

# MANAGEMENT, MERGERS AND ACQUISITIONS\*

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## Abstract

Using new Census data on management practices, we show a striking fact: better managed firms are significantly more active in plant acquisitions and disposals and openings and closings. We argue that better management practices allow firms to more cheaply change plant ownership, enabling them to engage in greater plant-level reallocation. Combining this with other Census and international management data showing better managed firms have higher productivity, have faster growth rates and birth better managed plants, we build a model of plant and firm management. We structurally estimate key parameters of the model and solve for the equilibrium. Using the model we develop three key results. First, mergers and acquisition activity increases management quality and productivity by almost 15%, second, greater competition improves management practices and productivity by over 10%, and finally, management practices account for about 30% of cross-country TFP differences.

**JEL No.** L2, M2, O32, O33.

**Keywords:** management practices, mergers and acquisitions, productivity, competition

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# 1 Introduction

Productivity differences between firms and between countries remain startling. For example, within the average four-digit Standard Industrial Classification (SIC) U.S. manufacturing industries, Syverson (2011) finds that labor productivity for plants at the 90<sup>th</sup> percentile was four times as high as plants at the 10<sup>th</sup> percentile. Even after controlling for other factors, Total Factor Productivity (TFP) was almost twice as high at the most productive plants. These differences persist over time and are robust to controlling for plant-specific prices in homogeneous goods industries.<sup>1</sup> Such TFP heterogeneity is evident in all other countries where data is available.<sup>2</sup> One explanation is that these persistent within industry productivity differentials are due to “hard” technological innovations, as embodied in patents or the adoption of advanced equipment. Another explanation, which is the focus of this paper, is that productivity differences reflect variations in management practices.

We advance the idea that some forms of management practices are like a “technology” in the sense that they raise TFP. This has a number of empirical implications that we examine and find support for in the data. Our perspective on management is distinct from the common “Design” paradigm in organizational economics, which views management as a question of optimal design depending on the very contingent features of a firm’s environment (Gibbons and Roberts, 2013). In this view of management practices, there is no sense in which any management styles are on average better than any others.

To date, empirical work to measure differences in management practices across firms and countries has been limited. Despite this lack of data, the core theories in many fields such as international trade, labor economics, industrial organization and macroeconomics are now incorporating firm heterogeneity as a central component.<sup>3</sup>

To address the lack of management data, we draw on two databases. First, the World Management Survey (WMS) where we have collected original survey data on management practices on over 11,000 firms in 34 countries. Besides its rich cross sectional nature, both in terms of countries and industries covered, this dataset also features a significant panel component built through four

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<sup>1</sup>These are revenue based measures of TFP (“TFPR”) so will also reflect firm-specific mark-ups. Foster, Haltiwanger and Syverson (2008) show large differences in TFP even within very homogeneous goods industries such as cement and block ice where they can observe plant specific prices (“TFPQ”). In what follows we will refer simply to TFP acknowledging that empirically we usually measure TFPR. Kitzgen, Lorenz and Zilibotti (2016) give an example of how differences in TFP could reflect technology differences even for *ex ante* identical firms. Hall and Jones (1999) show how the stark differences in productivity across countries account for a substantial fraction of the differences in average income.

<sup>2</sup>Usually productivity dispersion is even greater in other countries than in the U.S.—see Bartelsman, Haltiwanger and Scarpetta (2013), Hsieh and Klenow (2009) and OECD (2016).

<sup>3</sup>Different fields have different labels for what we regard as heterogeneity in management. In trade, the focus is on an initial productivity draw when the plant enters an industry that persists over time (e.g. Melitz, 2003). In industrial organization, the focus has traditionally been on cost heterogeneity due to entrepreneurial/managerial talent (e.g. Lucas, 1978). In macro, organizational capital is sometimes related to the firm specific managerial know-how built up over time (e.g. Prescott and Visscher 1980). In labor, there is a growing focus on how the wage distribution requires an understanding of the heterogeneity of firm productivity (e.g. Card, Heining and Kline, 2013).

different survey waves from 2004 to 2014. One purpose of this paper is to provide public use data to enable other researchers to address long-standing questions regarding firm organization.<sup>4</sup> Second, we worked with the US Census Bureau to produce data on management in around 60,000 US plants using large-scale surveys in 2010 and 2015. There is enormous variation in average management scores in both databases and a strong correlation with micro measures of performance such as TFP.

We detail a rich model of “Management As a Technology” (MAT) which incorporates management in the production function. Importantly, we allow both for (endogenous) plant level management capital as well as managerial inputs from the parent firm. Firms can grow organically by expanding existing plant’s outputs or opening up new plants (children) and can also grow or shrink through the M&A market by acquiring or disposing of existing plants. Headquarter managerial inputs (which are idiosyncratic and change stochastically over time) spread to all the plants a firm owns whether via organic birth or takeover. We allow both a heterogeneous initial draw of managerial ability (at the firm and plant level) at start-up and an endogenous investment decision in managerial (and non-managerial) capital in response to shocks to the environment. The model is useful to formalize our theoretical intuitions and enable structural estimation of key parameters. In particular, thanks to the panel variation present in the management data, we are able to identify the depreciation rate and adjustment costs of managerial capital using the Simulated Method of Moments (SMM).

After simulating the steady state of our economy, we compare many moments in the simulations to our new datasets, focusing on the covariance of management with other observables. We find that the data supports the predictions from the MAT model. The model makes several empirical predictions that are consistent with our data: (i) better managed plants have higher revenue; (ii) better managed firms give birth (absolutely and net of exit) to more plants and these “children” are themselves better managed; (iii) better managed firms do more M&A and improve the management (and productivity) of the plants they acquire; (iv) the level of management quality rises and the dispersion shrinks as firms age; and (v) in a more competitive economy, management practices are better (partly from improved allocation: better managed firms grow larger). Building on our model, we show that differences in management practices account for about 30% of cross-country TFP differences. Our estimates suggest that shutting down that M&A market would both reduce aggregate managerial quality and lower GDP by up to 15%.

In summary, this paper makes four major contributions over the existing literature. First, it show new facts on the relationship between management and extensive margin firm growth through entry, exit, acquisitions, and disposals. Second, it develops and structurally estimates a model of management practices in the production function. Third, it uses this model to determine the extent to which management can account for variations in productivity across firms and across a large number of countries. Finally, it produces a set of Public Use Micro Data which should facilitate future quantitative research in the area of managerial and organizational economics.

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<sup>4</sup>The methods and data are open source and available on our website <http://worldmanagementsurvey.org/survey-data/download-data/>.

Our paper relates to several literatures. First, there is a large body of empirical literature on the importance of management for variations in firm and national productivity, going back to Walker (1887) through to more recent papers like Ichniowski, Shaw and Prennushi (1997), Bertrand and Schoar (2003), Adhvaryu, Kala and Nyshadham (2016) and Bruhn, Karlan and Schoar (2016). Second, there is a growing macro literature on aggregate implications of firm management and organizational structure, ranging from Lucas (1978), to Gennaioli et al (2013), Guner and Ventura (2014), Garicano and Rossi-Hansberg (2015) and Akcigit, Alp and Peters (2016). Third, there is a long literature on the causes of the slow diffusion of new technologies and the implications for productivity differences (e.g. Griliches, 1957; Gancia, Mueller and Zilibotti, 2013). Finally, there is another growing literature focusing on explaining cross-country TFP in terms of the degree of reallocation of inputs to more productivity firms, most notably Hsieh and Klenow (2009) and Restuccia and Rogerson (2008).

The structure of the paper is as follows. We first describe our model of management in Section 2 and describe the data in Section 3. Section 4 describes how we numerically estimate our rich model. Section 5 compares the results from the theoretical simulations with the data from WMS and MOPS. We also perform some counterfactual welfare calculations, such as increasing the cost of M&A. Section 6 uses the framework to quantify the degree to which management can account for the cross country TFP dispersion. Section 7 presents some extensions and robustness checks. Section 8 offers some concluding comments. The online Appendices describe the data and how it can be accessed (A), further econometric analysis (B), details of the SMM procedure (C) and the CEO compensation data (D).

## 2 Models of Management

Firms are modeled as owning a collection of plants selling output into a monopolistically competitive industry. Beyond the standard set-up, the key novelties are: (A) multi-plant firms have plant level management practices and firm-level CEO ability, (B) plants explicitly invest in their management practices as an intangible capital stock, and (C) the cost of plant openings, closings, acquisitions, and disposals depends on firm’s management ability. We sketch our modeling approach here with more details in Appendix A.

### 2.1 Production and Demand

Value-added is produced as follows:

$$Y = F(\tilde{A}, L, K, M, C), \tag{1}$$

where  $\tilde{A}$  is an efficiency term,  $L$  is labor,  $K$  is physical capital,  $M$  is *plant*-level management practice capital, and  $C$  is *firm*-level CEO talent. We denote firms by subscript  $i$ , plants (establishments)

by  $e$ , and time by  $t$ . The overall model environment can be thought of as within a single industry. Time subscripts are omitted unless necessary for clarity. The plant's production technology is:

$$Y_{i,e} = \tilde{A}_{i,e} K_{i,e}^\alpha L_{i,e}^\beta \tilde{G}(C_i, M_{i,e}), \quad (2)$$

where  $\tilde{G}(M_{i,e}, C_i)$  is a management function combining management practices and CEO capital. This assumes the overall managerial quality of the plant depends on plant level management practices ( $M_{i,e}$ ) and on firm-level CEO capital ( $C_i$ ).

Demand derives from a final good sector (or, equivalently, a representative consumer) using a CES aggregator across individual inputs:

$$Y = N^{\frac{1}{1-\rho}} \left( \sum_{i=1}^N \sum_{e=1}^{R_i} Y_{i,e}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \quad (3)$$

where  $\rho > 1$  is the elasticity of substitution,  $R_i$  is the number of plants in firm  $i$ ,  $N$  is the number of firms and  $N^{\frac{1}{1-\rho}}$  is the standard adjustment factor to make the degree of substitution scale free (e.g. Alessandria and Choi, 2007). Applying the first order conditions and normalizing the industry price to be  $P = 1$  gives each plant an inverse demand curve with elasticity  $\rho$ :

$$P_{i,e} = \left( \frac{Y}{N} \right)^{\frac{1}{\rho}} Y_{i,e}^{-\frac{1}{\rho}} = B Y_{i,e}^{-\frac{1}{\rho}}, \quad (4)$$

where the demand shifter is  $B = \left( \frac{Y}{N} \right)^{\frac{1}{\rho}}$ . These production and demand curves generate the plant's revenue function:

$$P_{i,e} Y_{i,e} = A_{i,e} K_{i,e}^a L_{i,e}^b G(C_i, M_{i,e}),$$

where for analytical tractability we define  $A_{i,e} = \tilde{A}_{i,e}^{1-1/\rho} \left( \frac{Y}{N} \right)^{\frac{1}{\rho}}$ ,  $a = \alpha(1-1/\rho)$ ,  $b = \beta(1-1/\rho)$  and  $G(C_i, M_{i,e}) = \tilde{G}(C_i, M_{i,e})^{(1-1/\rho)}$ . Profits are defined as revenues less capital, labor, management costs ( $c_K(K)$ ,  $c_L(L)$  and  $c_M(M)$ ), and fixed costs  $F$ :<sup>5</sup>

$$\Pi_{i,e} = A_{i,e} K_{i,e}^a L_{i,e}^b G(C_i, M_{i,e}) - c_K(K_{i,e}) - c_L(L_{i,e}) - c_M(M_{i,e}) - F.$$

## 2.2 Managerial and Non-managerial Capital

We parameterize the management function as  $G(C_i, M_{i,e}) = (C_i \cdot M_{i,e})^c$ , so plant revenues are:

$$P_{i,e} Y_{i,e} = A_{i,e} K_{i,e}^a L_{i,e}^b (C_i \cdot M_{i,e})^c. \quad (5)$$

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<sup>5</sup>Since firms in our data are typically small in relation to their input and output markets, for tractability we ignore any general equilibrium effects, taking all input prices (for capital, labor and management) as constant.

We allow for the possibility that a plant's management can be endogenously improved by, for example, hiring management consultants or spending time improving organizational processes (e.g. Toyota's Kaizen meetings). Although managerial practices can be improved in this way, failure to invest may mean they depreciate over time like other tangible and intangible assets such as fixed tangible capital, R&D, and advertising. Hence, we set up a more general model that still has initial heterogeneous draws of plant-level management when firms enter, but treats plant-level management as an intangible capital stock with depreciation:

$$M_{i,e,t} = (1 - \delta_M)M_{i,e,t-1} + I_{i,e,t}^M \quad I_{i,e,t}^M \geq 0, \quad (6)$$

where  $I_{i,e,t}^M$  reflects investment in management practices, which has a non-negativity constraint reflecting the fact that managerial capital cannot be sold. On the other hand, we assume that the firm-level CEO capital  $C_i$  is drawn exogenously and evolves according to a Markov process. Apart from analytical tractability, we choose this to reflect the idea from multiple case studies that a firm's founder or entrepreneur leaves a strong imprint in the firm that is hard to endogenously change. Non-managerial capital accumulation is standard, and allows for capital resale (at a cost which we discuss later)

$$K_{i,e,t} = (1 - \delta_K)K_{i,e,t-1} + I_{i,e,t}^K. \quad (7)$$

### 2.3 Adjustment costs and dynamics

In general, changing a managerial or physical capital stock will involve adjustment costs. This could reflect, for example, the costs of organizational resistance to new management practices (e.g. Cyert and March, 1963, or Atkin et al., 2017). We assume changing plant-level management practices involves a quadratic adjustment cost:<sup>6</sup>

$$S_M(M_t, M_{t-1}) = \gamma_M M_{t-1} \left( \frac{\Delta M_t}{M_{t-1}} + \delta_M \right)^2, \quad (8)$$

where the cost is proportional to the squared change in management net of depreciation and scaled by lagged management to avoid firms outgrowing adjustment costs. This style of adjustment costs is common for capital (e.g. Chirinko, 1993) and seems reasonable for management where incremental changes in practices are likely to meet less resistance than large changes. Likewise, we also assume quadratic adjustment costs for non-managerial capital:

$$S_K(K_t, K_{t-1}) = \gamma_K K_{t-1} \left( \frac{K_t - K_{t-1}}{K_{t-1}} + \delta_K \right)^2 - I_t^K (1 - \phi_K \mathfrak{I}(I_t^K < 0)), \quad (9)$$

where  $\phi_K$  is the resale loss on capital and  $\mathfrak{I}(I_t^K < 0)$  is an indicator function for disinvestment.

We assume that changes to firm-level CEO quality  $C$  are free of adjustment costs and occur at random following a five-state Markov chain. These processes will generate the firm-specific dynamics

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<sup>6</sup>For brevity, in this section we omit the firm and plant subscripts.

in the model, which, alongside the random initial draws for management and business conditions, generate the stochastics in our model.

To economize on the number of state variables in the model, we assume labor is costlessly adjustable, but requires a per period wage rate of  $w$ . Given this assumption on labor, we can define the optimal choice of labor by  $\frac{\partial PY(A, K, L^*, M, C)}{\partial L} = w$ . Imposing this labor optimality condition and assuming the specification for management in the production function, we obtain:

$$Y^*(A, K, M, C) = A^* K^{\frac{a}{1-b}} (C \cdot M)^{\frac{c}{1-b}},$$

where  $A^* = b^{\frac{b}{1-b}} A^{\frac{1}{1-b}}$ .<sup>7</sup> Finally,  $\ln(A)$  is assumed to follow a standard AR(1) process so that  $\ln(A_t) = \ln A_0 + \rho_A \ln(A_{t-1}) + \sigma_A \varepsilon_t$  where  $\varepsilon_t \sim N(0, 1)$ .

## 2.4 Firm and Plant Entry

There are two types of entry in the model.

At the firm level, new firms enter operating a single plant. These *de novo* firms draw a triple of  $C_{i,0}$ ,  $M_{i,e,0}$ , and  $A_{i,e,0}$  randomly from a known distribution after paying a sunk entry cost  $F$ . Assuming that they decide to produce, after this first period of life, these entrant firms (alongside all other incumbents firms) can give birth to new plants (their “children”).

At the plant level, existing firms birth new plants. We model the entry of new plants as analagous to expanding varieties as in Klette and Kortum (2004). In their model, a single variety is destroyed at Poisson rate  $\mu$  and arrives at a Poisson rate  $\lambda$ , so a firm with  $n$  varieties has a Poisson rate  $\mu \cdot n$  of losing a variety and a Poisson rate  $\lambda \cdot n$  of gaining a variety. In our model, new plants take a draw of plant-level management practices and productivity while inheriting CEO capital from their parent firms. These plants start to operate if their initial value given these entry draws is greater than the entry cost  $D(C)$ . We assume that  $D(C)$  is decreasing in  $C$ , so that it is cheaper for better managed firms to enter new plants. This is critical to match the micro-data, and is naturally rationalized as better managed firms are more effective at integrating new plants into firms.

## 2.5 Plant Sales, Exits, and Acquisitions

Every period firms realize draws of  $C$ , plants realize draws of  $A$ , and plants then make investment decisions for  $M$  and  $K$ . These decisions include the option to close a plant or put a plant put up for sale. A plant will be put up for sale if the current value of the plant is less than the expected future value of the plant minus the transaction cost:

$$V(A, K, M, C) < \mathbb{E}_A[V(A, M, K, C)] - D(C),$$

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<sup>7</sup>We define the units for labor, management and capital so that their prices are unity.

where  $\mathbb{E}_A$  makes explicit that we are taking expectations over the future evolution of the plant's  $A$ . We assume that  $D(C)$  is decreasing in  $C$  for consistency with micro data, which we rationalize by assuming better managed firms can more easily execute the disposal of a plant. More generally, this can be seen as a tractable way of incorporating a Lucas (1978)-style span of control into the model while still keeping decision making at the plant level. Because of the complementarities between firm-level management and the other factors of production, better-managed firms are more willing to sell poorly performing plants to better use their CEO capital on a new plant.

