (Period Profits) *Given $\pi\,(G_{it}, K_{it}) = S_{it}\,(G_{it}, K_{it}, L_{it}^*\,(G_{it}, K_{it})\,, M_{it}^*\,(G_{it}, K_{it})) - p_L L_{it}^*\,(G_{it}, K_{it}) - p_M M_{it}^*\,(G_{it}, K_{it})$, then, $\pi\,(\lambda G_{it}, \lambda K_{it}) = \lambda \pi\,(G_{it}, K_{it})$.*

Lemma 6 (Capital Transition) $\lambda K_{it+1}(K_{it}, I_{it}) = K_{it+1}(\lambda K_{it}, \lambda I_{it})$

Lemma 7 (Adjustment Costs) $\lambda C_{it}(G_{it}, K_{it}, I_{it}) = C_{it}(\lambda G_{it}, \lambda K_{it}, \lambda I_{it})$

Lemma 8 (TFPR Transition) *Let process (B) be written in terms of g such that*

$$(1-a-b-c)\, g_{it+1} = \mu_i + (1-\rho)(1-a-b-c)\log\lambda + \rho(1-a-b-c)\, g_{it} + \sigma\epsilon_{it}$$

and let the associated distribution describing the transitions of G be $\phi_{(B)}(G_{it+1}|G_{it})$. Similarly, let (A) be written as in equation 22 and let the associated distribution describing the transitions of G be $\phi_{(A)}(G_{it+1}|G_{it})$. Then, fixing G_{it} and G_{it+1},

$$\phi_{(B)}(\lambda G_{it+1}|\lambda G_{it}) = \phi_{(A)}(G_{it+1}|G_{it})$$

Proof. This follows from Lemma 1 and 2, noting that $\lambda^{1-a-b-c} = \Lambda$. ■

We now turn to the value function, as defined in equation (24). Let $V_{(A)}(G, K)$ be the value function when the TFPR process is described by (A). Similarly, let $V_{(B)}(G, K)$ be the value function when the TFPR process is described by (B). That is,

$$V_{(B)}(G, K) = \max_I \pi(G, K) - C(G, K, I) + \beta \int_{G'} V_{(B)}(G', \delta K + I)\phi_{(A)}(dG'|G).$$

Lemma 9 (Value Function) *For any G and K, $V_{(B)}(\lambda G, \lambda K) = \lambda V_{(A)}(G, K)$*

Proof.
We begin by defining $I^*_{(A)}(G, K)$ as the optimal investment policy corresponding to $V_{(A)}(G, K)$. We next define $W_{(A)}(G, K, I)$ as the choice specific value function under process (A). That is, $W_{(A)}(G, K, I)$ is the value generated when investment in the current period is set at I, rather than $I^*_{(A)}(G, K)$. So,

$$W_{(A)}(G, K, I) = \pi(G, K) - C(G, K, I) + \beta \int_{G'} V_{(A)}(G', \delta K + I)\phi_{(A)}(dG'|G). \quad (25)$$

$W_{(B)}(G, K, I)$ is defined analogously.

The proof proceeds by assuming that the *future* value function, $V_{(B)}(G', \delta K + I)$, satisfies the Lemma, and showing that this implies that $W_{(B)}(G, K, I)$ has the same property. We then show that this, in turn, implies that the *present* value function, $V_{(B)}(G, K)$, satisfies the Lemma. Hence, in a stationary context, the proof exploits an inductive argument.

First, assume $V_{(B)}(\lambda G', \lambda(\delta K + I)) = \lambda V_{(A)}(G', \delta K + I)$. Now,

$$\begin{aligned}
W_{(B)}(\lambda G, \lambda K, \lambda I) &= \pi(\lambda G, \lambda K) - C(\lambda G, \lambda K, \lambda I) + \beta \int_{\lambda G'} V_{(B)}(\lambda G', \delta\lambda K + \lambda I)\phi_{(B)}(d\lambda G'|\lambda G) \\
&\quad \text{next, from Lemma 8:} \\
&= \pi(\lambda G, \lambda K) - C(\lambda G, \lambda K, \lambda I) + \beta \int_{G'} V_{(B)}(\lambda G', \delta\lambda K + \lambda I)\phi_{(A)}(dG'|G) \\
&\quad \text{then, from Lemmas 5, 6, and 7, and the maintained assumption:} \\
&= \lambda\pi(G, K) - \lambda C(G, K, I) + \lambda\beta \int_{G'} V_{(A)}(G', (\delta K + I))\phi_{(A)}(dG'|G). \\
&= \lambda W_{(A)}(G, K, I)
\end{aligned}$$

Next, we show that this implies that the *present* value function, $V_{(B)}(G,K)$, satisfies the Lemma. First note that if $I^*_{(A)}(G,K) = \arg\max_I W_{(A)}(G,K,I)$ then $\lambda I^*_{(A)}(G,K)$ solves $\arg\max_I W_{(B)}(\lambda G, \lambda K, I)$ since $W_{(B)}(\lambda G, \lambda K, \lambda I) = \lambda W_{(A)}(G,K,I)$. Next,

$$\begin{aligned} V_{(B)}(\lambda G, \lambda K) &= \max_I W_{(B)}(\lambda G, \lambda K, I) \\ &= W_{(B)}\left(\lambda G, \lambda K, \lambda I^*_{(A)}(G,K)\right) \\ &= \lambda W_{(A)}(G,K,I^*(G,K)) \\ &= \lambda V_{(A)}(G,K) \end{aligned}$$

Thus $V_{(B)}(\lambda G, \lambda K) = \lambda V_{(A)}(G,K)$. ■

Lemma 10 *Let $\{\epsilon_{it}\}_{t=0}^{\infty}$ be a path of realizations of ϵ_{it} and let g_{i0} and K_{i0} be the initial conditions of g and K under process (A) and $g_{i0} + \lambda$ and λK_{i0} be the initial conditions under process (B). Then, if $\{K_{it}\}_{t=0}^{\infty}$ is the path of capital under process (A) then $\{\lambda K_{it}\}_{t=0}^{\infty}$ is the path under process (B).*

Proof. This follows from Lemmas 1 and 8, and Lemma 9. As before, let $I^*(G,K)$ be the investment policy under process (A). Now, consider the optimal investment problem under process (B) with capital state λK.