Once a plant is put up for sale, all firms have the opportunity to purchase it, with the plant ultimately going to the highest bidder. This means a plant being sold by firm  $i$  will be sold to the firm  $j$  which maximizes the net surplus from the transaction

$$\mathbb{E}_A[V(K_{i,e}, M_{i,e}, C_j)] - D(C_j) - \varepsilon_{i,j}.$$

The cost of purchasing a plant  $D(C)$  is also decreasing in  $C$  as well, so that it is easier for better-managed firms to purchase new plants. We also introduce a random shock  $\varepsilon_{i,j}$  in the cost of purchasing a plant to eliminate ties, and give worse-managed firms some opportunity to buy plants if they have a particularly low draw of the purchasing cost shock. Finally, following this purchase, the acquiring firm draws a new TFP  $A_j$  for the purchased plant. If this new productivity draw is not too low, so that  $V(A_{j,e}, K_{i,e}, M_{i,e}, C_j) > 0$ , the plant  $e$  is purchased by the firm  $j$  and continues operations as part of the new firm. If the new productivity draw is very low, that is, if  $V(A_{j,e}, K_{i,e}, M_{i,e}, C_j) \leq 0$ , the plant exits.

## 2.6 Optimization and Equilibrium

Given the plant's four state variables—business conditions  $A$ , capital  $K$ , plant management  $M$ , and firm management  $C$ —we can write a value function (dropping  $i$ - and  $e$ - subscripts for brevity):

$$\begin{aligned} V(A_t, K_t, M_t, C_t) &= \max[V^c(A_t, K_t, M_t, C_t), \mathbb{E}_A[V(A, M, K, C)] - D(C)] \\ V^c(A_t, K_t, M_t, C_t) &= \max_{K_{t+1}, M_{t+1}} [Y_t^* - wL_t - S_K(K_{t+1}, K_t) - S_M(M_{t+1}, M_t) \\ &\quad - p_K I_{t+1}^K - p_M I_{t+1}^M - F \\ &\quad + r(1 - \mu)E_t V(A_{t+1}, K_{t+1}, M_{t+1}, C_{t+1})] + r(1 + \lambda)E_t V(A_0, K_0, M_0, C_{t+1})]. \end{aligned} \tag{10}$$

The first maximum reflects the decision to continue in operation or put the plant up for sale (where an attempted sale occurs when  $V^c < \mathbb{E}_A[V(A, M, K, C)] - D(C)$ ,  $V^c$  being the value for “continuers”), and the second maximum reflects the optimization of managerial and non-managerial capital conditional on operation. Note that  $r$  is the discount factor,  $\mu$  is the rate of exogenous exit, and  $\lambda$  is the marginal rate of plant entry due to each current plant.

Following Klette and Kortum (2004), our framework means that we can consider the value function at the plant rather than the firm-level, which substantially aids computational tractability. The only



way firm-level considerations enter the plant’s value function are through the firm-level management  $C$  and the value of possible additional plants. Because the plant cannot affect the technology, capital, or management of any additional plants, this term only matters for entry and exit decisions.

We assume there is a continuum of potential new entrants that would have to pay one period of fixed costs  $F$  to enter.<sup>8</sup> Upon entry, they take a stochastic draw of their productivity ( $A$ ), plant management ( $M$ ), and (if a de novo firm entrant) firm management ( $C$ ) from a known joint distribution  $H(A, M, C)$  and start with non-managerial capital  $K_0 = 0$ . Hence, entry occurs until the point that the expected value of entry equals the sunk cost of entry:

$$F = \int_{A, M, C} V(A, 0, M, C) dH(A, M, C).$$

We solve for the steady-state equilibrium by selecting the demand shifter ( $B = (\frac{Y}{N})^{\frac{1}{\rho}}$ ) that ensures that the expected cost of entry equals the expected value of entry given the optimal capital and management decisions. This equilibrium is characterized by a distribution of firms in terms of their state values  $A, K, M, C$ . The distribution of  $\ln A$  is assumed normal,  $M$  is assumed to be drawn from a uniform distribution, and  $C$  is a five-point distribution.<sup>9</sup>

### 3 Data

#### 3.1 WMS Survey method

We describe the datasets in more detail in Appendix A, but sketch out the important features here. To measure management practices, we developed a survey methodology known as the World Management Survey (WMS).<sup>10</sup> This uses an interview-based evaluation tool that defines 18 basic management practices and scores them from one (“worst practice”) to five (“best practice”) on a scoring grid. This evaluation tool was first developed by an international consulting firm and scores these practices in three broad areas.<sup>11</sup> The first practice area is *Monitoring*: how well do companies track what goes on inside their firms, and use this for continuous improvement? The second practice area is *Target setting*: do companies set the right targets, track outcomes, and take appropriate action if the two are inconsistent? The third practice is *Incentives/people management*<sup>12</sup>: are

<sup>8</sup>We can allow the entry sunk cost to be different from a one period fixed cost as in Bartelsman et al (2013). In an earlier version of the paper we used firm level exit rates to estimate sunk costs and generated qualitatively results to those presented below. Since nothing in the results hinges on this, we kept the current set-up for simplicity.

<sup>9</sup>Nothing fundamental hinges on the exact distributional assumptions.

<sup>10</sup>More details can be found at <http://worldmanagementsurvey.org/>

<sup>11</sup>Bertrand and Schoar (2003) focus on the characteristics and style of the CEO and CFO, and more specifically on differences in strategic management (e.g. decision making applied to mergers and acquisitions), while Lazear, Shaw and Stanton (2016) focus on individual supervisors. The type of practices we analyze in this paper are closer to operational and human resource practices, which has a long precedent in the management and strategy literature—for example, Osterman (1994), Huselid (1995) and Capelli and Neumark (2001).

<sup>12</sup>These practices are similar to those emphasized in earlier work on management practices, by for example Ichniowski, Prennushi and Shaw (1997) .

companies promoting and rewarding employees based on performance, and systematically trying to hire and retain their best employees?

To obtain accurate responses from firms, we interview production plant managers using a “double-blind” technique. One part of this technique is that managers are not told in advance they are being scored or shown the scoring grid. They are informed only that they are being “interviewed about management practices for a piece of work”. The other side of the double blind technique is that the interviewers do not know anything about the performance of the firm.

To run this blind scoring, we use “open” questions. For example, on the first monitoring question we start by asking the open question, “tell me how you monitor your production process”, rather than closed questions such as “Do you monitor your production daily? [yes/no]”. We continue with open questions focused on actual practices and examples until the interviewer can make an accurate assessment of the firm’s practices. For example, the second question on that performance tracking dimension is, “What kinds of measures would you use to track performance?” and the third is “If I walked around your factory, could I tell how each person was performing?”.<sup>13</sup>

The other side of the double-blind technique is that interviewers are not told anything about the firm’s performance in advance. They are only provided with the company name, telephone number, and industry. Since we randomly sample medium-sized manufacturing firms (employing between 50 and 5,000 workers) who are not usually reported in the business press, the interviewers will generally have not heard of these firms before, so they should have few preconceptions.<sup>14</sup>

The survey is targeted at plant managers, who are senior enough to have an overview of management practices but not so senior as to be detached from day-to-day operations. We also collect a series of “noise controls” on the interview process itself—such as the time of day, day of the week, characteristics of the interviewee, and the identity of the interviewer. Including these in our regression analysis typically helps to improve our estimation precision by stripping out some of the random measurement error.

We ensure high sample response rates and informative interviews in four ways. First, we hire students with some business experience and training to conduct interviews. Second, we obtained endorsements from respected institutions for the surveys in each country we covered. Third, we never ask interviewees for financial data and instead obtain this from independent sources on company accounts. Finally, we encourage the interviewers to be persistent—they run about two interviews a day lasting 45 minutes each on average, with the rest of the time (about 6 hours a day) spent repeatedly contacting managers to schedule interviews. This process, while time consuming and expensive, helped to yield a 41% response rate which was uncorrelated with the

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<sup>13</sup>The full list of questions for the grid is in Table A1 and (with more examples) at <http://worldmanagementsurvey.org/wp-content/images/2010/09/Manufacturing-Survey-Instrument.pdf>.

<sup>14</sup>We focus on firms over a size threshold because the formal management practices we consider are likely to be less important for smaller firms. We had a maximum size threshold because we only interviewed one or two plant managers in each firm, so would have too incomplete a picture for very large firms. Below, we show tests suggesting our results are not biased by using this sampling scheme (see Appendix B).

(independently collected) performance measures. Appendices A and B discuss and analyze selection issues for the sampling frame and responders.

### 3.2 Survey waves

We have administered the survey in several waves since 2004. There were five major waves in 2004, 2006, 2009/10, 2013, and 2014. In 2004 we surveyed four countries (France, Germany, the U.K. and the U.S.). In 2006 we expanded this to twelve countries (including Brazil, China, India, and Japan), continuing random sampling, but in addition to a refreshment sample for the 2004 countries we also re-contacted all of the original 2004 firms to establish a panel. In 2009/10 we re-contacted all the firms surveyed in 2004 and 2006, but did not do a refreshment sample (due to budgetary constraints). In 2013 we added an additional number of countries (mainly in Africa and Latin America). In 2014 we again did a refreshment sample, but also followed up the panel firms in the U.S. and some E.U. countries. The final sample includes 34 countries and a panel of up to four different years between 2004 and 2014 for some firms. In the full dataset we have 11,383 firms and 15,489 interviews where we have usable management information.

### 3.3 Internal validation

We re-surveyed a random sub-sample of firms using a second interviewer to independently survey a second plant manager in the same firm. The idea is that the two independent management interviews on different plants within the same firms reveal how consistently we are measuring management practices. We found that in this sample of 222 re-rater interviews, the correlation between our independently run first and second interview scores was 0.51 (p-value 0.001). Part of this difference across plants within the same firm is likely to be real internal variation in management practices, with the rest presumably reflecting survey measurement error. The highly significant correlation across the two interviews suggests that while our management score is clearly noisy, it is picking up significant management differences across firms.

### 3.4 Some descriptive statistics

Figure 1 plots the average (unweighted) management practice scores across countries. This shows that the U.S. has the highest average management practice score, with the Germans, Japanese, Swedes, and Canadians below, followed by a block of Western European countries (e.g. France, Italy and the U.K.) and Australia. Below this group is Southern European countries (e.g. Portugal and Greece) and Poland. Emerging economies (e.g. Brazil, China, and India) are next, and low income countries (mainly in Africa) are at the bottom. In one sense, this cross-country ranking is not surprising since it approximates the cross-country productivity ranking. However, the correlation is far from perfect –Southern European countries have worse management than we would expect

from their productivity, and other nations, like Poland and Mexico, do have better management than we would expect.<sup>15</sup>

A key question is whether management practices are uniformly better in some countries like the U.S. compared to India, or if differences in the shape of the distribution drive the averages. Figure A2 plots the firm-level histogram of management practices (solid bars) for all countries pooled (top left) and then for each country individually. This shows that management practices, just like firm-level productivity, display tremendous variation within countries. Of the total firm-level variation in management, only 13% is explained by the country in which a firm is located, a further 10% is explained by industry (measured at the three digit SIC level), and the remaining 77% of the variation is within country and industry. Interestingly, countries like Brazil and India have a far larger left tail of management (e.g. scores of two or less) than the U.S.<sup>16</sup> This immediately suggests that one reason for the better average performance in the U.S. is that the American economy is better at selecting out the badly managed firms. We pursue the idea that some of the U.S. advantage may be linked to stronger forces of competition below.

Figure A1 shows average management scores in domestic firms (i.e. those who are not part of groups with overseas plants) compared to plants belonging to foreign subsidiaries. The average scores in domestic plants look similar to those in Figure 1, which is unsurprising as most of our firms are domestic. More interesting is that plants belonging to foreign multinationals appear to score highly in almost every country, suggesting that such firms are able to transplant their management practices internationally. This finding is robust to controlling for many other factors (such as firm size, age and industry) and is consistent with the idea of a subset of global, productivity enhancing practices. Our model tries to build in some of these suggestive cross-plant transfer of firm management practices (e.g. Helpman, Melitz and Yeaple, 2004) both from direct spawning or through M&A.

### 3.5 Managerial and Organizational Practices Survey (MOPS)

In addition to the WMS survey, we have also implemented a similar survey with the U.S. Census Bureau that allows us to measure management practices for a larger number of firms within the U.S., measure individual plants within a firm, and link management practices to outcomes measured in other Census databases including the Longitudinal Business Database (LBD) and Annual Survey of Manufacturers (ASM). In the MOPS, we implement a more traditional closed question “tick box” survey design for MOPS which gives us management data on approximately 32,000 U.S. manufacturing plants in 2010 and a similar number in 2015. The question design was modeled on WMS and the response to the MOPS was very high as we worked with the U.S. Census Bureau and replies were legally mandatory. Details on MOPS are contained in Bloom et al (2019) and

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<sup>15</sup>Polish management appears to be better because of the influence of the large numbers of German multinational subsidiaries, while Mexico similarly benefits from a heavy U.S. multinational presence

<sup>16</sup>For example, the skewness of the firm level management distribution in the U.S. is 0.09, whereas the skewness of the distribution in Brazil is 0.16 and 0.36 in India.

Appendix A. One advantage of MOPS is that it has much more reliable information on the changing ownership of plants across firms, births and deaths of plants, and age than the WMS. Thus, we use MOPS for several of our theoretical predictions on the extensive margins of reallocation.

We link the MOPS to the Longitudinal Business Database (LBD) to identify plant entry and exit as well as changes in plant ownership. Entry and exit are relatively simple to identify: we define the entry year as the first year a plant appears in the LBD (which occurs in the first year the plant has at least one paid employee), and the exit year as the first year a plant disappears from the LBD. At the firm level, we define a plant entry as an event in which a new plant appears in the LBD under the firm identifier of the focal firm in the focal year. Similarly, we define a plant exit as an event in which an existing plant under the firm identifier of the focal firm disappears from the LBD in the focal year.

Defining changes in plant ownership is slightly more complex. The LBD records a firm identifier for each plant which indicates common ownership. Theoretically, changes in the firm identifier for an existing plant should correspond to changes in plant ownership. Thus, we identify an acquisition year as a year in which an existing plant has a new firm identifier recorded. At the firm level, we define an acquisition as an event in which an existing plant with a different firm identifier has its firm identifier change to that of the focal firm in the focal year. Conversely, we define a disposal as an event in which an existing plant with the firm identifier of the focal firm has its firm identifier change to that of a different firm in the focal year. Our results are robust to a stricter definition of acquisitions and disposals in which we eliminate changes in firm identifier that correspond to changes from single-unit to multi-unit status.

## 4 Quantitative Application: Structural Estimation and Simulations

We detail how we estimate the quantitative model in Appendix C, but sketch the approach here.

### 4.1 Calibration and Numerical Estimation

We choose values to calibrate the model from the literature and from our data. We obtain three of these values from a Simulated Method of Moments (SMM) estimate of a restricted version of the model where we switch off the creation and acquisition of plants by firms. We discuss the details of the estimation in Appendix C. In short, solving the model requires finding two nested fixed-points.<sup>17</sup> First, we solve for the value functions for incumbent firms using the contraction mapping (e.g. Stokey and Lucas, 1986), taking demand as given for each firm. The policy correspondences for  $M$  and  $K$  are formed from the optimal choices given these value functions, and for  $L$  from the

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<sup>17</sup>The full replication package for the simulation and SMM estimation is available on <http://web.stanford.edu/~nbloom/MAT.zip>.

static first-order condition. Second, we iterate over the demand curve to satisfy the zero-profit condition.<sup>18</sup> Once both fixed points are satisfied, we simulate data for 40,000 firms over 300 years to get to an ergodic steady-state, and then discard the first 290 periods to keep the last 10 years of data (to match the time span of our management panel data).

To solve and simulate this model we also need to define a set of 14 parameter values. We pre-define nine of these from accounting measurement (e.g. the labor share of GDP, the depreciation rate on capital) or estimates in the prior literature, we normalize two (fixed costs to 100 and the mean of  $\ln(\text{TFP})$  to 1) and estimate the remaining three parameters on our management and accounting data panel. The nine predefined parameters are listed in Table 1, and are all based on standard values in the literature.

Appendix C describes how we cross-checked these calibration values with our own WMS data. For example, the Cooper and Haltiwanger (2006) estimates of the standard deviation ( $\sigma_A$ ) and auto-correlation of TFP ( $\rho_A$ ) implicitly include managerial capital ( $M$ ), which we can observe in our data. The three unknown parameters that we choose to estimate are those where much less is known from the literature. The adjustment cost ( $\gamma_M$ ) and depreciation rates ( $\delta_M$ ) for management have never been estimated before, to our knowledge. We also estimate the adjustment cost for non-managerial capital ( $\gamma_K$ ). While prior papers have estimated labor and capital adjustment costs (e.g. Bloom, 2009, and the survey therein), they have typically ignored management as an input, so it is these parameters are not directly transferable to our set-up.

To estimate the simplified model by SMM we picked three data moments to match: the variance of the five-year growth rates of the three state variables (management capital, non-management capital, and TFP) to tie down the adjustment cost and depreciation parameters. These data moments were generated on the matched management-accounting panel dataset for all countries from 2004 to 2014 (described in more detail in the next section). To generate standard errors, we block-bootstrapped over firms the entire process 1,000 times to generate the variance-covariance matrix, which was also used to optimally weight the SMM criterion function.

## 4.2 Simulation results

The top panel of Table 2 contains the SMM estimates and standard errors values for the three estimated parameters, and the bottom panel contains the moments from the data used to estimate these. Because the model is exactly identified we can precisely match the moments within numerical rounding errors.

The estimation of the adjustment costs for management is one of the novel contributions of this paper. We obtain a slightly higher level of adjustment costs for management of 0.212 (compared to 0.195 for capital) which, alongside the irreversibility of management, helps generate smoother

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<sup>18</sup>If there is positive expected profit then net entry occurs and the demand shifter  $B = (\frac{Y}{N})^{\frac{1}{\rho}}$  falls, and if there is negative expected profit then net exit occurs.

management five-year growth moments compared to capital five-year growth moments (see the bottom panel of Table 2).<sup>19</sup> These magnitudes are *prima facie* plausible as prior research in this area (Cyert and March, 1963) and anecdotal evidence from the private equity and management consulting industry suggest that management practices are likely to as hard or even harder to change than plant or equipment (e.g. Davis et al, 2014). Depreciation of management capital is 12.9%, similar to the level of the depreciation of capital (10%, see Table 1).<sup>20</sup>

## 5 Model Implications

We turn to presenting a comparison of the many moments in the data and simulations from the model to assess the performance of a model. Most of our visual evidence will present a left hand side panel (A) of data (from MOPS and/or WMS) and a right hand side panel (B) of simulations from the model. We first look at “own effects,” then move to extensive margins of adjustment (greenfield and brownfield, i.e. M&A). We then look at the association of changes in ownership via M&A with changes in management and firm performance. Finally we look at market level outcomes: changes as a cohort ages, product market competition and M&A.

Note that the empirical counterpart to management at the plant level will be a mix of firm management ( $C$ ) and plant management ( $M$ ). These are a bundle and not separately identified.

### 5.1 Management Dispersion and Productivity

We begin with some very basic relationships that we have effectively assumed in the model. The questions are whether (i) these are present in the data and (ii) the model simulation generates the intuitive relationships that we would expect (since there are multiple things going on - e.g. in real TFP vs. the empirically measured TFPR).

#### 5.1.1 Dispersion of Managerial Practices

One of the strongest findings from MOPS and WMS parallels much of firm level work on productivity (Syverson, 2011): there is tremendous heterogeneity in management across firms and plants. In Figure 2, we start by comparing the distribution of management practices of a random draw of 15,489 firm-years from our simulation to the 15,489 firm-year surveys in the WMS panel data, revealing similar cross-sectional distributions.<sup>21</sup> While this is not a formal test of our model, it

<sup>19</sup>If we allow management to have the same 50% resale loss as capital its adjustment cost is estimated to be 0.290, about 50% higher than the value for capital.

<sup>20</sup>One interpretation is that management capital is tied to the identity of plant managers. The average job tenure for plant managers in our survey is 6.4 year in the post and 13.0 years in the company, which would imply post and company quit rates of about 15% to 7% spanning the depreciation estimate of 13%. Indeed, in the 8-year follow-up to the Bloom et al. (2013) India experiment the largest reasons for a deterioration in management practices in the treatment plants was the attrition of the plant manager.

<sup>21</sup>To scale our management practices we take logs of the management variable, and normalize the lowest value to 1 and the higher value to 5 to replicate our management survey scoring tool.

does confirm it can generate the wide spread of management practices that is a striking finding of the management survey data.

### 5.1.2 Performance and Management Practices

Perhaps the most obvious implication of the MAT model is that high management scores should be associated with better firm performance. Panel A of Figure 3 presents a non-parametric lowess plot for WMS firm TFPR and management scores using local linear regressions (Figure A2 does the same using sales as an outcome). There is a clear positive and monotonic relationship. Panel B does the same for our model and shows a similar finding.

To probe this bivariate relationship more formally, we run some simple regressions. We z-score each individual practice, average across all 18 questions, and z-scored this average so the management index has a standard deviation of unity.<sup>22</sup> Table 3 examines the correlation between different measures of firm performance and management. To measure firm performance we use company accounts data,<sup>23</sup> estimating production functions where  $Q_{it}$  is measured by the value added of firm  $i$  at time  $t$ :

$$\ln Q_{it} = \alpha_M M_{it} + \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \alpha_X x_{it} + u_{it}, \quad (11)$$

where  $M_{it}$  is the empirical management score<sup>24</sup>,  $x_{it}$  is a vector of other controls such as the proportion of employees with a college degree, firm age, noise controls (e.g. interviewer dummies), country and three-digit SIC industry dummies and  $u_{it}$  is an error term. In column (1) of Table B1 we regress  $\ln(\text{value added})$  on  $\ln(\text{employment})$  and the management score, finding a highly significant coefficient of 0.316. This suggests that firms with one standard deviation of the management score are associated with 32 log points higher labor productivity (i.e. about 37%). In column (2) we add the capital stock and other controls which causes the coefficient on management to drop to 0.148, although it remains significant. Column (3) conditions on a sub-sample where we observe each firm in at least two years to show the effects are stable, while column (4) re-estimates the specification on this sub-sample including a full set of firm fixed effects to identify from changes in management over time, a very tough test given the likelihood of attenuation bias. The coefficient on management (and labor and capital) does fall, but it remains positive and significant.<sup>25</sup> In

<sup>22</sup>We have experimented with other ways of aggregating the management scores such as using principal component analysis. Since the 18 questions are all positively correlated these more sophisticated alternatives produce broadly similar results to those developed here. Sub-section 4.5 below describes some other ways of dis-aggregating the scores into sub-components that reveals evidence for the Design perspective.

<sup>23</sup>Our sampling frame contained 90% private firms and 10% publicly listed firms. In most OECD countries both public and private firms publish basic accounts. In the U.S., Canada and India, however, private firms do not publish (sufficiently detailed) accounts so no performance data is available. Hence, these performance regressions use data for all firms except privately held ones in the U.S., Canada and India.

<sup>24</sup>Note that empirical measure of management here,  $M$ , corresponds to the log of the managerial capital stock ( $\ln M$ ) in the theory. This seems reasonable given the evidence of Figure 2 of the log-normal distribution of the empirical score.

<sup>25</sup>Note that these correlations are not simply driven by the “Anglo-Saxon” countries, as one might suspect if the management measures were culturally biased. We cannot reject that the coefficient on management is the same across all countries: the F-test (p-value) on the inclusion of a full set of management\*country dummies is 0.790 (0.642).



column (5) we use the Olley and Pakes (1996) estimator of productivity and obtain a coefficient on management of 0.102, lying between the levels OLS and fixed effects specification.<sup>26</sup>

As discussed above, one of the most basic predictions is that better managed firms should be larger than poorly managed firms. Column (6) of Table B1 shows that better managed firms are significantly larger than poorly managed firms: a one standard deviation of management is associated with a 40 log point increase in employment size. In column (7) we use profitability as the dependent variable as measured by ROCE (Return on Capital Employed) and show again a positive association with management. Considering more dynamic measures, column (8) uses sales growth as a dependent variable, revealing that better managed firms are significantly more likely to grow. Column (9) estimates a model with Tobin’s average  $q$  as the dependent variable, which is a forward looking measure of performance. Although this can only be implemented for the publicly listed firms, we see again a positive and significant association with this stock market based measure. Finally, column (10) examines bankruptcy/death and finds that better managed firms are significantly more likely to survive.

Bloom et al (2019) perform similar exercises on the MOPS data and generate consistent results to the new WMS results detailed here.

These are conditional correlations that are consistent with the MAT model, but are obviously not to be taken as causal. However, the randomized control trial (RCT) evidence in Indian textile firms (Bloom et al, 2013) showed that increasing WMS style management scores by one standard deviation in management caused a 10% increase in TFP. This estimate is consistent with the Olley-Pakes in column (5) of Table 3. Other well identified estimates of the causal impact of management practices such as the RCT evidence from Mexico discussed in Bruhn, Karlan and Schoar (2016) and the management assistance natural experiment from the Marshall plan discussed in Giorcelli (2016) find similarly large impacts of management practices on firm productivity (see also the literature surveys by McKenzie and Woodruff, 2013, 2017, on smaller firms).

## 5.2 Extensive Margin Reallocation: entry and M&A

We now examine changes in the extensive margin. In Figure 4 we calculate the management score at the firm level in MOPS in an initial year and then look at changes in entry over the next five years.<sup>27</sup> We calculate the management score of a MOPS firm in year  $t$  by averaging the management score of all the plants it owns for which we have a management score. We then follow the plants that are born from this parent firm in the subsequent five years through 2015. Because we need only the

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<sup>26</sup>In Appendix B1 (e.g. Table B2) we discuss a variety of other robustness tests of these productivity equations such as using an output rather than value added production function and including materials as an additional input; using the System-GMM approach of Blundell and Bond (2000) as well as alternative control function approaches to Olley-Pakes as discussed by Akerberg, Caves and Frazer (2015); using a Solow-residual based measure of conventional TFP and using the wage bill instead of employment as a measure of labor services. The importance of management remained in all of these experiments.

<sup>27</sup>Note that we cannot do this for the WMS because the vast majority of firms only have one management observation per year, and we cannot track the establishments of WMS firms .

LBD to detect new entrants, we can examine entry over two waves of MOPS: entry 2010-2015 as a function of 2010 firm management and entry 2015-19 as a function of the 2015 firm management score.<sup>28</sup> We express entry rates as a proportion of the number of plants who existed in the firm in 2010. The y-axis shows that unsurprisingly, there are relatively few new plants born (this is manufacturing, which is a declining sector): most entry rates are between 1% and 4%. Notably, however, there is a positive correlation between the average firm management score and the plant entry rate. Panel B shows that this upward sloping relationship—better managed firms give birth to more children—is also true in the simulated data.

Panel A of Figure 5 is symmetric to Figure 4, but examines plant exit. Perhaps surprisingly, well-managed firms also exit a disproportionately large fraction of their plants. This implies that such firms have a higher rate of creative destruction, consistent with the findings from Private Equity takeovers in Davis et al (2014). In the model, we have a lower cost of exit and entry for well managed firms, which produces simulation results in Panel B that are consistent with the MOPS data. As shown in the data in Figure 6 Panel A, the entry effect outweighs the exit effect, so if we calculate net entry (the number of entering plants minus exiting plants from the same firm), this is higher for firms with a higher initial management score. This is also clear in the simulation model in Panel B.

Figures 7 and 8 perform the same analysis, but instead of analyzing extensive margin growth in terms of firms organically creating more new plants, we examine what they do in the M&A market. Overall, we see surprisingly consistent patterns. Figure 7 shows that firms with higher management score acquired proportionately more plants both in the data (Panel A) and simulations (Panel B). Similarly, they also disposed of a greater proportion of plants in the data and simulations (Figure 8 Panels A and B respectively). Even though such plants are more active on both dimensions of creative destruction, the acquisition effect outweighs the disposal effect: Panels C and D show that net acquisition rates (the number of acquired plants less the number of disposed plants as a fraction of the initial number of plants) are greater for well managed firms.

### 5.3 The transferal of management practices across plants within firms

Earlier analysis of MOPS has shown that although there is much dispersion of management practices within firms across plants, there is still a strong “firm effect” (about half of all variance of management in multi-plant firms seems due to a firm effect - see Bloom et al, 2019). Much case study work, as well as our formal model, ascribes this to the (partially) non-rival nature of management within a firm. To examine whether management really does spread from the parent firm to the child plant, we examine two margins. First, do well managed firms not only have more children (though directly giving birth and also adopting), but also produce children with higher management scores? Second, when a well managed firm takes over a plant from a more poorly managed firm, does the plant’s management proportionately improve?

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<sup>28</sup>At the time of analysis the 2020 LBD was not yet available.

### 5.3.1 Well managed firms spawn better managed plants

Figure 10 examines the management scores of plants “born” to firms of different management scores in MOPS. The firm score is the average across all the plants belonging to a firm that we observe in the relevant year of MOPS. We calculate the management score of a MOPS firm in year  $t$  by averaging the management score of all the plants it owns for which we have a management score. We then follow the plants that are born from this parent firm in the subsequent five years through 2015 and examine their management scores in 2015 from the later wave of MOPS.

Panel A shows that the “children” of well-managed firms are much more likely to have high management scores themselves. Panel B shows that we also obtain an upwards slope from the simulation, although this relationship flattens after a certain point.

### 5.3.2 Well managed firms increase the management score (and performance) in plants they acquire

To test the hypothesis of transferal of management practices from acquirer to target, we compare how management practices change when a plant is acquired by a new firm. To do this, we limit the sample to plants that are acquired between 2010 and 2015, and regress the change in plant management on the difference between the management scores of the adoptive (new) and birth parent (old) firms:

$$M_{e,j,t} - M_{e,j,t-5} = \beta(M_{j,t-5} - M_{i,t-5}) + v_{it}. \quad (12)$$

The dependent variable in equation (12) is the change in an acquired plant  $e$ ’s management score over the five year period 2010-15. The right hand side variable is the average management score in the acquiring firm  $j$  compared to the target firm  $i$ . Note that we use the lagged value of firm  $i$ ’s management to avoid conflating the current plant’s score with that of the acquiring firm. Our hypothesis is that  $\beta > 0$  if there is transferal of the acquiring firm’s management practices to the target plant.

Table 1 presents these regression results from the MOPS data. Consistent with the hypothesis we find that  $\hat{\beta} > 0$  in the data. Because the firm management score ( $M_{i,t-5}$ ) is constructed partially from the management score of the target plant itself, column (2) constructs the firm management scores on the non-target plant’s management scores, showing that the results are robust.

A corollary of this fact is that performance should improve faster in plants who move to a relatively better managed firm, i.e. when  $(M_{j,t-5} - M_{i,t-5})$  is greater. We show this in Table 2, where we regress the change in productivity, measured as log revenue per worker, of acquired plants on the management scores of the adoptive and birth parent firm and the difference between these management scores. We do find that productivity improves more at plants that are acquired by better-managed firms, and it improves even more if the birth parent firm is poorly managed.

## 5.4 Market Equilibrium Effects: Age, Competition and M&A costs

We next consider a variety of tougher tests based on the market equilibrium of our simulated economy.

### 5.4.1 Plant Age and Management

The model has some predictions over what we expect of management as a firm ages. Examining age in WMS is complicated by the fact that the “date of incorporation” information in company accounts refers to the year in which the company was formed, even if this is due to a merger or acquisition.<sup>29</sup> Consequently, we focus on MOPS<sup>30</sup>. As a cohort of plants age, there is a selection effect such that plants who began with low draws of management will tend to exit the economy, so that the remaining older establishments will be better managed than average. The truncation of the lower tail will also mean that the variance of management will also fall as plants get older. Although there are many other effects in our model economy (e.g. selection also operates on TFP and the low draw of management may be offset by a relatively high TFP causing the plant to remain operating and accumulating more managerial capital), the simulation in panel B of Figure 11 seems consistent with these two predictions. Panel A, drawn from the data put into five year bins, also shows this pattern with the selection effects being particularly strong in the first 5 years of life.

### 5.4.2 Competition and management

An important question is the equilibrium effect of production market competition on management. We can adjust this in the model by increasing the elasticity of demand, i.e. the degree of consumer substitutability between varieties. Figure 12 shows five economies from our model simulation where we change the demand elasticity with the blue bar representing the simple average of managerial capital and the red line representing the employment size-weighted value of management. Our benchmark calibration was  $\rho = 4$ , and we immediately see the intuitive result that the weighted management score is greater than the unweighted score. This is because firms with higher management scores are larger, partly because the market allocates more activity to better managed firms. We consider decreasing competition to  $\rho = 3$  and raising it in increments to  $\rho = 8$ . Two results stand out. First, it is clear that the unweighted average management score is increasing in the degree of competition, mainly for the intuitive reason that poorly managed plants will tend to exit the market. Second, the weighted management score is also increasing in the degree of competition,

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<sup>29</sup>For example, a company like GSK is denoted as formed in 2001 when Glaxo Wellcome merged with Smithkline-Beecham, even though Glaxo-Wellcome has a history dating back to late Nineteenth Century (Jason Nathan and Company, started in 1873, merged with Burroughs Wellcome and Company, started by Henry Wellcome and Silas Burroughs in 1880).

<sup>30</sup>Plant age in the Census is measured from the first year of existence in the Census/IRS Business Registry, which is built from social security and income tax records.

with a sharper gradient than the weighted score. This is because of reallocation on the intensive margin (as well as the extensive margin in the unweighted case). As competition increases the covariance between management and size also tends to increase.

To examine these predictions in the data, Figure 13 shows the correlations of management with three alternative measures of competition in the WMS data. First, we begin with the inverse industry Lerner index measured in an industry by country by period cell. The Lerner index is a classic measure of competition (Aghion et al, 2005), and is calculated as the median price cost margin within an industry-country cell using all firms in the ORBIS accounting database.<sup>31</sup> Since profits data is not generally reported for firms in developing countries, we focus on OECD countries. We build a time varying Lerner index using data relative to three different periods (2003-2006; 2008-2011; 2012-2013).<sup>32</sup> These industry by country by period variables are then correlated with the management scores conducted over the same time periods.

As an alternative to the Lerner measure of competition, we use a measure of import penetration (imports over apparent consumption) in the country by industry by period cell, again measured in the same periods and for the same set of OECD countries using industry by country by year data from the World Input-Output Database (WIOD). Finally, to take into account the fact that observed changes in import competition may be endogenous, we build an alternative measure of import penetration from WIOD which includes only imports from China, as these have been shown in other papers (e.g. Autor, Dorn and Hansen (2013) and Bloom, Draca and Van Reenen, 2016) to be overwhelmingly driven by policy changes such as Chinese accession to the WTO and the subsequent reduction in tariffs and quotas (e.g. the dismantling of the Multi-Fiber Agreement).