From Lemma 9 we know that $\lambda I^*_{(A)}(G,K) = I^*_{(B)}(\lambda G, \lambda K)$. That is, if $I^*_{(A)}(G,K)$ is the solution when $\lambda = 0$ (i.e. process (A)), then $\lambda I^*_{(A)}(G,K)$ is the solution when $\lambda > 0$ (i.e. process (B)). Hence, under process (B), the path of the capital stock is a level shift of that under process (A). That is, if $\{K_{it}\}_{t=0}^{\infty}$ is the path of capital under process (A) then $\{\lambda K_{it}\}_{t=0}^{\infty}$ is the path under process (B). ■

Together, Lemmas 3, 4 and 10 allow us to compare $std(s_{it} - x_{it})$ and $std(x_{it} - x_{it-1})$ under processes (A) and (B). Holding all else constant, if s_{it}, x_{it} and x_{it-1} are the realizations under (A), then $s_{it} + log(\lambda)$, $x_{it} + log(\lambda)$ and $x_{it-1} + log(\lambda)$ are the realizations under (B). Since constants will be cancelled out in the computing of differences, the theorem is established. ■

B Data Appendix

We employ multiple datasets in our analysis. We classify these datasets into two tiers, shown in Table 1. Tier 1 consists of country-specific high-quality producer-level data from eight countries: the United States, Chile, France, India, Mexico, Romania, Slovenia, and Spain. Each of these data sets has been used extensively in the literature; most commonly in the analysis of productivity.[43] Tier 2 consists of the World Bank Enterprise Survey (WBES). We discuss the details of each dataset below. For a description of the measurement of productivity see Section 3.1.2. We also include additional robustness results, adding to those reported in Section 3.

[43] See, for instance, Tybout and Westbrook (1995), Roberts (1996), Pavcnik (2002), Rankin, Söderbom, and Teal (2006), Van Biesebroeck (2005), De Loecker and Konings (2006); De Loecker (2007), Goldberg, Khandelwal, Pavcnik, and Topalova (2009), Bloom, Draca, and Van Reenen (2011), Konings and Vandenbussche (2005).

B.1 United States

The data for the United States comes from the U.S. Census Bureau's Research Data Center Program. We use data on manufacturing plants from the Census of Manufacturers (henceforth, CMF), and the Annual Survey of Manufacturers (henceforth, ASM) from 1972 to 1997.[44] The CMF sends a questionnaire to all manufacturing plants in the United States with more than 5 employees every five years, while the ASM is a four-year rotating panel with replacement, sent to approximately a third of manufacturing plants, with large plants being over-represented in the sampling scheme.

Labor is measured using the total number of employees at the plant. Materials are measured using total cost of parts and raw materials. Capital is constructed in two ways. For the majority of plants, including all plants in the CMF, capital is measured using a question on total assets – be they machines or buildings – at the plant. For the remaining observations, capital is constructed using the perpetual inventory method, using industry-specific depreciation rates and investment deflators from the Bureau of Economic Analysis and the National Bureau of Economic Research. Capital, materials and sales are deflated using the NBER-CES industry-level deflators into 1997 dollars.

The original dataset has approximately 3 million plants. However, only 1.8 million of these have sufficient; i.e. – non-zero and non-missing, data on sales, labor, capital and materials, required to construct productivity. Out of these, we keep plant-years for which we have observations in consecutive years, which allow us to measure changes in productivity. There are several industries (measured by the four-digit SIC code), which have a small number of plants. We drop industries which either: a) have less than 50 plants in any given year, or b) with less than 1,000 plants over the entire sample period. The omission of these small-plant-number industries has little effect on our estimates, and they represent a limited number of plants in the data; but dropping these small plant-number industries is essential for the disclosure of our results. The final dataset has 735,342 plants over a 26 year period.

B.2 Chile

Annual plant-level data on all manufacturing plants with at least ten workers were provided by Chile's Instituto Nacional de Estadistica (INE). These data, which cover the period 1979-1986, include production, employment, investment, intermediate input, and balance-sheet variables. The data were prepared for analysis by INE: standardization of variable definitions across years, identification of entering and exiting plants and adjustment for inflation distortions, and construction of capital stock variables. Industries are classified according to the four digit ISIC industry code.

Output and input price indices are constructed at the three digit industry and obtained directly from average price indices produced by the Central Bank of Chile. Data on nominal and real values of the various capital goods are reported, including buildings, machinery, furniture, vehicles and others, and allow the construction of price deflators. We directly observe total number of employees, total real value of production, total real intermediate input, total real book-value of fixed assets, total real salaries. In total there are 37,600 plant-year observations reporting employment, with a minimum of 4,205 plants in 1983 and 5,814 plants in 1979.

The data were generously provided by Jim Tybout through a license at the International Economics Section of Princeton University. See Pavcnik (2002) for a productivity study using these data.

B.3 France, Romania and Spain

Annual firm-level data on manufacturing firms for France, Romania and Spain are obtained from Bureau Van Dijck's (BvD) Amadeus dataset and cover firms reporting

[44] We use a version of these files that has been processed for productivity analysis by the staff at the Center for Economic Studies at the U.S. Census Bureau, and more information on the construction of this data can be found in the productivity database files at Census.

to the local tax authorities and/or data collection agencies for the period 1999-2007. We selected three relatively large European countries at different stages of economic development. The coverage for all three countries is substantial in that we cover approximately 90 percent of economic activity in each of the three manufacturing sectors. For example, for France, in 2000, we record total sales of 739 billion Euros, whereas the OECD reports total sales to be 768 billion Euros. This implies coverage of 96 percent of total economic activity in manufacturing. For Spain we find, using the same coverage calculation, coverage of 88 percent. The collection protocol of BvD is consistent across countries. We focus on the manufacturing sector to facilitate the measurement of productivity.

The data include standard production data where we observe Total Operating Revenue (production), Total Number of Employees (employment), Total Material Costs (intermediate input), Total Costs of Employees (wagebill), Total Fixed Assets and all the subcomponents of the capital stock such as Buildings, Furniture, Vehicles, Equipment and Others, as well as other standard income statement and balance-sheet variables. The data also provide information on the firm's legal status, whether the firm is active and its consolidation code. We use this information to make sure we only include firms actively producing in a specific industry and only use their unconsolidated accounts to for instance avoid including total sales of a multinational across affiliates located in different countries. This data is known to slightly under-represent small firms due to the threshold on either firm size or total number of employees (see Table 1 above). In Section B.7, below, we verify that our results are invariant to imposing a common threshold across all our datasets.

Industries are classified according to the two digit NACE Rev 1.1. code for all three countries. Our data covers sectors firms primarily active in sectors NACE Rev 1.1. 15 to 36.

The manufacturing sector in each country leaves us with 391,422, 174,435 and 457,934 firm-year observations for France, Romania and Spain. Two digit NACE rev.1.1. industry producer prices are used to deflate all nominal values and are downloaded from EUROSTAT's online statistics database.[45]

Access to Bureau Van Dijck's Amadeus was obtained through Princeton University's Library license. For recent work drawing on the AMADEUS data see Bloom, Draca, and Van Reenen (2011) and the discussion therein.

B.4 India

Annual firm-level data on manufacturing firms were provided by Prowess, and are collected by the Centre for Monitoring the Indian Economy (CMIE). Prowess is a panel that tracks firm performance over time. These data cover the period 1989-2003 and contain mainly medium and large Indian firms.

Industries are classified according to the NIC classification code (India's industrial classification system) and firms report the principal industry activity at the four digit PNIC level.

These data include various production, employment, investment, intermediate input, and balance-sheet variables. In particular we observe Total Sales, Total Material Costs, Total Fixed Assets and Total Wage-bill. The data reports both product-level sales and total sales. We aggregate product-level sales to the firm level. The Indian data does not report the wage-bill separate from the number of workers. We do, however, take care to appropriately deflate the wage-bill. All nominal values are converted to real values using a two digit producer prices. In total there are 30,709 firm-year observations reporting a wage-bill, and there are 4,154 firms active throughout the sample period.

The data are used in Goldberg, Khandelwal and Pavcnik (2011) and were bought under a license by Goldberg, Khandelwal and Pavcnik. For recent work using the

[45]See `http://appsso.eurostat.ec.europa.eu/nui/setupModifyTableLayout.do`. The data are found under "Industry, trade and services> Short-term business statistics > Producer prices in industry".

same data in the context of production function estimation see De Loecker, Goldberg, Khandelwal, and Pavcnik (2012), and more details on the data are discussed therein.

B.5 Mexico

Annual plant-level data on manufacturing plants are recorded by Mexico's Annual Industrial Survey and are provided by Mexico's Secretary of Commerce and Industrial Development (SEC-OFI). The sample of plants (the 3200 largest manufacturing firms) represents approximately eight percent of total output, where the excluded plants are the smallest ones. For each plant and year we observe the usual data on production, input use, investment, inventories, and costs, as well as industry codes and plant identity codes that allow us to track establishments over time.

Industries are classified according to the Mexican Industrial Classification (a four digit industrial classification system).

These data, which cover the period 1984-1990, include production, employment, investment, intermediate input, and balance-sheet variables. In particular we use Total Value of Output, Total Employment, Total Material Costs and Total Fixed Assets. SECOFI also provided price indices at the industry level for output and intermediate inputs, and sector-wide deflators for machinery and equipment, buildings, and land, which we used to convert all nominal values to real values. In total there are 21,180 plant-year observations reporting employment, with a minimum of 2,958 plants in 1989 and 3,175 plants in 1984.

The data were generously provided by Jim Tybout through a license at IES Princeton University. Tybout and Westbrook (1995) contains more details and contains an application to productivity analysis.

B.6 Slovenia

The data are taken from the Slovenian Central Statistical Office and are the full company accounts of all firms operating in the manufacturing sector between 1994 and 2000. The original accounting data for the period between 1994 and 2002 was provided by AJPES (Agency of the Republic of Slovenia for Public Legal Records and Related Services).

We have information on 7,915 firms: an unbalanced panel with information on production, employment, investment, intermediate input, and balance-sheet variables. In particular we observe: Total Sales, Total Material Costs, Total Fixed Assets, Total Cost of Employees and Total number of employees. All monetary variables are recorded in Slovenian Tolars and have been deflated using the consumer price index (for data relating to capital stock) and a producer price index (at the 2-digit NACE industry level). In total there are 29,058 firm-year observations reporting employment, with a minimum of 3,355 in 1994 and a maximum of 4,788 firms in 2000. The sharp increase in the number of firms, unlike in datasets with thresholds on firm size, reflects the sharp growth of Slovenia and the manufacturing sector in particular. See for example De Loecker and Konings (2006) for a discussion on the entry of *de novo* firms during the transition period – which is covered in our sample period.

Industries are classified according to the two digit NACE Rev 1.1. code for all three countries. Our data covers sectors firms primarily active in sectors NACE Rev 1.1. 15 to 36.

We would like to thank Joze Damijan at Ljublijana University for sharing the data. We refer the reader to De Loecker and Konings (2006) and De Loecker (2007) for more on the data, and an application to production function estimation.

B.7 Sample Frame Differences

Lastly, given the heterogeneity in sampling frames across the countries we use, we investigate the extent to which Tier 1 results reported in Section 3 are sensitive to changing the sampling based on firm size. Table B.1 imposes alternative minimum size thresholds on the non-U.S. data sets and presents regression coefficients from projecting various moments on TFPR volatility.[46] As can be seen, adopting alternative sampling based on size appears to have little qualitative impact on our results.

Table B.1: Robustness of Main Results to Firm Size Threshold

	Employment ≥ 25	Employment ≥ 10
MRPK (All I)	0.31***	0.30***
	(0.09)	(0.14)
MRPK (All II)	0.30***	0.22***
	(0.10)	(0.09)
sd(Δ MRPK)	0.47***	0.44***
	(0.07)	(0.06)

Note: We report the results of across all countries excluding the U.S. and India (which does not report employment). The results are robust for each country and for brevity we only report the cross country specifications. 'All I' and 'All II' consider the cross country relationship between the dispersion in MRPK and volatility and corrects for year and country fixed effects and standard errors are clustered by country. 'All I' refers to the unweighted regression, whereas 'All II' refers to a weighted regression with the weights the number of observations in a country – i.e., an industry-year observation.