We bin the three competition measures into terciles and plotting the mean management score in each bin. Panel A of Table 12 shows this for cross sectional “levels” (after subtracting the overall industry means and overall country means in both the competition measure and the management score), revealing a robustly positively relationship for all three competition measures. Panel B reports a similar graphic for “changes” in management over time *within* a country by industry pair (i.e. subtracting the country by industry means) against changes in competition over time, again displaying a robustly positive relationship.

To examine the role of management, competition and reallocation in more depth we run regressions of the form:

$$M_{p,c,k,t} = \gamma_1 COMPETITION_{c,k,t} + \gamma_2 z_{p,t} + \eta_t + \xi_{c,k} + \nu_{p,c,k,t} \quad (13)$$

where where  $M_{p,c,k,t}$  is the empirical management score of plant  $p$  in country  $c$  in industry  $k$  at

<sup>31</sup>In the simulated data we confirm that this empirical measure of the Lerner Index is highly correlated with our consumer price sensitivity parameter,  $\rho$ . For example, the Lerner has a correlation of 0.928 with price sensitivity across simulations in which we increase  $\rho$  in unit increments from 3 to 15.

<sup>32</sup>See the Appendix for details on the construction of the measures of competition. These roughly correspond to blocks of time before, during and after the Great Recession/Euro Crisis. 2013 is the last full year of the ORBIS database currently available.

time  $t$ ,  $COMPETITION_{c,k,t}$  are the three alternative competition measures noted above,  $z_{p,t}$  is a vector of other firm controls (the proportion of employees with a college degree, log firm and plant size, log firm age and noise controls),  $\eta_t$  denotes year dummies,  $\xi_{c,t}$  denotes a full set of three digit industry by country dummies, and  $\nu_{p,c,k,t}$  is an error term. Table B3 contains the results of estimating equation (13) with the unweighted OLS results in the odd columns and the regressions weighted by firm size in the even columns. Across all specifications  $\gamma_1$  is positive and significant consistent with Figure 13. Moreover, consistent with Figure 12, the weighted correlations are much stronger than their unweighted counterparts. For example, the coefficient on the Inverse Lerner index rises from 0.99 (unweighted) to 1.75 (weighted).

Another way to examine the reallocative impact of competition is to consider whether factors that reduce the degree of competition reduce the covariance between management practices and firm size, implying  $\delta_1 < 0$  in the following equation:

$$Size_{p,t} = \delta_1 (M * COMPETITION)_{p,t} + \delta_2 M_{p,t} + \delta_3 COMPETITION_p + \delta_4 x_{p,j,t} + \epsilon_{p,j,t} \quad (14)$$

Appendix B confirms that better managed firms are significantly larger (an increase in the management score by one standard deviation is associated with an extra 183 workers.). But we then examines several proxies for  $COMPETITION$ . First, we countries grouped into regions to proxy competitive frictions, and show that  $\delta_1$  is significantly larger in regions where market frictions are likely to be lower (e.g. the U.S) than in others (e.g. southern Europe and Africa). Second, we investigated explicit measures of market-friction variables that can reduce competition such as employment regulation, trade costs and detailed country by industry measures of tariffs. All these measures indicated that the size-management covariance was stronger when competition was greater.

Taken as a whole, these findings on competition appear very consistent with the theoretical model.

### 5.4.3 Increasing M&A Costs

There is much current discussion about reforming the rules over anti-trust. One view is that M&A should be made generally much more costly as it leads to exploitation of consumers. Our model does not have strategic interaction in the product market so we cannot really account for this. But we do have an efficiency rationale for the M&A market as a way to reallocate plants more appropriately across firms, in particular as a way to improve management practices.

We can use our simulation model as a way of investigating the impact of making mergers more costly. In Figure 14, we consider a boundary case where we make M&A so expensive it closes down the market completely. The bar labeled “baseline model” is GDP (“value”) in our simulated model and the bar labeled “Ban M&A” is the counterfactual where M&A is made prohibitively expensive.

In this counterfactual, a firm will not be able to access the M&A market to dispose of (or buy) plants - the only way to spin off a plant is to exit it from the economy. In such a counterfactual GDP is about half the level of the baseline. This is clearly an extreme case, but it does suggest that there is substantial benefits from having opportunity to buy and sell establishments. The results from this exercise, however, are preliminary.

## 6 Accounting for cross-country TFP differences with Management

We now return to a long-standing question in economics, stretching back to at least Walker (1887). To what degree do management practices account for the large variation in productivity both across countries and also within countries, across-firms? We begin at the national level by defining an aggregate country management index and decomposing this into a within firm and between firm component in an analogous way to the standard Olley and Pakes (1996) productivity decomposition method:

$$M = \sum_i M_i s_i = \sum_i [(M_i - \bar{M}_i)(s_i - \bar{s}_i)] + \bar{M}_i = OP + \bar{M}_i$$

where  $M_i$  is the management score for firm  $i$ ,  $s_i$  is a size-weight (the firm's share of employment in the country),  $\bar{M}$  is the unweighted average management score across firms and OP indicates the "Olley Pakes" covariance term,  $\sum_i [(M_i - \bar{M}_i)(s_i - \bar{s}_i)]$ . The OP term simply divides management into a within and a between/reallocation term.

Next, comparing any two countries  $k$  and  $k'$ , the difference in weighted scores can be decomposed into the difference in reallocation and unweighted management scores:

$$M^k - M^{k'} = (OP^k - OP^{k'}) + (\bar{M}_i^k - \bar{M}_i^{k'})$$

A deficit in aggregate management is composed of a difference in the reallocation effect  $(OP^k - OP^{k'})$  and the average unweighted firm management scores  $(\bar{M}_i^k - \bar{M}_i^{k'})$ .

Table C1 reports the results of this decomposition (more details in Appendix C1) using the U.S. as the base country ( $k' = US$ ) as it has the highest management scores. In column (1) we present the employment share-weighted management scores ( $M$ ) in z-scores, so all differences can be read in standard deviations from the sample mean of 0. These differ from those presented earlier in Figure 1 because we have dropped multinationals (to focus on clean national differences), size-weighted the management scores and use z-scores (normalized so that mean=0 and standard-deviation=1). In column (2) we show the unweighted average management score ( $\bar{M}_i$ ), and in column (3) the Olley Pakes covariance term. From this we can see that, for example, the leading country—the U.S.—has a size-weighted management score of 0.90, which is split almost half in between a reallocation effect (0.40) and an unweighted average management score effect (0.50). Thus, the U.S. not only has the

highest unweighted management score but it also has a comparatively high degree of reallocation as discussed above in sub-section 4.2.<sup>33</sup>

We next calculate each country’s management gap with the U.S. Column (4) does this for the overall management gap and column (5) reports the share of this gap arising from differences in reallocation. These results are also presented graphically in Figure A4, which shows that reallocation accounts for a non-trivial fraction of the management gap in just about all countries, ranging from 8% in Tanzania to 94% in Japan.

We can push this analysis further by examining how much management could explain cross country differences in TFP. Column (6) of Table C1 contains the country’s TFP gap with the U.S. using the latest Penn World Tables (Feenstra, Inklaar and Timmer, 2015).<sup>34</sup> Following the randomized control trial (Bloom et al, 2013) and non-experimental evidence in Table B1, we assume that a one standard deviation increase in management causes a 10% increase in TFP. For example, we can estimate that improving Greece’s weighted average management score to that of the U.S. (a 1.3 standard deviation increase) would increase Greek TFP by 13%, about a third of the 37.5% TFP gap between Greece and the U.S. Column (7) contains similar calculations for the other countries. Overall, on average 30% of the cross country gap in TFP appears to be management related (see base of column (7)).<sup>35</sup> This fraction varies a lot between countries. In general we account for a smaller fraction of the TFP gap between the U.S. and low income countries like Zambia (6.2%), Ghana (9.7%), and Tanzania (12%), which is likely to be because these countries have much greater productivity impediments than just management quality. We account for a larger fraction of the TFP gap between the U.S. and richer countries like Sweden (43.9%), Italy (48.9%) and France (52.3%). Figure 15 graphically illustrates this, showing that more developed countries have a higher share of their TFP gap accounted for by differences in management.

In conclusion, this suggests that a substantial amount of the cross country differences in TFP are due to management capital.

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<sup>33</sup>Interestingly, these results are broadly consistent with Bartelsman et al (2013) who conducted a similar analysis for productivity on a smaller number of countries but with larger samples of firms. Although the countries we examine do not perfectly overlap, the ranking in Bartelsman et al (2013) also has the U.S. at the top with Germany second and then France. Britain does somewhat better in our analysis, being above France, but our data is more recent (2006-2014 compared to their 1992-2001) and Bartelsman et al (2013) note that Britain’s reallocation position improved in the 2000s (their footnote 9).

<sup>34</sup>We used the latest information from 2011, but qualitative results are stable if we take an average over a larger number of years. When data was missing we impute using values in Jones and Romer (2010).

<sup>35</sup>For the seven countries where it is possible to calculate manufacturing TFP, the correlation with whole economy TFP is 0.94. The average proportion of the manufacturing TFP gap accounted for by management in these countries was 32.6%. We also find that our manufacturing management scores are highly correlated with the management scores in other sectors like retail, healthcare, schools and government services (see Chong et al. 2014), so that the manufacturing management score appears to be a good measure of overall national management quality.



## 7 Extensions

### 7.1 Managerial Compensation and Management Practices

One view of management practices is that they simply reflect the quality of the firm’s CEO. For example, Edmans and Gabaix (2017) show that the canonical Lucas (1978) model implies a relationship between the value added of the firm and the talent,  $T$ , of the CEO:

$$Y_i = \lambda_1 \ln T_i + \lambda_2 \ln K_i + \lambda_3 L_i \quad (15)$$

Obviously, this bears a close relationship to our MAT production function where managerial capital,  $M$ , is now simply CEO talent. For example, if we considered the investment in management capital ( $I^M$ ) represented the cost of managerial talent then in steady state  $I_M = \delta_M M$  so  $\ln I^M = \ln \delta_M + \ln M$ . Hence, we would expect to see a positive relationship between CEO remuneration and management practices. Motivated by this idea, we gathered information on CEO pay for firms in four countries: China, India, the UK and US. We focused on publicly listed firms because CEO pay is not usually disclosed for smaller firms (see Appendix D for data details). We were able to gather data on a sample of 532 firms of our firms (912 observations). There is a statistically significant and economically important relationship between CEO pay and management practices whether or not we control for a wide variety of factors. For example, column (1) of Table A6 suggests that a 0.1 increase in the standard deviation of management is associated with a 3% increase in CEO salary. Figure A4 shows the relationship for the UK and US (where we have the richest data).

An alternative use of the CEO pay data is to compare the compensation to managers with the factor share paid to management implied by the model. The Cobb-Douglas coefficient on management— $\gamma$  in equation (11)—is calibrated at 0.1, which implies a 10% cost share for management capital. To evaluate the plausibility of this figure, we look at the compensation paid to senior employees in firms, whose activities are likely to be primarily management. Using the Social Security Administration data on all employees in all US firms (public and private) from in Song et al (2019), we calculate that in 2013 the fraction of earnings going to the top 1% and 5% in all firms with 20+ employees is 7% and 22%.<sup>36</sup>

### 7.2 Management by Design

An alternative approach to our MAT approach is to assume that management practices are contingent on a firm’s environment, so that increases in  $M$  do not always increase output. In some

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<sup>36</sup>In large firms with 10,000+ employees these pay shares are very similar at 8%, 23% and 32% for the same percentiles of employee pay. We provide three different pay shares as it is not clear what fraction of top employees can be thought of as management. Certainly the top 1% of employees in larger firms will be almost exclusively focused on management, while those at the top 10% will be heavily focused on this but will also include senior engineers, lawyers etc. who are not completely (or even mainly) managers. Therefore, some mid-point in these figures is likely to provide the best guess of the wage costs of managerial inputs.

sectors, high values of  $M$  will increase output, and in others they will reduce output depending on the specific features of the industry. We assume that optimal management practices may vary by industry and country, but this could also occur across other characteristics like firm age, size, or growth rate. For example, industries employing large numbers of highly skilled employees, like pharmaceuticals, will require large investments in careful hiring, tying rewards to performance and monitoring output, while low-tech industries can make do without these costly human resource practices. Likewise, optimal management practices could vary by country if, for example, some cultures are more comfortable with firing persistently under-performing employees (e.g. the U.S.) while others emphasize loyalty to long-serving employees (e.g. Japan).

There are many ways to set up a Design model. As a simple example we define  $G(M_i) = 1/(1 + \theta|M_i - \bar{M}|)$  where  $\theta \geq 0$  and  $G(M_i) \in (0, 1]$  is decreasing in the absolute deviation of  $M$  from its optimal level  $\bar{M}$ .<sup>37</sup> There are of course many other ways to model this idea, and our approach is certainly not meant to represent the wide range of Design approaches, rather we see it as a simple example to illustrate the implications of a  $\tilde{G}(M_i)$  function which attains an interior maximum. The predictions of the Management as a Technology model on performance, competition and age are all consistent with the results from the WMS and MOPS management datasets. Our admittedly extremely stylized version of the Management by Design model does less well. This Design model does successfully predict the dispersion of management (compare Figure 3 with Figure A5 Panel A) and the falling dispersion of management with age (compare Figure 10 with Figure A5 Panel C). However, the predictions of a non-monotonic relationship between firm performance and management are rejected (compare Figure 3 with Figure A5 Panel D) as is the flat relationship between management and competition (compare Figure 11 with Figure A5 Panel B) and management and age (compare Figure 10 dark bars with Figure A5 Panel C). Of course, more subtle versions of the Design model could fit the stylized facts in the data better, but it is striking that the MAT model does this in a more straightforward manner.

One set of results that is instead consistent with the Design approach relates to the contingency of specific types of management practices on different industry characteristics. More specifically, the Design approach suggests we might expect sectors that make intensive use of tangible fixed capital to specialize more in monitoring/targets management, whereas human capital intensive sectors focus more on people/incentives management. This is indeed what we tend to observe when we correlate our management data with four digit U.S. industry data on the capital-labor ratio (NBER) and R&D per employee (NSF), as shown in Panel A of Table D1.<sup>38</sup> Although both people management (column (1)) and monitoring/targets management (column (2)) are positively associated with fixed capital intensity, the relationship is much stronger for monitoring/targets, as shown when we regress the relative variable (people/incentives score minus monitoring/targets score) on capital intensity in column (3). The opposite is true for R&D intensity as shown in

<sup>37</sup>Our baseline case also assumes that  $M$  is a choice variable that does not have to be paid for on an ongoing basis so that  $\delta_M = 0$  although this assumption is not material.

<sup>38</sup>This is implicitly assuming that the U.S. values are picking up underlying technological differences between industries that are true across countries.

the next three columns: in high tech industries, people management is relatively more important. These findings are robust to including them together with skills in the final three columns.

As an alternative empirical strategy in Panel B of Table D1, we use country by industry specific values of these variables from the EU-KLEMS dataset. In these specifications we are using the country-specific variation in capital and R&D intensity within the same industry. The results are qualitatively similar to Panel A—capital intensive industries have higher monitoring/target management practices, while R&D intensive industries have higher people management practices scores, consistent with a basic Design model.

In summary, MAT appears to provide the best all around fit for the data, particularly in terms of firm performance. We will use the implications of this model in the next section to calculate what share of cross-country differences in TFP can be attributed to differences in management practices. However, there is some support for the Design model in terms of contingent management styles, suggesting that a hybrid model could offer a better fit of the empirical data at the expense of greater complexity.

### 7.3 Management as Capital?

We initially debated calling our main approach “Management as Capital” (rather than “Management as a Technology”), viewing management as an intangible capital stock (see for example Bruhn, Karlan and Schoar, 2016). In the end, because of the evidence suggesting management spillovers across plants within firms and between different firms<sup>39</sup> we thought modeling management as a technology seemed more appropriate. However, we recognize that either terminology could be used. Indeed, the classic technology input—the R&D knowledge stock—is recorded as an intangible capital input by the Bureau of Economic Activity in U.S. National Accounts.

## 8 Conclusions

Economists, business people and many policymakers have long believed that management practices are an important element in productivity. We collect original cross sectional and panel data on over 11,000 firms across 34 countries (WMS) and 60,000 US plants (MOPS) to provide robust firm-level measures of management in an internationally comparable way.

We document several new facts about the relationship between management and the boundaries of the firm. First, we show that firms with more structured management practices not only birth and acquire more new plants, but they also close and dispose of on the M&A market more existing plants. Thus, it seems that better managed firms not only grow faster, but also experience more churn in their stock of plants. This suggests that better management practices are associated with

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<sup>39</sup>For example, Greenstone, Hornbeck and Moretti (2010), Atalay, Hortascu and Syverson (2014), Braguinsky et al. (2015) and Bloom et al. (2017).

a stronger ability to assess the quality of individual plants. Second, we show that management practices spread across plants within a firm, both to newly birthed plants and to acquired plants. This gives credence to our model approach of “Management as a Technology,” because it does appear that management has non-rival elements which can travel freely across plants within the firm.

We also detail a formal model where our management measures have “technological” elements to match the new facts we have shown in the data. In the model, management enters as an intangible capital stock in the plant-level production function both from plant management and firm headquarters inputs. We allow entrants to have an idiosyncratic endowment of managerial ability, but also to endogenously change management over time (alongside other factor inputs, some of which are also costly to adjust like non-managerial capital). We also have multi-plant firms who can give birth to new plants as well as acquiring establishments on the M&A market. We show how the qualitative predictions of this simulated model are consistent with the data, as well as presenting structural estimates to recover some key parameters (such as the cost of adjustment and depreciation rates of managerial capital).