B.8 World Bank Data

The World Bank Enterprise Research Data were collected by the World Bank across 41 countries and many different industries between 2002 and 2006. Standard output and input measures are reported in a harmonized fashion. In particular, we observe sales, intermediate inputs, various measures of capital, and employment, during (and covering up to) a three-year period, which allows us to compute changes in TFPR and capital. Out of the 41 countries in the data, 33 have usable firm-level observations. This is primarily because, for many years and countries, the World Bank did not collect multi-year data on capital stock. Table B.2 lists the countries we are able to use, together with the number of observations on each country. The data are available from `http://www.enterprisesurveys.org`, accessed on December 15th, 2010. Extensive documentation is available from the same website.

The survey documentation describes the sampling universe as follows: "*6. The population of industries to be included in the Enterprise Surveys and Indicator Surveys, the Universe of the study, includes the following list (according to ISIC, revision 3.1): all manufacturing sectors (group D), construction (group F), services (groups G and H), transport, storage, and communications (group I), and subsector 72 (from Group K). Also, to limit the surveys to the formal economy the sample frame for each country should include only establishments with five (5) or more employees. Fully government owned establishments are excluded as the Universe is defined as the non-agricultural*

[46]We omit the U.S. due to the census disclosure burden, given that our other data sets indicate that there is reason to expect adopting a minimum size threshold would affect results.

private sector."[47]

The survey used a stratified sampling procedure, in which firms were sampled randomly within groups based on the firm's sector of activity, firm size, and geographical location. The structure of the sampling leads to an oversampling of larger firms (relative to random sampling of all firms in the economy). The exact structure of the stratification varies by the size of the economy in question. We have chosen to not do any sampling correction, preferring to maintain as much transparency as possible as to the mapping from data to findings, being mindful of the fact that we can use data from only 7 percent of the sampled firms in any case and, most importantly, considering the absence of a well-defined criterion that could be used to guide any such correction. In any case, the results in the paper are robust to controlling for differences in the size and industrial composition of firms across countries.

The firms in the data are drawn from the manufacturing, construction, services, and transport, storage, and communications sectors. As would be expected, the precise industry composition (defined at the two-digit ISIC level) varies by country. The majority of firms within a country were surveyed in the same year. The survey asked questions about activity in the current year and the previous two years. Thus, the panel-data aspect of these data, relating to activity in year $t-1$, comes from the recollections and records of managers in year t.

To construct data on TFPR and the change in TFPR we need two years of information on sales, assets, intermediate inputs and employment. 5,558 firms across our 33 countries meet this criterion.[48] For some of the countries in the World Bank Enterprise Data, a number of issues emerged in the calculation of TFPR. In particular, labor use is typically reported as the number of employees or a wage bill converted to the number of employees with no correction for hours worked. Moreover, sales and gross output data are not corrected for inventories, and the capital stock is based on book values. These are standard data restrictions researchers face using this type of data.

Sales are directly measured in the data. Hence, for many firm-years in the data, we can compute TFPR directly. However, for some firm-years, we observe only the firm's wage bill and not the number of workers. To address this issue, we use the median country-industry wage, $\tilde{w}$, (imputed from observations with both the wage bill and the number of workers) as a deflator and apply it to the wage bill to give a measure of labor. That is, to compute L_{it} we use $L_{it} = \frac{wL_{it}}{\tilde{w}}$. In what is presented in this paper, we use this measure for all firm-year observations. Finally, we rely on the book value of capital as measured by either total assets or net book value. We experimented with both measures and our results are invariant. When we consider a measure of value added, we compute it by netting the sales variable from the use of intermediate inputs.

Finally, we convert all relevant variables into real values using detailed producer price and input price deflators where available. For the 33 countries covered in the World Bank data, we rely on the World Bank deflators to convert all monetary variables into USD. To do this, we use the World Bank's measure of purchasing power parity (PA.NUS.PPP). Note that we account for differences in the rate of inflation across countries by using a year-specific measure of PPP. Since TFPR is a ratio, these PPP conversions get netted out in many specifications, but they are useful when, for instance, we use controls for firm size.

While there are over 41,000 observations in the data, only 5,558 have information on capital over several years, which is needed to compute TFPR volatility. Table B.3 presents summary statistics of the data, where for each variable, the first line refers to the data that we use, while the second presents the data that we dropped due to insufficient information to compute changes in TFPR. The dropped observations are usually smaller firms with lower sales and fewer employees. However, changes in inputs (such as changes in capital or labor) are comparable across the data we did and did not use. Notice that the dispersion of TFPR is similar between the two data sets, with a standard deviation of 1.0 (our data) versus 1.2 (dropped data), as well as the dispersion

[47] From page 3 in 'Enterprise Survey and Indicator Surveys Sampling Methodology' August 29th, 2009 at `http://www.enterprisesurveys.org/Documents/Sampling_Note.pdf` downloaded 23 April, 2011.

[48] We also drop countries with fewer than 25 observations. This has little effect on our results.

of the sales to capital ratio which is 1.1 (our data) versus 1.3 (dropped data). Thus, the sampling bias will slightly understate the level of TFPR and MRPK dispersion, but this effect is small relative to the large differences in dispersion across countries.

Table B.2: Countries in the World Bank data sample

Region	**Country**	**Std.(MRPK)**	**Firms**
North Africa			
	Morocco	0.75	376
Sub-Saharan Africa			
	Benin	0.81	66
	Ethiopia	1.31	211
	Madagascar	0 .93	84
	Malawi	1.03	125
	Mauritius	1.49	52
	South Africa	1.29	199
	Tanzania	1.65	58
	Zambia	0.82	157
Central Asia			
	Kyrgyzstan	0.53	94
	Tajikistan	0.87	94
	Uzbekistan	0.89	92
Middle East			
	Syria	1.13	55
South Asia			
	Bangladesh	1.28	134
	Sri Lanka	0.96	114
South East Asia			
	Indonesia	1.53	426
	Philippines	1.06	278
	Thailand	0.75	214
	Vietnam	0.95	448
Central America			
	Costa Rica	1.22	273
	Ecuador	1.51	109
	El Salvador	0.95	190
	Guatemala	0.95	162
	Honduras	1.10	203
	Nicaragua	1.14	222
South America			
	Brazil	1.00	85
	Chile	1.40	745
	Guyana	2.37	29
	Peru	0.85	31
Europe			
	Moldova	0.94	72
	Lithuania	1.37	66
	Poland	0.58	63
	Turkey	1.87	36

Table B.3: Selection Bias due to Missing Data in World Bank Data

Variable	**Mean**	**Std. Dev.**	**N**
Log Sales	7.0	3.1	5579
	6.7	3.3	51043
Log Value Added	6.0	3.1	4719
	5.9	3.3	42230
Log Materials	6.4	3.3	5579
	5.2	3.5	46642
Log Capital	6.9	3.1	5579
	7.5	3.0	12728
Log Labor	5.2	2.9	4715
	4.8	3.1	23696
Workers	284	874	5579
	145	1010	50891
Productivity	2.3	1.0	5579
	2.4	1.2	4750
Sales to Capital Ratio	0.1	1.1	5579
	0.2	1.3	12528
Sales to Labor Ratio	2.9	2.2	5579
	3.1	3.2	37918
Change in Capital	0.1	0.5	5579
	0.1	0.5	11268
Change in Labor	0.2	0.7	4626
	0.1	0.6	14360
Change in the Sales to Capital Ratio	0.0	0.7	5579
	0.0	0.7	11017

Note: The first row shows the data used in the paper, and the second row indicates data that we dropped due to some missing observation.

B.9 Measures of Countries Economic Environment

In this section we provide additional detail on the measures used for the regression in Table 12.

Cost of Contract Enforcement and Time to Enforce Contract: The World Bank Doing Business Survey (WBDBS)[49] measures the cost of enforcement of contracts as a percentage of a claim. The data for the survey were collected yearly from 2004 to 2012, and we use the survey responses for 2012. From the documentation, the enforcement cost is measured in the following way:

> *Enforcement of contracts: cost as % of claim: Cost is recorded as a percentage of the claim, assumed to be equivalent to 200% of income per capita. No bribes are recorded. Three types of costs are recorded: court costs, enforcement costs and average attorney fees. Court costs include all court costs that Seller (plaintiff) must advance to the court, regardless of the final cost to Seller. Enforcement costs are all costs that Seller (plaintiff) must advance to enforce the judgment through a public sale of Buyer's movable assets, regardless of the final cost to Seller. Average attorney fees are the fees that Seller (plaintiff) must advance to a local attorney to represent Seller in the standardized case.*

The WBDBS measures the time to enforce a contract as:

> *Time is recorded in calendar days, counted from the moment the plaintiff decides to file the lawsuit in court until payment. This includes both the days when actions take place and the waiting periods between. The average duration of different stages of dispute resolution is recorded: the completion of service of process (time to file and serve the case), the issuance of judgment (time for the trial and obtaining the judgment) and the moment of payment (time for enforcement of the judgment).*

Political Stability Index: We rely on the Economists Intelligence Unit's measure of political stability. It is an index meant to capture the extent to which a country is in a state of political unrest. These data attempt to measure unrest over the period 2009-2010. See `http://viewswire.eiu.com/site_info.asp?info_name=social_unrest_table&page=noads` for more details on the methodology and data. The data were downloaded on April 25, 2013.

Natural Disaster Index: The data on disasters comes from the EM-DAT The International Disaster Database (at `http://www.emdat.be/` accessed on 5/13/2013) and counts the number of disasters (dating back to 1900) including natural, meteorological and climatological disasters and to obtain a meaningful measure we divide the number of disasters in recent years, the last decade (2002-2012) in particular, by the appropriate land area.

C Model Computation

The parameters we use are found in Table C.1. Parameters for the elasticity of demand, depreciation rate, and discount rate follow those adopted by Bloom (2009). The last set of parameters we need to fix are the σ, ρ and μ terms in the AR(1) process, which governs the evolution of productivity over time. We compute the model for values of σ between 0.1 and 1.4, which covers the range we observe in data. For ρ we pick

[49] The World Bank Doing Business Survey is at `http://www.doingbusiness.org/methodology/~/media/GIAWB/Doing\%20Business/Documents/Methodology/Supporting-Papers/DB-Methodology-Courts.pdf`. Accessed February 5, 2013.

three values, 0.65, 0.85 and 0.94. Lastly, we set $\mu = 0$. We also implicitly normalize the prices of non-capital inputs by setting $\lambda = 1$. More precisely, what we are are normalizing is λ, a function of these non-capital input prices. The functional form of λ puts structure on the relative prices of non-capital inputs. Subject to this structure, normalizing λ is equivalent to a normalization of one of the non-capital input prices.

Table C.1: Simulation parameters

Parameter	Comments
$\epsilon = -4$ $\delta = 10\%$ $\beta = \frac{1}{1+6.5\%}$	Values also used in Bloom (2009).
$\beta_K = 0.12$ $\beta_M = 0.40$ $\beta_L = 0.23$	Mean values in U.S. Census Data.
$C_K^F = 0.09$ $C_K^Q = 8.8$	Estimated using U.S. Census Data, see Section 4.1.2.
$\rho \in \{0.65, 0.85, 0.94\}$ $\sigma \in [0.1, 1.4]$	Selected to fall within range of estimated values for the U.S. Census.
$\lambda = 1$	Scaling parameter that normalizes the price of non-capital inputs.
$\mu = 0$	Normalization that has no effect on computed moments, by Theorem 1.

We compute the optimal investment policies for the value function in equation (9). We solve this model using a discretized version of the state space (Ω_{it}, K_{it}). Specifically, we use a grid of capital states ranging from log capital 3 to log capital equal to 20, in increments of 0.03. Moreover, we use a grid of productivity with 30 grid points, whose transition matrix and grid points are computed using Tauchen (1986)'s method. The model is solved using policy iteration with a sparse transition matrix (since there are 17,000 states). Using the computed optimal policies, we simulate the evolution of a country, or industry, for 10,000 firms over 1,000 periods. We use the output from the 1,000th and 988th periods to compute the reported results (corresponding to years t and $t-1$; recall that we interpret a period as a month).