We find several important results using our approach. First, there are large costs to increasing the costs of M&A - switching this reallocation route off completely could cut GDP by up to half. Second, management accounts for about 30% of differences in cross-country TFP levels. Third, competition is an important factor in improving management.

There are many directions to take this work. It would be useful to examine the determinants of management practices in greater detail. We have focused on market-based incentives, but informational frictions and coordination may be equally if not more important. Gibbons and Henderson (2012), for example, argue that the need to coordinate a multitude of dispersed agents within a firm is critical.<sup>40</sup>

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<sup>40</sup>The coordination role of CEOs is empirically explored in Bandiera et al. (2017).

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## Figures

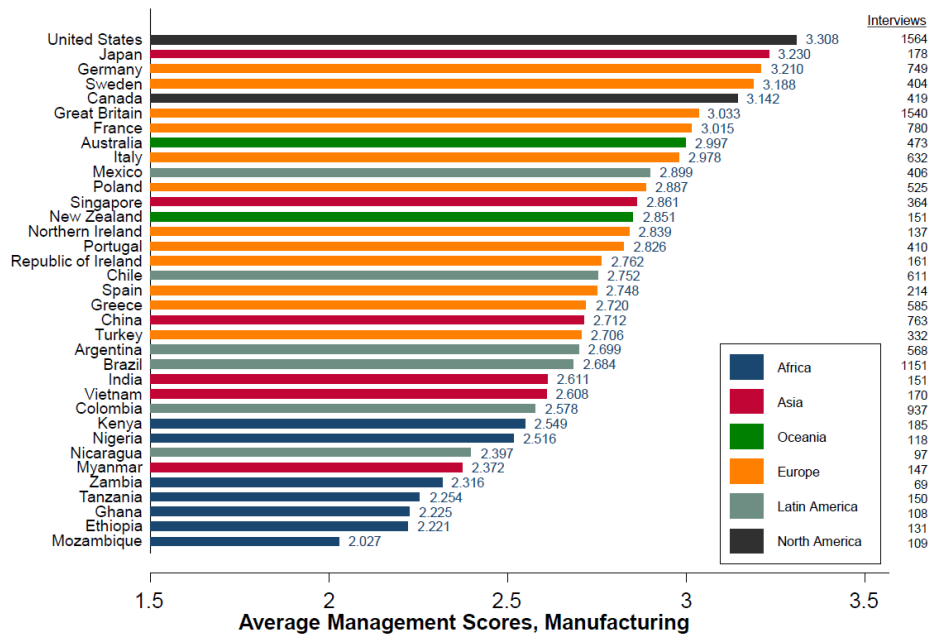
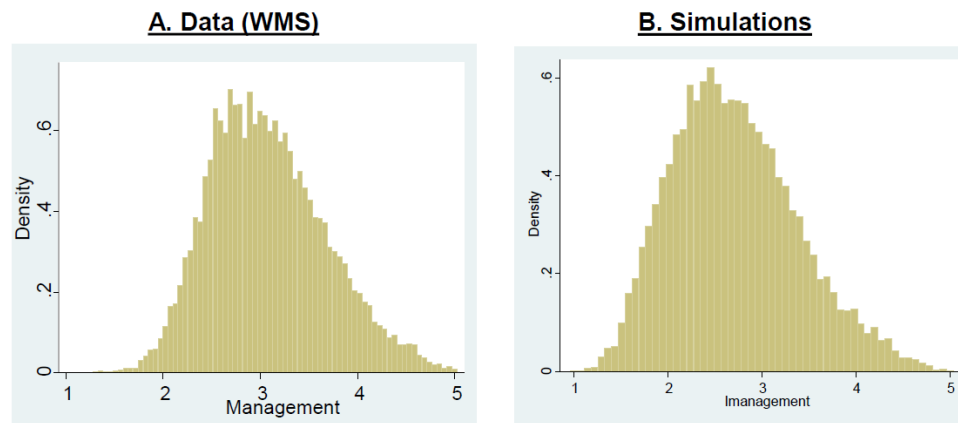


Figure 1: Average Management Scores by Country



**Notes:** The left plot is the management distribution for our entire sample of 15,489 firm surveys. The right plot is the histogram for a simulation of 15,489 simulated firm-years, where management has been logged and scaled onto a 1 to 5 range. Replication file on <http://web.stanford.edu/~nbloom/MAT.zip>

Figure 2: Distribution of Management Scores

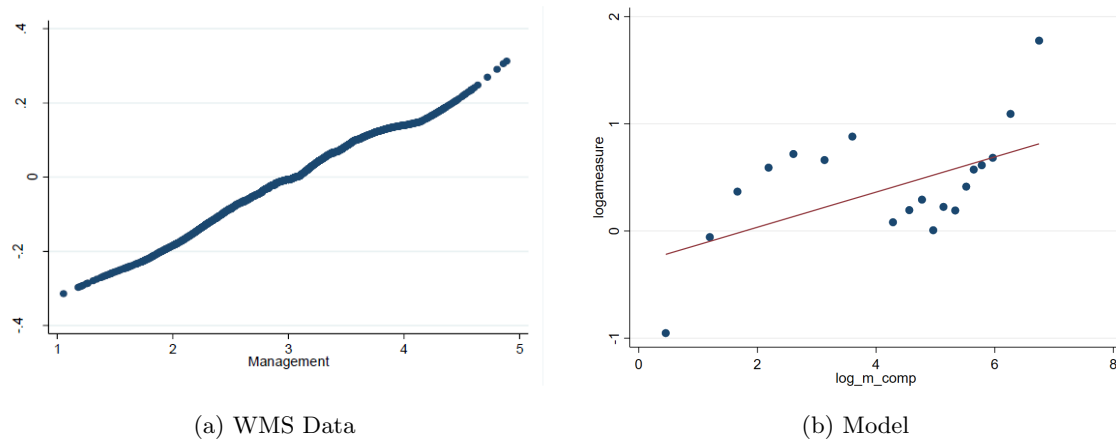


Figure 3: Firm TFP and Management

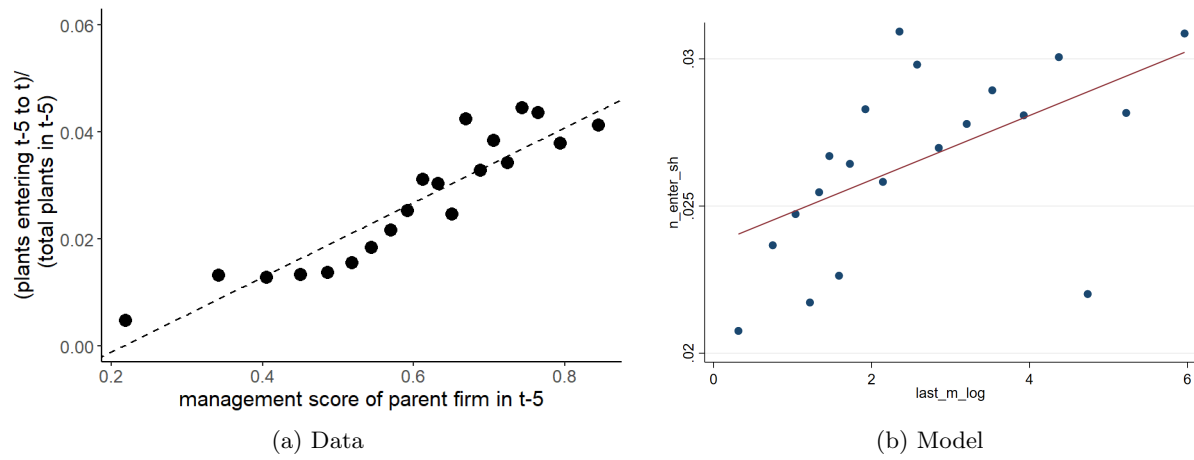


Figure 4: Share of Entering Plants vs. Lagged Management

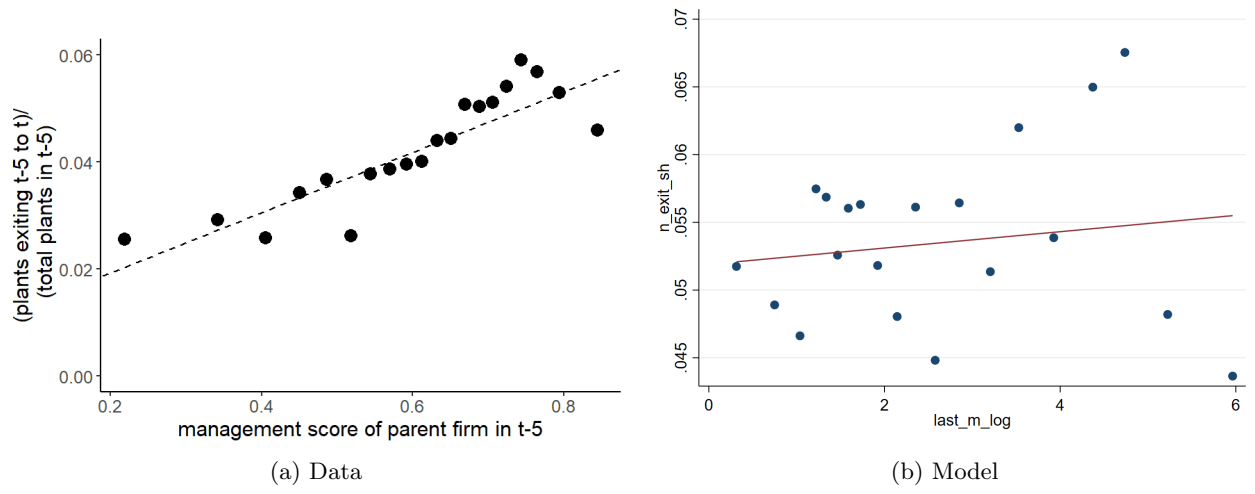


Figure 5: Share of Exiting Plants vs. Lagged Firm Management

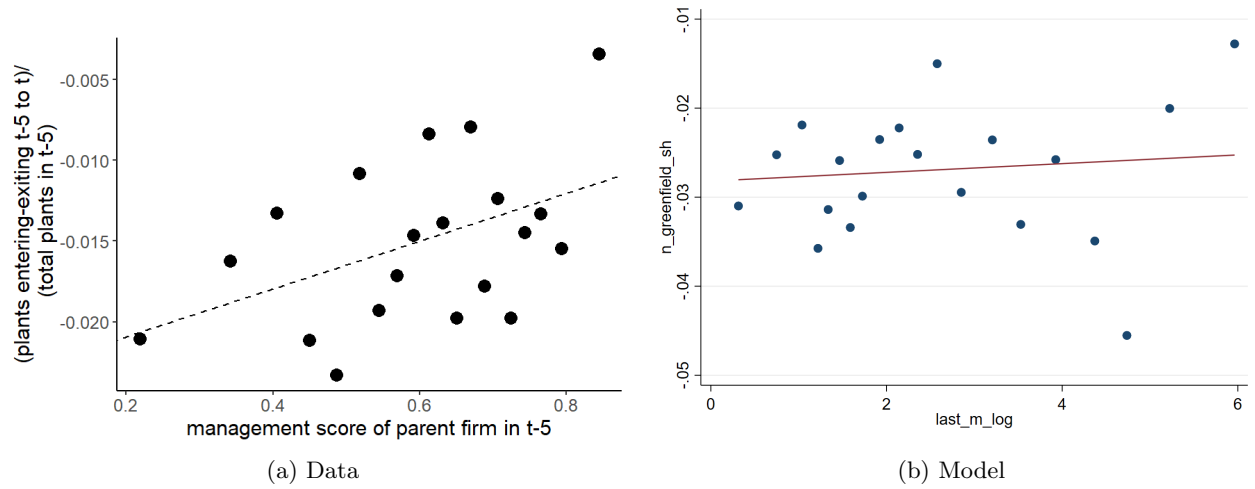


Figure 6: Share of Net Greenfield Entry/Exit vs. Lagged Firm Management

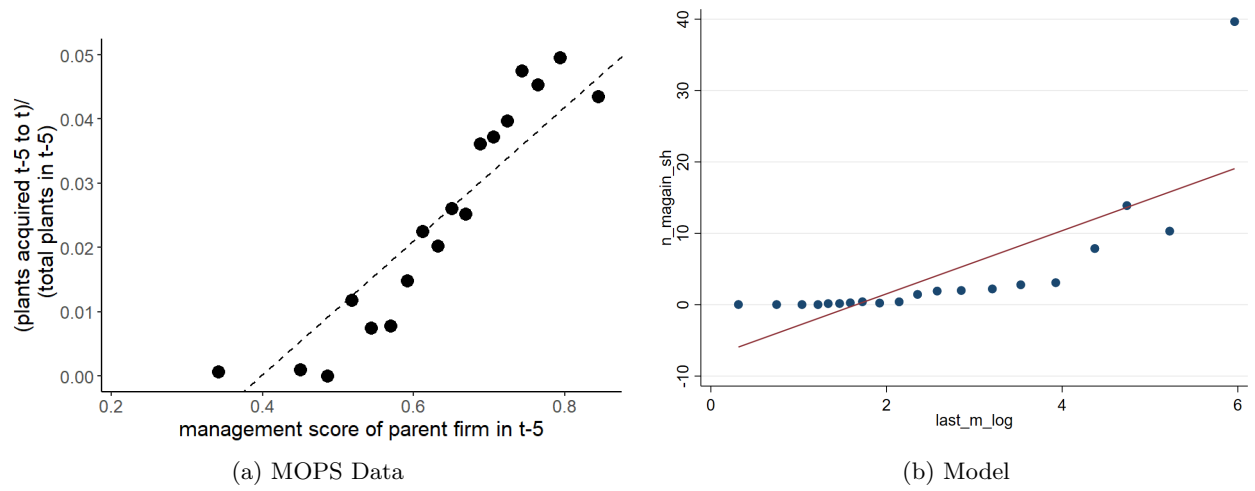


Figure 7: Share of Acquired Plants vs. Lagged Firm Management

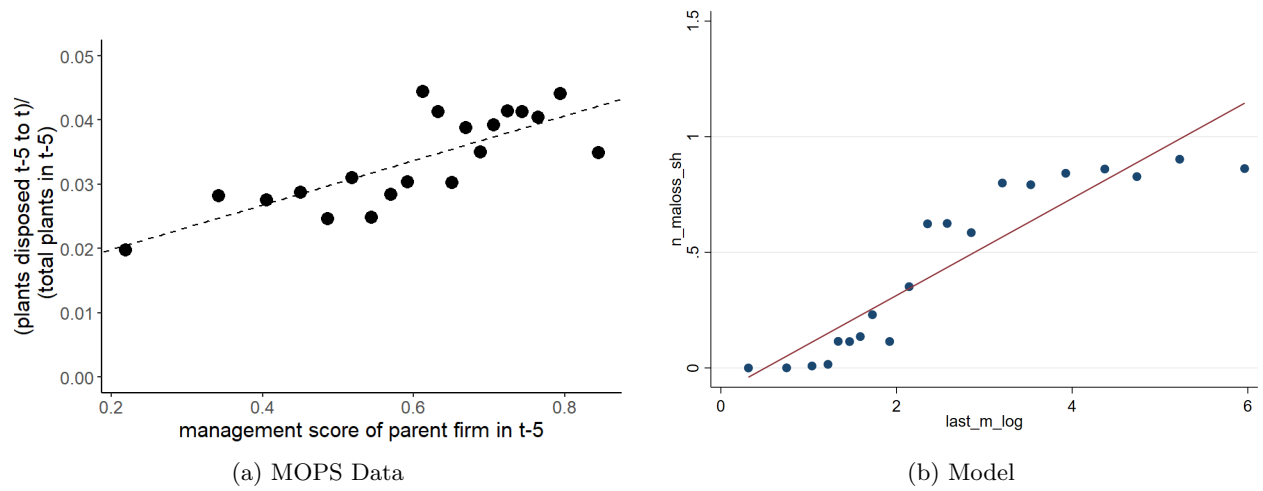


Figure 8: Share of Disposed Plants vs. Lagged Firm Management

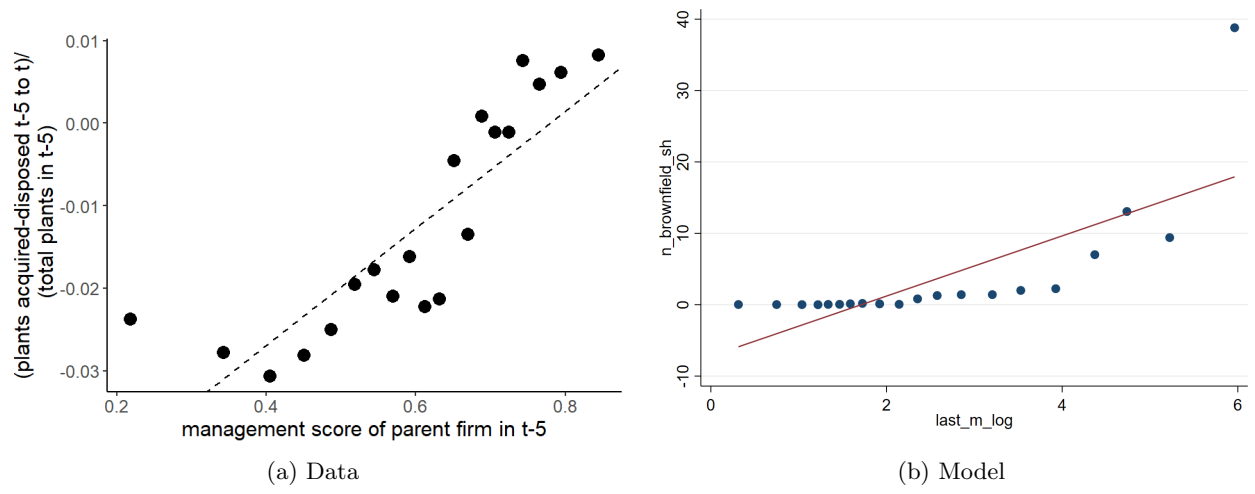


Figure 9: Share of Net Brownfield Acquisitions/Disposals vs. Lagged Firm Management