D ONLINE Appendix to *Dynamic Inputs and Resource (Mis)Allocation*- Not For Publication

This section gives additional tables and figures that provide the details behind comments made in footnotes and text. Some tables are also provided merely to give more detail to the interested reader. The majority of the appendix is devoted to robustness and further detail regarding the analysis of the World Bank data contained in Section 5.

Below, we list the figures and tables, with a brief description and a reference to the sections of the paper that they supplement.

- Figure D.1 shows simulation results for the standard deviation in the change in MRPK, using the same parameters used to create Figure 1 in the paper. This set of results are described to in Subsection 3.3.2 in discussing the results in Table 7.
- Table D.1 shows the S^2 measure of fit for the model in capturing the standard deviation in the change in capital, for Tier 1 countries. This is described in footnote 36 of the paper.
- Table D.2 shows the S^2 measure of fit for the model in caputuring dispersion in MRPK, under alternative AR(1) specifications which include firm fixed effects. Including the fixed effects can change the estimates of ρ and σ in the AR(1) somewhat, and we show robustness to these alternate estimates. By Theorem 1, the model predictions, conditional on the ρ and σ, are unaffected by the inclusion of firm FE's. These results are described in footnote 27 of the paper.
- Tables D.4 and D.3 report the results of a barrage of robustness checks on the correlation between dispersion in MRPK and TFPR volatility reported in Table 11 in section 5 of the paper, using the World Bank data. These robustness tests are briefly described in footnote 38 of the paper.
- Tables D.5 and D.6: In order to test whether our results from the World Bank data (WBES) could be plagued by remaining measurement error, we follow Hsieh and Klenow (2009) and relate our measure of productivity to decision variables that plausibly have little room for measurement error.

  Regardless of the ultimate hypothesized source of measurement error, if measured TFPR were mere measurement error, we would not expect actual behavior to be correlated with measured TFPR.[1]

  With this in mind, we ran a probit with an indicator for positive investment as the dependent variable, and TFPR, log capital and country fixed effects as the explanatory variables. See Table D.5. The average marginal effect on TFPR was estimated to be 0.11 with a standard error of 0.01, making it significant at better than one percent. The pseudo-R-squared was 0.16.

  We also ran an OLS regression with the log investment to capital ratio as the dependent variable, and (again) TFPR, log capital and country fixed effects as the explanatory variables (using the World Bank data). See Table D.6. The coefficient on productivity was 0.34, again significant at better than one percent. The R-squared was 0.12. We also ran the same regression with just log investment as the dependent variable, with no change in results.

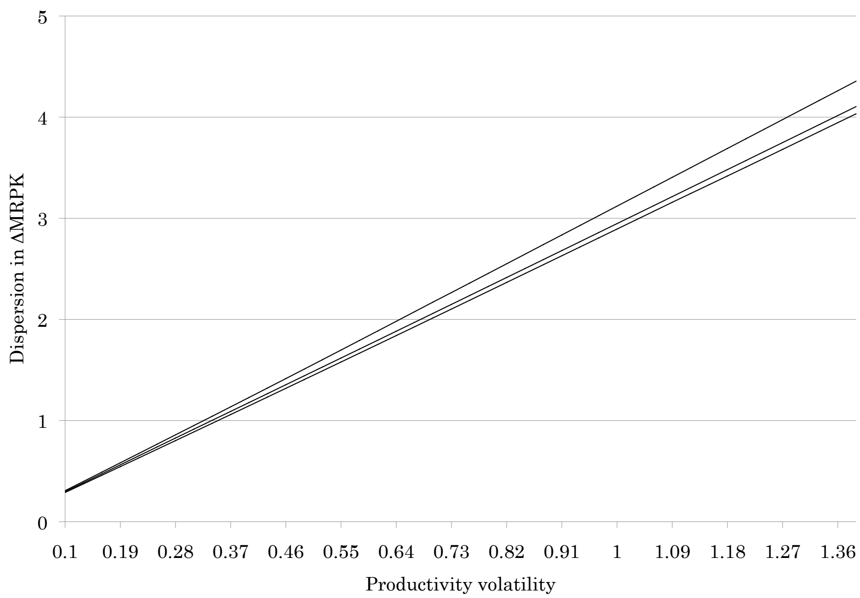
  The indicator for positive investment is likely to be well measured and is positively, and significantly, correlated with productivity. The log investment to

[1] A plausible specification for measurement error would be to add an i.i.d. shock to measured TFPR of the form: $\omega^*_{it} = \omega_{it} + \epsilon_{it}$. Notice that for the issue of dynamic inputs, it is irrelevant if these i.i.d. shocks ϵ_{it} are measurement error, or real shocks that are revealed after a firm has chosen inputs. In either case, ϵ_{it} will not be part of the firm's state variables when making investment decisions. Thus it will be difficult to separate transitory shocks to TFPR from i.i.d. measurement error, as these generate identical behavior (with the exception that true shocks have an impact on profits, since they enter in a non-linear way). Clearly, the dispersion of marginal products generated by these error shocks is irrelevant for welfare.

capital ratio, while arguably more prone to measurement error, displays the same pattern. This constitutes evidence that plausibly well-measured decision variables are correlated with productivity.

- Tables D.7 and D.8 report the AR(1) estimates that are used in Section 5.3 to computed the model predictions for the WBES sample. Specification (5) in Table D.7 (equiv. Table D.8) are the primary estimates of interest.
- Table D.9 reports the country specific production coefficients for the WBES sample.

Figure D.1: Volatility and Change in MRPK: Model Simulations



Notes: Volatility is the σ_c term in the AR(1) process. Values used in this simulation are: $\epsilon = -4, \delta = 10\%, \beta = \frac{1}{1+0.065}, \beta_K = 0.12, \beta_M = 0.40, \beta_L = 0.23, C_K^F = 0.09, C_K^Q = 8.8, \lambda = 1, \mu = 0, \rho_c \in \{0.65, 0.85, 0.94\}, \sigma_C \in [0.1, 1.4]$. We use the means in the U.S. Census Data to get our β's and use estimates of adjustment costs for the United States discussed in Section 4.

Table D.1: $\text{Std}_s(\Delta k)$, S^2 measures of model fit by specification

Country	Specification (1)	(2)	(3)	(4)	(5)
United States	0.769	0.921	0.921	0.836	-17.902
France	0.577	0.977	0.568	0.459	0.899
Chile	0.948	0.957	0.935	0.790	-7.113
India	0.825	0.908	0.8019	0.679	-5.239
Mexico	0.575	0.773	0.503	0.377	0.667
Romania	0.542	0.952	0.476	0.303	0.214
Slovenia	0.552	0.982	0.552	0.416	0.521
Spain	0.640	0.902	0.613	0.494	-0.051
All (ex U.S.)	0.599	0.919	0.566	0.432	0.067
All	0.619	0.919	0.608	0.480	-2.045

Note: The unit of observation is the country-industry. Specifications are: (1) All countries have the U.S.'s estimated adjustment costs and production coefficients equal to the U.S. averages across industries; (2) Industry-country specific production coefficients (except for Slovenia see section 3.1.2), country specific adjustment costs, industry-country specific AR(1); (3) as for (2), but with the U.S.'s estimated adjustment costs for all countries; (4) as for (3), but with twice the U.S.'s estimated adjustment costs for all countries; and, (5) as for (3), but with zero adjustment costs (other than the one period time-to-build) for all countries. In all specifications, the AR(1) is estimated using TFPR computed using the production coefficients used in the model specification.

Table D.2: Dispersion in MRPK, S^2 measures of model fit by alternate AR(1) specification

Country	Specification			
	(1)	(2)	(3)	(4)
United States (OLS, FE)	0.850	0.856	0.748	0.816
United States (A-B)	0.485	0.569	0.754	0.759

Note: The unit of observation is the industry (the data are for the U.S. only). Specifications are: (1) All industries have the U.S.'s estimated adjustment costs (the estimates from the paper using the simple AR(1)) and production coefficients equal to the U.S. averages across industries; (2) As for (1) but with industry specific production coefficients; (3) as for (2), but with twice the U.S.'s estimated adjustment costs; and, (4) as for (3), but with zero adjustment costs (other than the one period time-to-build). (OLS, FE) refers to a specification in which the AR(1) is estimated with firm fixed effects. (A-B) refers to estimates adjusted according to the correction for the σ estimate suggested by Arellano and Bond (1992).

Table D.3: WBES Robustness Checks: Productivity Measurement

Dep. Var.: Dispersion of MRPK	Coeff. on Std.($\omega_{it} - \omega_{it-1}$)
Baseline	0.67**
	(0.21)
Firm-Level Input Shares	0.47*
	(0.23)
Less Elastic Demand ($\epsilon = 2$)	0.65**
	(0.18)
More Elastic Demand ($\epsilon = 6$)	0.69***
	(0.15)
Productivity Estimated via OLS	0.77***
(with industry-country fixed effects)	(0.13)
Drop top and bottom decile for each country	1.10***
	(0.22)
Interquartile Range	0.54**
	(0.16)

Note: All regressions share a common specification: y_{it} = constant + Std.($\omega_{it} - \omega_{it-1}$). We use a weighted OLS with weights equal to the number of firms per country. 'Baseline' refers to specification I of panel A in Table 11. 'Firm-Level Input Shares' uses firm-level labor and material shares to compute firm-level production function coefficients β_{it}. 'Less and More Elastic' computes productivity assuming either $\epsilon = 2$ or $\epsilon = 6$ (the results in the Baseline specification assume $\epsilon = 4$). 'Productivity estimated via OLS' computes production function coefficients as the coefficients of an OLS regression of log sales on log labor, materials and capital. These coefficients are allowed to vary by country-industry pair, and include a country-industry specific intercept. 'Interquartile Range' computes the dependent variables as interquartile ranges rather than standard deviations.

Table D.4: WBES Robustness Checks: Sample Composition

Dependent Variable: MRPK Dispersion	(1)	(2)	(3)	(4)	(5)
Standard Deviation of	0.667***	0.436*	0.684***	0.180	0.497*
Change in TFPR	(0.170)	(0.165)	(0.168)	(0.542)	(0.201)
Constant	0.781***	0.851***	0.769***	1.022***	0.833***
	(0.098)	(0.098)	(0.097)	(0.213)	(0.096)
All	X				
Manufacturing Only		X			
More than 10 workers			X		
More than 50 workers				X	
Factor Share for Materials and Labor					X
in 10-90 percentile					
r^2	0.33	0.21	0.39	0.01	0.22
F-stat	15.38	7.02	16.51	0.11	6.13
Countries	33	29	28	12	24
Firm-level Observations	5563	3872	4801	2909	3667

Note: Standard errors clustered by country. Factor Share for Materials and Labor drops firms whose factor shares for materials or labor are outside the 10-90th percentile across all firms in the WBES data.

Table D.5: WBES, Positive Investment and TFPR

Dep. Var.: Positive Investment Indictator	(1)	(2)	(3)
TFPR	0.11***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)
Log Capital		0.04***	0.04***
		(0.00)	(0.00)
Country FE		X	
Country-Industry FE			X
Firm-level Observations	5532	5532	5388
Countries	32	32	32

Note: Marginal Effects from a Probit are reported. Fixed-effects implemented by estimating country dummies, and country-industry dummies. Results from a conditional logit produce similar coefficients. The number of countries is 32, due to the fact that the Peruvian data in the WBES reports zero investment for all firms.

Table D.6: WBES, Investment and TFPR

Dep. Var.:	Log Investment to Capital Ratio		Log Investment	
	(1)	(2)	(3)	(4)
TFPR	0.34***	0.24**	0.34***	0.24**
	(0.09)	(0.07)	(0.09)	(0.07)
Log Capital	-0.30***	-0.33***	0.70***	0.67***
	(0.04)	(0.03)	(0.04)	(0.03)
Country-Industry FE		X		X
Firm-level Observations	2740	2740	2740	2740
Country	32	32	32	32
R-Squared	.12	.19	.62	.65

Note: The number of countries is 32, due to the fact that the Peruvian data in the WBES reports zero investment for all firms. Firms with zero investment are not included.