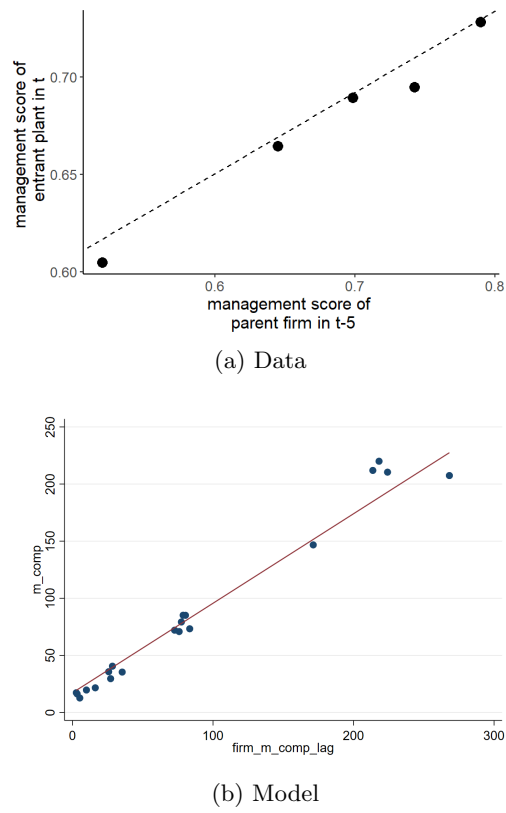


Figure 10: Management Scores of New Entrant Plants and Parent Firms

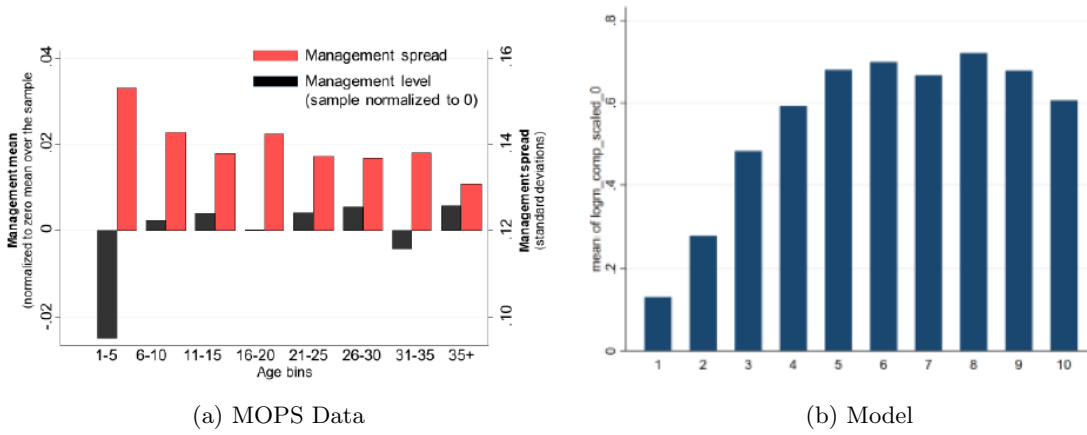


Figure 11: Management and Plant Age

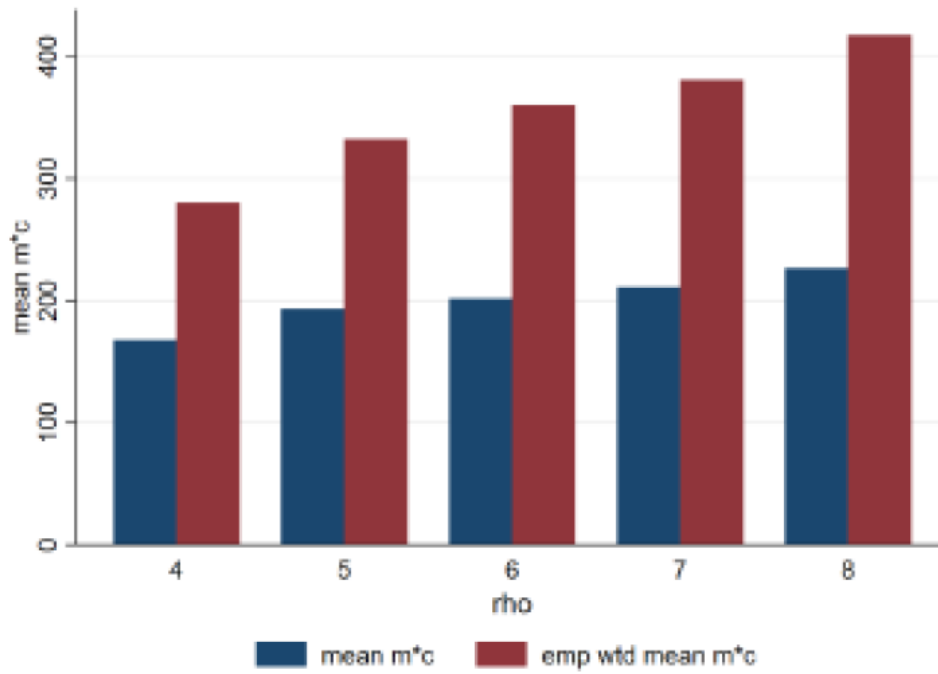


Figure 12: Management and Competition, Model Simulation

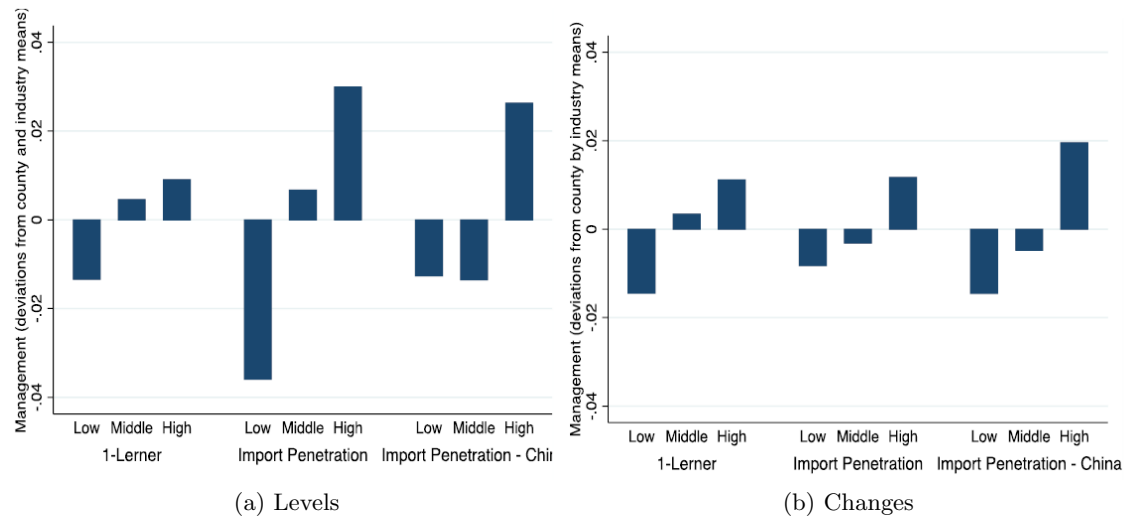


Figure 13: Management and Competition, WMS Data

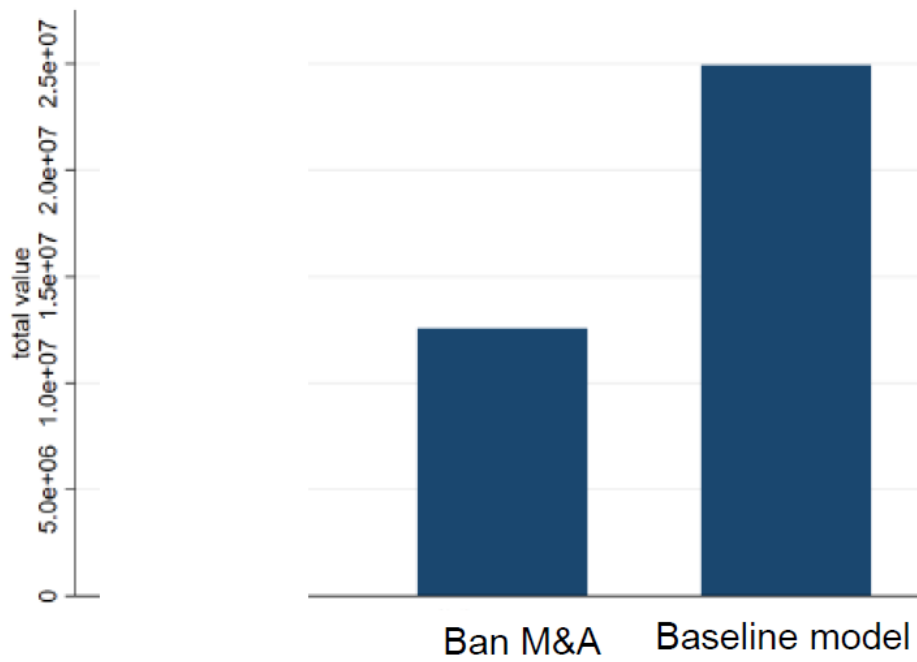


Figure 14: Change in Total Output without M&A, Model Simulation



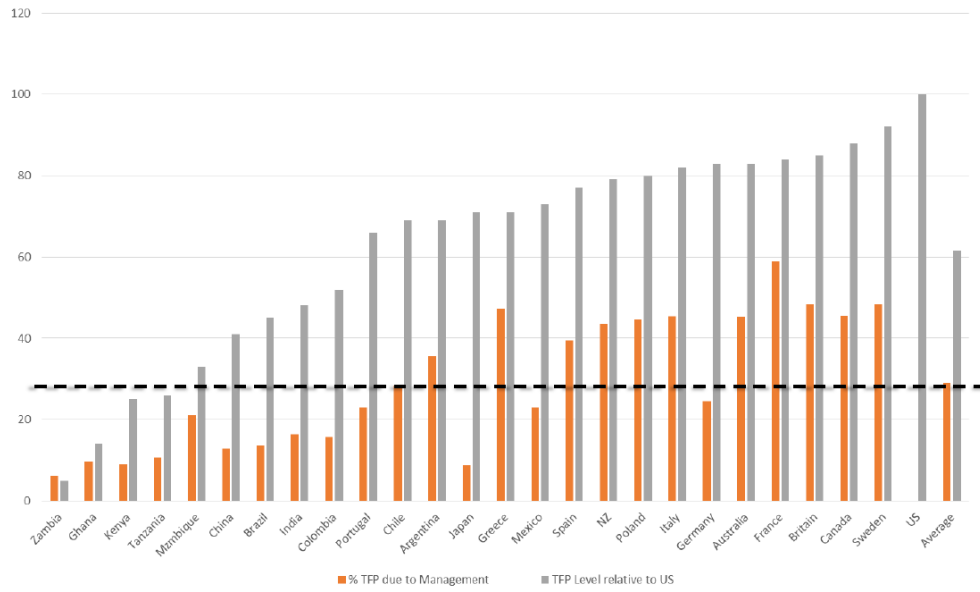


Figure 15: Decomposition of Cross-Country TFP Differences, WMS Data

Table 1: Change in Management of Acquired Plants, MOPS

	Dependent Variable: Change in Plant Management, 2010-2015					
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Adoptive Firm Management	0.3076					
- Birth Firm Management	0.09460					
Lagged Adoptive Firm Management		0.2212	0.1846	0.2160	0.2197	
- Leave-out Birth Firm Management		0.09585	0.1170	0.09357	0.1222	
Lagged Adoptive Firm Management						0.2900
						0.1566
<sup>42</sup> Lagged Leave-out Birth Firm Management						-0.1318
						0.1152
N (same for all columns)	850					
4-digit NAICS FE	no	no	yes	no	yes	yes
State FE	no	no	no	yes	yes	yes
Weight	n mscore	n mscore	n mscore	n mscore	n mscore	n mscore

Standard errors in second row.

This table shows the regressions of the change in management between 2010 and 2015 for plants that were acquired (changed firm identifier) between 2010 and 2015 on the difference between the management scores of the adoptive and parent firms in 2010 (with or without leave-out mean for birth parent firm) or the management scores of the adoptive and birth parent firm separately.

Table 2: Change in Log Sales per Worker for Acquired Plants, MOPS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variable: Change in Log Sales per Worker, 2010-2015 and 2015-2019									
Lagged Adoptive Firm	0.2098	0.2825	0.2825				0.3986	0.4549	0.4699
Management Score	0.1028	0.1118	0.1125				0.1476	0.1577	0.1585
Lagged Adoptive Firm M				0.3150	0.3361	0.3549			
- Lagged Birth Firm M				0.1345	0.1415	0.1426			
Lagged Birth Firm M							-0.2474	-0.2367	-0.2577
							0.1434	0.1493	0.1508
Constant	-0.1797	-0.2293	-0.2810	-0.03949	-0.03966	-0.09081	-0.1419	-0.1874	-0.2364
	0.07219	0.07675	0.09795	0.01051	0.01035	0.05846	0.07614	0.08041	0.1007
N (same for all columns)	4400								
4-digit NAICS FE	no	yes	yes	no	yes	yes	no	yes	yes
State FE	no	no	yes	no	no	yes	no	no	yes

Standard errors in second row.

This table shows regressions of the change in log sales per worker between 2012 and 2017 for plants that were acquired (changed firm identifier) between 2012 and 2017 on the management score of the adoptive firm in 2010, the difference between the management scores of the adoptive and parent firm in 2010, or the management scores of the adoptive and birth firms separately in 2010.

## A APPENDIX: DATA

We overview the datasets in this Appendix. More information on an earlier version of the WMS dataset can be found in Bloom, Sadun and Van Reenen (2012b) and Bloom and Van Reenen (2007). More information on the management survey in general (including datasets, methods and an online benchmarking tool) is available on <http://worldmanagementsurvey.org/>. Details on the MOPS data is in Bloom et al (2017).

### A.1 Firm-level Accounting Databases

#### *Manufacturing firm sampling frame*

For the WMS we focus on medium sized manufacturing firms, so to conduct our surveys we would ideally draw a sampling frame from a business registry of firms. Unfortunately, the names of these firms in administrative data from business registers (where it exists) are usually confidential. Three exceptions were Chile, Colombia and Singapore. In Chile we worked directly with the government, so it was possible to use the confidential business register data to phone firms - the Industrial Annual Survey Sample of Firms (Encuesta Nacional Industrial Annual - ENIA), which covers all manufacturing firms with more than 10 employees. We used a similar model in Colombia, working with the Business Ministry and World Bank. In Singapore the Ministry of Trade and Industry ran the survey (with our training) using their population business register.<sup>41</sup>

For other countries we use publicly available data sources.<sup>42</sup> Our main sampling frame was based on various accounting databases supplied by Bureau van Dijk (BVD), a private sector organization that seeks to compile accounting information on companies from all over the world. BVD ORBIS has names, industry, addresses, status (e.g. active or bankrupt), and accounting information such as employment and sales. ORBIS is constructed from a range of sources, primarily the national registries of companies (such as Companies House in the U.K.). The full sources for the sampling frame are listed in column (3) of Table A2.<sup>43</sup> In some countries we were concerned about incomplete coverage by ORBIS so we supplemented it with other sources. We also used Dun & Bradstreet for Australia and New Zealand. In India we use CMIE Firstsource 2005.<sup>44</sup> Low income countries pose

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<sup>41</sup>Unlike in Chile and Colombia, we were not able to obtain the characteristics of the non-responders in the sampling frame from the Singaporean government due to confidentiality reasons.

<sup>42</sup>There is usually a fee to be paid for access to the data compiled in an easy to use form, but the names and addresses of the firms are given in this data (unlike administrative government data where names are not revealed) as they are in the public domain.

<sup>43</sup>The firm-level databases underlying ORBIS are sometimes packaged under different names in different regions of the world by BVD (for a given country, the same firms are covered but sometimes with more fields of data). For example, in Europe the firm database is called AMADEUS (France, Germany, Greece, Great Britain, Italy, Ireland, Northern Ireland, Poland, Portugal, Spain, Sweden and Turkey); in North America it is called ICARUS (U.S. and Canada) and in parts of Asia it is called ORIANA (China, Japan). Other countries where we simply used ORBIS include Argentina, Brazil, Mexico and Viet Nam. In Table A2 we simply refer to all of these as ORBIS as this is the same overall list of firms.