Table D.7: Time series process, AR(1), for productivity: Using the World Bank data

Dependent Var: Productivity ω_{it}	(1)	(2)	(3)	(4)	(5)
ω_{it-1}	0.88***	0.92***	0.79**	0.91***	0.91***
	(0.05)	(0.12)	(0.30)	(0.04)	(0.04)
$(\omega_{it-1}) \bullet$(Country Dummy)				X	X
Var.				0.07	0.16
ω^2_{it-1}		0.13*	0.15		
		(0.06)	(0.14)		
ω^3_{it-1}		-0.04**	-0.03		
		(0.01)	(0.03)		
ω^4_{it-1}		0.00**	0.00		
		(0.00)	(0.00)		
Constant	0.33*	0.01	0.09	0.22	0.49
	(0.15)	(0.11)	(0.24)	(0.11)	
Country Specific Constant					X
Var.					0.06
Variance σ					
Constant	0.56***	0.43***	0.56***	0.56***	0.45
	(0.06)	(0.04)	(0.00)	(0.00)	
Country Specific Variance			X	X	X
Var.			.23	.24	.23
Log Assets		0.02*			
		(0.01)			
Observations	5563	5563	5563	5563	5274
Countries	33	33	33	33	33
Log-Likelihood	-4636	-4366	-3355	-3352	-3352

Note: Productivity is measured using gross output. Standard Errors (in parentheses) clustered by country. 'Var.' indicates the standard deviation of the set of parameters indicated in the row above. For specification (5), averages from country-level regressions are presented. The full set of coefficients and standard errors, together with those estimated using the other data sets, are presented in Table D.8.

Table D.8: Country-specific AR(1) coefficients: Using the World Bank Data

Specification: $\omega_{it} = \mu_c + \rho_c \omega_{it-1} + \sigma_c \eta_{it}$						
Country	ρ_c	se(ρ_c)	σ_c	se(σ_c)	μ_c	se(μ_c)
Bangladesh	0.92	0.08	0.56	0.03	0.19	0.23
Benin	0.80	0.05	0.36	0.03	0.54	0.12
Brazil	0.94	0.04	0.26	0.02	0.26	0.12
Chile	0.68	0.02	0.70	0.02	1.08	0.07
Costa Rica	0.85	0.03	0.48	0.02	-0.09	0.03
Ecuador	0.99	0.07	0.44	0.03	0.02	0.19
El Salvador	0.86	0.03	0.36	0.02	0.14	0.05
Ethiopia	0.84	0.04	0.55	0.03	0.36	0.09
Guatemala	0.30	0.04	0.60	0.03	1.81	0.12
Guyana	1.05	0.10	0.69	0.09	-0.06	0.50
Honduras	0.71	0.03	0.50	0.02	0.66	0.10
Indonesia	0.74	0.03	0.90	0.03	0.81	0.11
Kyrgyzstan	1.00	0.03	0.11	0.01	0.01	0.05
Lithuania	0.81	0.06	0.37	0.03	0.58	0.16
Madagascar	0.79	0.06	0.44	0.03	0.66	0.20
Malawi	0.92	0.04	0.37	0.02	0.29	0.12
Mauritius	0.61	0.13	1.04	0.10	1.08	0.41
Moldova	0.94	0.03	0.14	0.01	0.14	0.08
Morocco	0.56	0.03	0.47	0.02	1.34	0.10
Nicaragua	0.76	0.03	0.38	0.02	0.54	0.08
Peru	0.98	0.04	0.20	0.03	0.11	0.12
Philippines	1.01	0.01	0.18	0.01	-0.01	0.03
Poland	1.03	0.04	0.12	0.01	-0.05	0.10
South Africa	0.95	0.03	0.24	0.01	0.28	0.10
Sri Lanka	0.85	0.03	0.38	0.03	0.41	0.10
Syria	0.92	0.10	0.49	0.05	0.12	0.21
Tajikistan	1.03	0.04	0.14	0.01	-0.13	0.08
Tanzania	1.00	0.06	0.38	0.04	0.06	0.16
Thailand	0.84	0.02	0.24	0.01	0.57	0.08
Turkey	0.93	0.05	0.40	0.05	0.27	0.16
Uzbekistan	0.97	0.07	0.33	0.02	-0.04	0.13
Vietnam	0.84	0.03	0.39	0.01	0.50	0.08
Zambia	0.68	0.05	0.33	0.02	0.89	0.12

Note: the μ coefficients will not be comparable across data sets due to the use of different measurement units.

Table D.9: WBES Production function coefficients: Mean estimates by country

	Labor Coefficient β_l	Material Coefficient β_m	Capital Coefficient β_k
Bangladesh	0.14	0.50	0.11
Benin	0.17	0.48	0.10
Brazil	0.17	0.48	0.11
Chile	0.15	0.44	0.16
Costa Rica	0.17	0.47	0.12
Ecuador	0.15	0.48	0.12
El Salvador	0.15	0.48	0.12
Ethiopia	0.18	0.46	0.11
Guatemala	0.17	0.47	0.11
Guyana	0.12	0.50	0.13
Honduras	0.16	0.47	0.12
Indonesia	0.15	0.48	0.12
Kyrgyzstan	0.16	0.47	0.12
Lithuania	0.17	0.44	0.14
Madagascar	0.17	0.46	0.12
Malawi	0.14	0.48	0.12
Mauritius	0.14	0.48	0.12
Moldova	0.16	0.47	0.12
Morocco	0.16	0.48	0.11
Nicaragua	0.16	0.47	0.11
Peru	0.17	0.47	0.11
Philippines	0.14	0.49	0.12
Poland	0.15	0.48	0.12
South Africa	0.16	0.47	0.12
Sri Lanka	0.15	0.48	0.11
Syria	0.16	0.48	0.11
Tajikistan	0.17	0.47	0.11
Tanzania	0.14	0.49	0.11
Thailand	0.15	0.49	0.11
Turkey	0.13	0.49	0.13
Uzbekistan	0.16	0.48	0.12
Vietnam	0.16	0.47	0.12
Zambia	0.13	0.50	0.12