<sup>44</sup>CMIE is constructed from the Registry of Companies in India. Icarus is constructed from the Dun & Bradstreet

a particular challenge, as there is generally no well maintained business register to draw upon. We used a larger variety of data sources to construct sampling frames for these countries complementing ORBIS with country specific “enterprise maps” put together by researchers such as John Sutton at the London School of Economics’ International Growth Centre (IGC), who worked with local consultants. For full details on the African sampling frame, see Lemos and Scur (2015). Briefly, in addition to ORBIS and the enterprise maps in Ethiopia (Sutton and Kellow, 2010), we also used trade directories and the online yellow pages; in Ghana we supplemented Sutton and Kpentey (2012) with the Ghana Free Zones Board and Business Ghana Directory; in Kenya we supplemented ORBIS with the Kenya Association of Manufacturers; in Mozambique we supplemented Sutton, Pimpao, Simone, Zhang and Zita (2014) with the Ministry of Commerce’s database and FACIM; in Nigeria we supplemented ORBIS with VConnect; in Tanzania we supplemented Sutton and Olomi (2012) with the Ministry of Trade database; in Zambia we supplemented Sutton and Langmead (2013) with the Zambia Association of Manufacturers. In Myanmar we supplemented the PEDL Enterprise Map with industry directories and lists of manufacturers provided by the Myanmar Industry Association (see Tanaka, 2015) and in Nicaragua we used business directories and an IADB database.

These databases all provide sufficient information on companies to conduct a stratified telephone survey (company name, address, and a size indicator). They also typically have some accounting information on employment, sales, and capital. We did not insist on having accounting information to form the sampling frame, however.

### *Representativeness of the sampling frame*

How representative are our sampling frames of the underlying population of manufacturing firms? For most of the countries we have evidence that the data is reasonably comprehensive. For example, when comparing aggregate employment in the ORBIS populations to those from census data, we usually find a reasonably close match (e.g. Kalemli-Ozcan et al, 2015; Bloom, Draca and Van Reenen, 2016).

In Bloom, Sadun and Van Reenen (2012b) we analyze this in more detail. For example, we compare the number of employees for different size bands from our sampling frame with the figures for the corresponding manufacturing populations obtained from national census data from each of the countries where this is available. There are several reasons for a mismatch between Census data and firm level accounts.<sup>45</sup> Despite these potential differences, our sampling frame appears to cover

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database, which is a private database of over 5 million US trading locations built up from credit records, business telephone directories and direct research. Oriana is constructed from Huaxia credit in China and Teikoku Database in Japan, covering all public and all private firms with one of the following: 150 or more employees, 10 million US\$ of sales, or 20 million US\$ of assets.

<sup>45</sup>First, even though we only use unconsolidated firm accounts, employment may include some jobs in overseas branches. Second, the time of when employment is recorded in a census year will differ from that recorded in firm accounts. Third, the precise definition of “enterprise” in the census may not correspond to the “firm” in company accounts. Fourth, we keep firms whose primary industry is manufacturing whereas census data includes only

near to the population of all firms for most countries.<sup>46</sup>

Mismatch between the true population and our sampling frame could be a problem if our sampling frame was non-randomly omitting firms - for example under-representing smaller firms - because it would bias our cross-country comparisons. We tried several approaches to address this. First, in almost all the regression tables we include country fixed effects to control for any differences across countries in sample selection bias. Hence, our key results are identified by within country variation. Second, we ran experiments where we dropped problematic countries (e.g. Portugal and Sweden) from the analysis to show that the results are robust.

It is harder to make such comparisons between our sampling frame and the full population of firms in some of the poorer countries as there is no reliable employment aggregate numbers to compare to. The enterprise maps by Sutton and others that we draw our sampling frames from are probably the most reliable sources. Given this, we should interpret some of the results from the African countries with more caution than those of the other nations.

### *Medium sized manufacturing firms vs. all manufacturing firms*

A further concern that is that even if our sampling frame is fully comprehensive, the proportion of employment covered by medium sized firms differs systematically across countries. Using Census sources on firm populations, Table A3 shows the employment distribution for the countries where it is available. Firms employing between 50 and 5,000 workers account for about half of all manufacturing workers in most countries, although the proportion was larger in some countries such as Ireland (72%) and Poland (71%). The proportion employed by very large firms with over 5,000 workers varies more between nations. The patterns are broadly consistent with our MAT model. In countries where competition is strong and reallocation easier, there is a larger fraction of jobs in very large firms (e.g. 34.7% in the U.S.) and a small fraction in small firms with under 50 employees (e.g. 16.2% in the U.S.). Germany, also a high productivity and high management score country, looks similar to the U.S. (34.9% in large firms vs. 16.5% in small firms). By contrast, in countries like Italy and Greece, only 6.4% and 6.2% of employees respectively are in these large firms compared to 45.1% and 41.3% in small firms. In Appendix B we provide some corrections to our cross country decompositions to deal with the fact that we are missing management scores in the very large firms in some countries (e.g. the U.S. and Germany) compared to other countries, like those in southern Europe. As expected, these corrections strengthen our overall findings as

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plants whose primary industry code is manufacturing. Fifth, there may be duplication of employment in accounting databases due to the treatment of consolidated accounts. Finally, reporting of employment is not mandatory for the accounts of all firms in all countries. This was particularly a problem for Indian and Japanese firms, so for these countries we imputed the missing employment numbers based on a regression of sales on employment for firms where we had both variables.

<sup>46</sup>In two countries the coverage from accounting databases underestimates the aggregate: the Swedish data covers only 62% of Census data and the Portuguese accounting database covers 72%. This is due to incomplete coverage in ORBIS of these smaller nations.

the “corrected” relative average management scores for the U.S. and Germany rise compared to southern Europe.

A caveat to Table A3 is that total employment in firms with over 5,000 workers is not disclosed in all countries (because of concerns it would reveal individual firm’s identities). In the U.S. and Japan we have the exact Census numbers from public use tables and in the U.K. we had access to confidential Census micro-data to do this ourselves. In the other countries we used accounting data from ORBIS and other sources to estimate employment for the very large firms. Since these firms are so large, data is relatively plentiful as they are almost all publicly listed and so followed closely by market analysts.<sup>47</sup>

## A.2 The World Management Survey

In every country the sampling frame for the management survey was all firms with a manufacturing primary industry code and that employed between 50 and 5,000 workers<sup>48</sup> on average over the most recent three years of data prior to the survey.<sup>49</sup> Interviewers were each given a randomly selected list of firms from the sampling frame. The size of this sampling frame by country is shown in column (5) of Table A2 for the first year that we interviewed a firm. We have conducted the surveys over multiple years as noted in column (6). The five major waves were in 2004, 2006, 2009/10, 2013 and 2014<sup>50</sup>, although we had smaller scale surveys in some of the intervening years (e.g. China in 2007; Brazil, Canada and Ireland<sup>51</sup> in 2008).

In the first survey in 2004 we covered 732 firms in France, Germany, the U.K. and the U.S.<sup>52</sup> In 2006 we covered eight countries (China, Greece, India, Italy, Japan, Poland, Portugal and Sweden) as well as the four core countries. In addition to the new countries and a refreshment sample of the four 2004 countries we also re-contacted all firms from 2004 to form a short panel. In

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<sup>47</sup>Corrections have to be made to estimate the number of domestic employees (which is the Census concept) if this is not revealed directly by the firms. To do this we ran country specific regressions of the proportion of domestic over total global employment on a polynomial of total employment, industry dummies, and multinational status. Then we used this to impute the number of domestic workers for the firms who did not disclose domestic employment.

<sup>48</sup>In Japan and China we used all manufacturing firms with 150 to 5000 employees since Oriana only samples firms with over 150 employees. Note that the Oriana database does include firms with less than 150 employees if they meet the sales or assets criteria, but we excluded this to avoid using a selected sample. We checked the results by conditioning on common size bands (above 150 in all countries) to ensure that the results were robust.

<sup>49</sup>In the U.S. only the most recent year of employment is provided. In India, employment is not reported for private firms, so for these companies we used forecast employment, predicted from their total assets (which are reported) using the coefficients from regressing  $\ln(\text{employees})$  on  $\ln(\text{assets})$  for public firms.

<sup>50</sup>Major waves were started in early summer, but sometimes stretched throughout the year. In 2009, the wave stretched through to the following February. We kept information on when the interview took place to control for any seasonal influences (a noise control).

<sup>51</sup>We split out Northern Ireland from the rest of the U.K. in Table A2 as we did an additional wave specifically of Northern Irish firms in 2008. Some of the Northern Irish firms were also surveyed in 2004, 2006 and 2010 as part of the general U.K. waves, but only a smaller number as the region is only a small part of the U.K..

<sup>52</sup>This sample was drawn from the BVD Amadeus dataset for Europe and the Compustat dataset for the U.S. Only companies with accounting data were selected. So, for the U.K. and France, this sampling frame was very similar to the 2006 sampling frame. For Germany it is more heavily skewed towards publicly quoted firms since smaller privately held firms report little balance sheet information. For the U.S. it comprised only publicly quoted firms. As a robustness test we drop the firms that were resurveyed from 2004.

2009/10 we again resurveyed all firms interviewed 2006 including the original 2004 firms (if they were still alive). For budgetary reasons we did not do a refreshment sample in this wave although we did add New Zealand and Australia. In 2013 we mainly surveyed low income countries in Africa (Ethiopia, Ghana, Mozambique, Nigeria, Tanzania and Zambia) and Latin America (Colombia and Nicaragua) for the first time. But we also followed Argentina, Mexico and Brazil in the panel and surveyed Spain and Turkey for the first time. In 2014 we included new countries (Kenya, Myanmar and Vietnam) and performed refreshment samples of the U.S. and the main EU countries (France, Germany, Greece, Italy, Portugal and the U.K.). This included attempting to re-survey all the panel firms from the these EU countries and the U.S. that we had from earlier waves.

### *The Survey response rate*

Column (4) of Table A2 shows the response rates by country. Of the firms we contacted 41% took part in the survey, a high success rate given the voluntary nature of participation. Of the remaining firms, 16% refused to be surveyed, while the remaining 43% were in the process of being scheduled when the survey ended.

There are clear differences by country, with the response rate being lowest in Japan and highest in Nigeria. Table A4 analyzes the probability of being interviewed.<sup>53</sup> All columns condition on country dummies, industry dummies and time dummies (for year of interview and year the accounting data is taken from if different). The first column simply includes employment as a measure of size. The size variable is significant suggesting that there was a tendency for large firms to respond more frequently, although the coefficient is not large: a doubling of firm size is associated with only a 6% higher probability of response.

In column (2) of Table A4 we add in labor productivity and reassuringly find that firms with higher revenues per employee are not significantly more likely to agree to be interviewed than others. Column (3) includes the return on capital employed (ROCE) as an alternative performance measure which is also insignificant. These are important results as they suggest we are not interviewing particularly high or low performing firms. In columns (4), (5) and (6) we find that multinational status, firm age, and capital are also all insignificant in the selection equations.

In summary, within a country, industry, and year, respondents were not significantly more productive, profitable, or capital intensive than non responders. Respondents did tend to be slightly larger, but were not more likely to be older or multinationals. Since all regressions include size, country, industry, and time dummies, this potential source of bias is controlled for.

One concern, however, is that when we make cross country comparisons these selection effects could create biases. Hence in our decomposition analysis we re-weight the data to allow for country

<sup>53</sup>The responders sample implicit in Table A4 is smaller than the total number of observations in Figure 1 for three reasons. First, we look only at the first time we contact a firm: this is because firms that appear in the panel are likely to be better managed and more productive (since they survived longer). Second, we conduct the analysis at the levels of the firm's accounts and there may be multiple plants analyzed for the same firm in the same year. Third, we do not include Singapore because (as noted above) we do not have access to the non-responders.



specific sampling bias (see Appendix B and main text). Specifically, we ran probits of whether a firm responded compared to others in the sampling frame where the right hand side variables are employment, firm age, industry dummies and time dummies. We then calculated the probability of sample response and used the inverse of the sampling probability as weights (winsorizing the top and bottom percentiles).

### ***Management - Accounting panel dataset***

As described above, we have a panel element to the database. This is built by combining the management survey waves with the accounting panel data, and then interpolating (but never extrapolating) the management and accounting data to fill in the missing years. For example, if we measure management practices every three years, we linearly interpolate the data in the intervening years. This helps to increase the sample sizes for the five year difference moment since we do not need to have exactly five years between survey waves (for example, without interpolating, if we survey firms every three years we can never generate a five year difference). But, to confirm our results are not dependent on interpolating, we checked we can successfully replicate Table 3 using non-interpolated data finding very similar results. We also have about 5% of firm-years with multiple survey values, for which we take the average value of all continuous variables (including all the overall management score) and the value from the chronologically first survey for the discrete values (e.g. “plant county of location”, “ownership type” etc).<sup>54</sup> All regression standard errors are clustered by firm so that the standard-errors are appropriately corrected for any potential serial correlation in the errors induced by interpolation.

The sample size in the regressions depend on the number of non-missing variables (and specific regressions will drop observations that are effectively redundant if they are absorbed by the controls). In terms of sample size for the overall panel, we have 15,003 firm-year observations between 2004 and 2014 inclusive for the non-interpolated data and 25,953 observations for the interpolated data. Only a sub-set of these observations have non-missing values on the elements for the production functions. In addition, we condition on having a minimum number of 20 firm-year observations per country in the regressions. This leaves us with 15,001 observations in the panel distributed over 18 countries –Argentina, Australia, Brazil, Chile, China, France, Germany, Greece, Ireland, Italy, Japan, Mexico, Poland, Portugal, Spain, Sweden, the UK and US.

### ***Firm-level variables***

We have firm accounting data on sales, employment, capital, materials, profits, shareholder equity, long-term debt, market values (for quoted firms), and payroll (the wage bill). Value added is

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<sup>54</sup>For example, the coefficients (standard errors) on management for columns (1) to (4) from Table 3 with non-interpolated data are 0.274 (0.017), 0.142 (0.015), 0.123 (0.016) and 0.038 (0.014) respectively.

calculated as sales minus materials.<sup>55</sup> We also collected information on whether the firm was part of a multinational enterprise during the survey interview. We supplemented and verified this information through BVD, web searches, and direct telephone inquiries to the firms. We also collected specific questions on the multinational status of the firm (whether it owned plants abroad and the country where the parent company is headquartered) to be able to distinguish domestic multinationals from foreign multinationals.

We collected many variables through our survey, including information on plant and firm employment, the fraction of employees with a degree, organizational structure, how many competitors managers thought they faced, etc.

Management practices were scored following the methodology of Bloom and Van Reenen (2007), with practices grouped into four areas: *operations* (three practices), *monitoring* (five practices), *targets* (five practices), and *incentives* (five practices). The shop-floor operations section focuses on the introduction of lean manufacturing techniques, the documentation of processes improvements, and the rationale behind introductions of improvements. The monitoring section focuses on the tracking of performance of individuals, reviewing performance, and consequence management.<sup>56</sup> The targets section examines the type of targets, the realism of the targets, the transparency of targets, and the range and interconnection of targets. Finally, the incentives/people management section includes promotion criteria, pay and bonuses, and fixing or firing bad performers, where best practice is deemed the approach that gives strong rewards for those with both ability and effort. Our management measure averages the z-scores of all 18 dimensions and then z-scores this average again.

### ***Industry level variables***

Our basic industry code is the U.S. SIC (1997) three digit level - which is our common industry definition in all countries except otherwise noted. We allocate each firm to its main three digit sector (based on sales), covering 135 unique three-digit industries. There are at least ten sampled firms in each industry for 97% of the sample.

The “Lerner index of competition” is constructed, as in Aghion et al (2005), as the cross-firm median of  $(1 - \text{profit}/\text{sales})$  in a country-industry-time period cell. Profits are defined as EBIT (earnings before interest and taxation) to include the costs of labor, materials, and capital, but exclude any financing or tax costs. The source of accounting data used to build the index is ORBIS population data for all countries (i.e. we do not condition on having any management data). We first build the median Lerner index for every country-industry-year cell.<sup>57</sup> We then average the

<sup>55</sup>Some firms report “costs of good sold” and not materials. In this case we estimate materials as costs of goods sold minus the wage bill. For observations which still had missing values for materials we assumed that the fraction of materials in sales was equal to the industry-year average.

<sup>56</sup>Since the operations and monitoring concepts overlap we often group them together as “monitoring”.

<sup>57</sup>To reduce the influence of outliers, we drop observations below the 1th and above the 99th percentile of the Lerner index.

yearly values over three three-years sub-periods: period 1, including years between 2004 and 2006; period 2, including years between 2008 and 2010; and period 3, including 2012 and 2013 data (2013 being the last year for which we have full ORBIS extractions). This timing roughly corresponds to pre-crisis, crisis and post-crisis periods. These time varying measures of the Lerner index are matched to the management interviews according to the year in which these were conducted (2004-2006 for period 1; 2008-2010 for period 2; and 2012-2014 for period 3).

The variable “Import penetration” is built using data drawn from the World Input-Output Database (WIOD). Import penetration is built as the share of imports over apparent consumption (total production minus exports plus imports). This measure is built at the country by industry by year level and then, similarly to the Lerner index, averaged across sub-periods. Since the last available year for the WIOD is 2011, we use only two sub-periods, 2004-2006 (matched with management data collected between 2004-2006) and 2008-2010 (matched with management data collected between 2008-2014). The industry classification is ISIC, Rev 3.

The variable “Import penetration from China” is built exactly as the “Import Penetration” variable, except that it includes only imports originating from China in the numerator.

Tariff data was kindly supplied by Feenstra and Romalis (2015) and is at the country by industry (SITC, Rev 4) by year (2000-2006) level. Since we have limited time series variation, we collapse the data to the country by industry level.

### *Country level variables*

We take country level measures of GDP per capita and TFP from the latest Penn World Tables (Timmer et al, 2015). The OECD “Difficulty of Hiring” index (ranging from 1 to 100) is the variable EPRC\_V2 (available for all years in the interval 1998-2013), and is drawn from their indicators of employment protection. These are synthetic indicators of the strictness of regulation on dismissals and the use of temporary contracts, compiled from 21 items covering three different aspects of employment protection regulations as they were in force on January 1st of each year. We also employ the variable “Cost to export (US\$ per container)” drawn from the World Bank “Doing Business” dataset (2015) which reflects the cost of obtaining export licenses and average container costs.

## **A.3 Management and Organizational Practices Survey (MOPS)**

MOPS was jointly funded by the U.S. Census Bureau and the National Science Foundation as a supplement to the Annual Survey of Manufactures (ASM). The original design was based on the same concepts as the WMS and was adapted to the U.S. through several months of development and cognitive testing by the Census Bureau. It was sent by mail and electronically to the ASM respondent for each establishment, which was typically the accounting, establishment, or human-resource manager. Most respondents (58.4%) completed the survey electronically, with the

remainder completing the survey by paper (41.6%). Non-respondents were given up to three follow-up telephone calls if no response had been received within three months. The survey comprised 36 multiple choice questions about the establishment, taking about 20 to 30 minutes to complete. The survey included 16 questions on management practices covering (like WMS) monitoring, targets and incentives.

The monitoring section asked firms about their collection and use of information to monitor and improve the production process. For example, firms were asked how frequently performance indicators were tracked at the establishment, with options ranging from “never” to “hourly or more frequently”. The targets section asked about the design, integration, and realism of production targets. For example, firms were asked what the time-frame of production targets was, ranging from “no production targets” to “combination of short-term and long-term production targets”. Finally, the incentives section asked about non-managerial and managerial bonus, promotion and reassignment/dismissal practices. For example, it asked how managers were promoted at the establishment, with answers ranging from “mainly on factors other than performance and ability, for example tenure or family connections” to “solely on performance and ability”. The full questionnaire is available on <http://bhs.econ.census.gov/bhs/mops/form.html>.

In our analysis, we aggregate the results from these 16 check box questions into a single measure of structured management. The structured management score is the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0-1 scale. Thus the summary measure is scaled from 0 to 1, with 0 representing an establishment that selected the bottom category (little structure around performance monitoring, targets, and incentives) on all 16 management dimensions, and a 1 representing an establishment that selected the top category (an explicit focus on performance monitoring, detailed targets, and strong performance incentives) on all 16 dimensions. As with WMS, we asked a range of questions about the characteristics of the workers, firms, and collected variables that we used to approximate for interview noise (interviewee, interview and interviewer characteristics).

The MOPS survey was sent to all ASM establishments in the ASM mail-out sample. 37,177 filled surveys were received, implying a response rate of 78%, which is extremely high for firm surveys. We further restricted the sample for establishments with at least 11 non-missing responses to management questions and also have positive value added, positive employment and positive imputed capital in the ASM. In addition to our management data we use establishment level data on sales, value-added and labor inputs from the ASM. The mean establishment size is 167 employees and the median is 80. The average establishment in our sample has been in operation for 22 years, 44% of managers and 9% of non-managers have college degrees, 13% of their workers are in unions, 42% export and 69% are part of larger multi-plant firms.

More details on the MOPS survey are contained in Bloom et al (2017).

## B APPENDIX: FURTHER RESULTS

### B.1 Alternative Methods of estimating the productivity equation

We considered a large number of alternative approaches to estimating the productivity regression, some of which are contained in Table A5. First, in column (1) we consider a standard “Solow Residual” approach deducting  $\ln(\text{labor})$  and  $\ln(\text{capital})$  from  $\ln(\text{value added})$  using three-digit industry-specific shares in nominal value added as weights for the factor inputs. A regression of this TFP measure on management has a highly significant coefficient of 0.080.

The next three columns embody alternative popular econometric approaches to estimating production functions. Column (2) reports the Blundell and Bond (2000) system GMM approach for our standard specification of column (2) in Table 3. Here, we treat all factor inputs as endogenous and use lags as instruments (lagged levels in the difference equations and lagged differences in the levels equation). The unrestricted specification includes a lagged dependent variable and lags of the factor inputs (see Appendix C.1 below). The common factor (COMFAC) restrictions are imposed by minimum distance and the structural coefficients presented in the table. The management coefficient is about 0.05.<sup>58</sup> Column (3) presents the Levinsohn and Petrin (2003) approach where we use materials (rather than investment) as the proxy variable. Column (4) reports the Olley-Pakes approach (as in column (5) of Table 3) except we use the Akerberg, Caves and Frazer (2015) correction. The range of the estimates of the management coefficient is significant and positive throughout and in magnitude lies within the range of those in Table 3 with Blundell-Bond giving the lowest estimates and Levinsohn-Petrin the highest.

In columns (5) through (10) of Table A5 we repeat the specifications in Table 3 except we implement output based production functions instead of value added based version. Hence we also include material inputs on the right hand side. Column (5) has the whole sample, column (6) conditions on firms surveyed in at least two years, column (7) presents firm fixed effects and column (8) has the Blundell-Bond results. As expected, the factor input coefficients tend to be smaller in magnitude than their counterparts for the value added function, but all remain significant.

The last four columns again present results with sales as the dependent variable, but drop materials from the right hand side. Although the magnitude of the coefficient on management varies with the different estimation approaches, it is positive and significant in every specification. We also considered a wide variety of other approaches to production function estimation, for example using the wage bill instead of employment as a measure of labor services (as in Hsieh and Klenow, 2009). The significance of management remained in all of these experiments.

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<sup>58</sup>Note that this is the econometric specification closest to the theoretical model—lags are legitimate instruments under the quadratic adjustment model we have assumed (Bond and Soderbom, 2005). We generalize the theory model slightly as we (implicitly) also allow labor to also have adjustment costs alongside capital and management. Interestingly, the sum of the coefficients on the factor inputs is 0.8, lower than the OLS levels and Olley-Pakes estimates in Table 3. This is consistent with the calibrated parameter values from Table 1 which has constant returns in production but CES monopolistic competition with a demand elasticity of 5 which means the coefficients in the revenue function should be 20% smaller than the output elasticities in the production function.

## B.2 Competition and Management

As noted in the text to examine the role of management, competition and reallocation we run regressions of the form:

$$M_{p,c,k,t} = \gamma_1 COMPETITION_{c,k,t} + \gamma_2 z_{p,t} + \eta_t + \xi_{c,k} + \nu_{p,c,k,t} \quad (16)$$

where  $M_{p,c,k,t}$  is the empirical management score of plant  $p$  in country  $c$  in industry  $k$  at time  $t$ ,  $COMPETITION_{c,k,t}$  are the three alternative competition measures noted above,  $z_{p,t}$  is a vector of other firm controls (the proportion of employees with a college degree, log firm and plant size, log firm age and noise controls),  $\eta_t$  denotes year dummies,  $\xi_{c,k}$  denotes a full set of three digit industry by country dummies, and  $\nu_{p,c,k,t}$  is an error term. Table B3 contains the results of estimating equation (13) with the unweighted OLS results in the odd columns and the regressions weighted by firm size in the even columns. The dependent variable across all columns is the standardized value of the management score. Column (1) reports the correlation between management and competition including industry by country fixed effects, time dummies and other standard firm-level controls. The Inverse Lerner Index has a positive and significant correlation with management. The simulation model suggests that this relationship should be stronger if we size-weight management due to better reallocation in more competitive sectors. Column (2) implements this idea using as a weight the firm's share of employment in the industry by country cell, and indeed, the coefficient on the Lerner measure rises from 0.99 to 1.75. The next four columns repeat the specifications but use import penetration, including imports from all countries in columns (3) and (4) and then just imports from China in columns (5) and (6), as an alternative measure of competition. The pattern of results shows a larger coefficient on the competition measures for the size-weighted regressions compared to the unweighted regressions, consistent with the findings from using the Lerner index.<sup>59</sup>

Overall, the results suggest that higher competition is associated with significant improvements in management, and the magnitude of the coefficient is larger when we weight the regressions by firm size. In terms of magnitudes a one standard deviation change in the Lerner index in the unweighted regression is associated with a 0.06 of a standard deviation change in management, compared to 0.02 using the import penetration measure and 0.05 using Chinese imports. The equivalent numbers for the weighted regressions are 0.11, 0.05 and 0.05.<sup>60</sup>

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<sup>59</sup>We also considered a fourth measure of competition from our survey data: the number of rivals as perceived by the plant manager. The advantage of this indicator is that it is available for all countries in our survey. Empirically, the variable is also linked to improvements in management. In a specification like column (1) of Table B3, the coefficient (standard error) on this measure of competition was 0.033 (0.017) on a sample of 14,305 observations including all countries with management data, and 0.059 (0.022) on the sample of OECD countries overlapping with the one used in Table B3 (8,414 observations as there are a few some missing values on the number of competitors variable). The disadvantage of the number of rivals measure is that it is not tightly linked to the theory simulations. For example, although falls in barriers to entry will tend to increase the number of firms in the MAT model, increases in consumer sensitivity to price can lead to an equilibrium reduction in the number of firms.

<sup>60</sup>To check whether the difference between the weighted and the unweighted results was significant, we compared

As noted in the main text, another way to confirm the reallocative impact of competition predicted by the model is to consider whether factors that reduce the degree of competition reduce the covariance between management practices and firm size, implying  $\delta_1 < 0$  in the following equation:

$$Size_{p,t} = \delta_1 (M * COMPETITION)_{p,t} + \delta_2 M_{p,t} + \delta_3 COMPETITION_p + \delta_4 x_{p,j,t} + \epsilon_{p,j,t} \quad (17)$$

The simplest method of testing this idea is to use countries grouped into regions to proxy competitive frictions, as it is likely that competition is stronger in some regions (e.g. the U.S.) than others (e.g. southern Europe).

Column (1) of Table B4 reports the results of a regression of firm employment on the average management score and a set of industry, year and country dummies.<sup>61</sup> The results indicate that increasing a firm's management score by one standard deviation is associated with an extra 183 workers. In column (2) we allow the management coefficient to vary by region, with the U.S. as the omitted base. The negative coefficients on the interactions indicate that there is a stronger relationship between size and management in the U.S. compared to other regions. This difference is significant for Africa, Latin America and southern Europe, but not for Asia or northern Europe. A one standard deviation increase in management is associated with 268 extra employees in the U.S. but only 68 ( $= 268.4 - 199.5$ ) extra workers in southern Europe.<sup>62</sup> These results suggest that reallocation is stronger in the U.S. than in the other countries, which is consistent with the findings on productivity in Bartelsman, Haltiwanger and Scarpetta (2013) and Hsieh and Klenow (2009).

We also investigate explicit measures of market-friction variables that can reduce competition. In columns (3) to (5) of Table B4 we use country-wide measures of employment regulation from the OECD and trade costs from the World Bank. Both of these reduce the covariance between firm size and management practices. Finally in column (6) we use the more detailed country by industry measures of tariffs from Feenstra and Romalis (2012) in deviations from their country and industry mean, and again find a significant negative interaction. This implies that within a sector (like steel), countries with higher tariffs (such as Brazil) will allocate less activity to better managed firms than those with lower tariffs (such as the U.K.).

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the distribution of the estimated coefficients with and without weights bootstrapping with 500 replications. The weighted coefficients were larger than the unweighted coefficients 84% of the times for the Lerner index, 76% of the times with the import penetration variable, and 52% of the times using imports from China.

<sup>61</sup>This is the measure of firm size reported by the plant manager. For a multinational this may be ambiguous as the plant manager may report the global multinational size which is not necessarily closely related to the management practices of the plant we survey. Consequently, Table B4 drops multinationals and their subsidiaries, but we show robustness of this procedure below.

<sup>62</sup>These results are for covariances based on size. Using a dynamic version of this moment—the covariance between employment growth and management—generates qualitatively similar results. For example, re-running column (2) using the growth (rather than the level) of employment also has negative interactions on all the regional interactions. For example, a one standard deviation increase in management in the U.S. raises sales growth by 6.9% compared to a (significantly lower) 0.5% faster growth in Asia from a similar increase in management.

### B.3 The contribution of management to cross country TFP gaps: Robustness

In Section 5 we decomposed share-weighted management into reallocation and unweighted average components and use this to estimate the contribution to cross country TFP. In doing that, we made a variety of assumptions that we now relax to see if they materially alter our results. Recall that (i) the sample we used in the analysis is a sub-sample of that underlying Figure 1 as we drop multinationals because it is unclear what the appropriate measure of size is for such firms (we also show robustness to including multinationals); and (ii) we weight the management data according to a firm’s country-specific employment share and adjust for non-random selection through sampling weights.

These are summarized in Table C2. Row 1 gives the baseline result from Table C1. Row 2 drops pre-2006 data and row 3 drops all panel observations apart from the entry year. We change the selection equation underlying the sample weights used to correct for non-random response by using only size (dropping listing status, age and industry dummies) in row 4. Row 5 gives the results without any selection correction, Row 6 includes multinationals, and Row 7 uses an alternative measure of size, using an index of weighted inputs (capital and labor). We were concerned that we did not run our survey on very small (under 50 workers) and very large firms (over 5,000 workers), so we repeated our analysis on a sub-sample of countries where we have detailed information on the firm size distribution in the population. Knowing the full size distribution allows us to make a selection correction for the fact we only observe medium sized firms (Appendix B.2). Row 8 has the baseline results on these countries and row 8 implements the correction.

Although the exact quantitative findings change across Table C2, the qualitative results are very robust to these alternative modeling details. The fraction of the TFP gap explained by management is non-trivial, ranging from 20% to 50% (column (5)). The correlation of relative management gaps between the baseline estimates and alternatives estimation techniques (column (3)) never falls below 0.85 and the correlation of the fraction of TFP explained by management (column (6)) with baseline results never falls below 0.89.

We can also look at the within country/cross-firm dimension for those countries where we have detailed productivity data. For example, the average industry TFP spread between the 90<sup>th</sup> and 10<sup>th</sup> percentiles is 90% in U.S. manufacturing (Syverson, 2011), so with our spread of management (2.55 standard deviations between the 90-10) we can account for 28% of the TFP spread ( $= (2.55 * 0.1) / 0.9$ ).<sup>63</sup> Repeating the same calculations for other countries in our sample for which reliable information exists on TFP dispersion (Australia, Chile, France, Italy, Japan, New Zealand, Sweden and the U.K.) using data drawn from the OECD (2016)<sup>64</sup> and Disney et al. (2000), shows

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<sup>63</sup>We obtain a similar share of dispersion potentially accounted for by management if instead we examine TFPQ using the results from Foster, Haltiwanger and Syverson (2008). While Foster et al. (2008) do not provide data on the 90-10 spread for TFPQ in their data they do provide the standard deviation which is 0.67 (compared to 0.56 for TFP) which for a normal distribution would imply a 90-10 spread of 95%, implying management would again account for about 27% of the dispersion.

<sup>64</sup>We are grateful to Chiara Criscuolo for making the TFP data accessible to us.



that on average 19% of the 90-10 TFPR spread is management-related as shown in Table C3. Hence, variations in management practices appear to account for about one-fifth of the dispersion in TFP across firms within countries.

### B.3.1 Differential response rates to the survey

There are several potential sources of sample selection, the most obvious one being that the firms who responded from the sampling frame were non-random in some dimension. Appendix A examined the overall evidence on sampling bias and argued that these were relatively small. Nevertheless, the baseline results in Table C1 control for this by calculating (country-specific) weights for the sample response probabilities. We do this by running country-specific probit models where the control variables are  $\ln(\text{employment size})$ , firm age, a dummy for whether the firm was publicly listed and industry dummies. We chose these controls because they are available for responders and non-responders, and there was some evidence from Appendix A that larger firms were more likely to respond. We then calculated the weights as the inverse of the probability of response.

We experimented with an alternative first stage probit to look into sample response bias, based on just using employment rather than the larger set of controls. The results are summarized in Table 8. Row 1 presents a summary of the baseline results that we use in Table 7. Row 2 shows what happens when we drop pre-2006 data. This is motivated by the fact that 2004 was our first (and smallest) survey wave. The fraction of the TFP gap accounted for by management rises to 33% (from 30%). We also show in column (6) that the correlation of this fraction explained with the baseline in row 1 is very high (0.992) and the correlation of the gaps in management with the baseline of Row 1 are also very high (0.998 in column (3)). Row 3 drops all observations which are in the panel part of the dataset except the first year. The motivation for doing this is that firms who have been in the panel for one year are more likely to respond in subsequent years than a randomly chosen firm. Since we attempt to re-sample panel firms in subsequent years this could potentially generate a bias. In the baseline results of Row 1 we down-weight these firms appropriately using estimate from the probits. Row 3 shows that our results are robust to just dropping them from the sample (32% of TFP accounted for). We also looked at the sensitivity of the first stage probit to the controls by dropping all covariates except size (row 4) and not using any sample weights (row 5). Not using any selection correction generates the smallest fraction of the TFP explained in Table 8 (20%).

In Table 7, we dropped multinationals because of the difficulty of measuring group size appropriately for such companies. To check the robustness of these results, we included them in row 6, but also included multinational status into the selection equation used to calculate the sample response rate weights (multinationals were slightly more likely to participate in the survey). We account for a bit less of the average TFP gap (24% compared to 30% in the baseline) and the cross country correlation remains reasonably high (0.89).

We have focused on employment as our key measure of size as it is simple, a volume indicator which is straightforward to measure across countries. An alternative way to measure size is to look at a measure of weighted inputs, so we follow Bartelsman et al (2013) and construct a measure using capital stock information from Orbis where our composite input measure was  $\exp[0.7 \cdot \ln(\text{labor}) + 0.3 \cdot \ln(\text{capital})]$ . The results are in row 7 of Table 8 and are again similar to the baseline, although with slightly more of TFP accounted for by management (34.5%).

### B.3.2 Sampling biases associated with dropping very small and very large firms

Our management surveys focus on medium sized firms defined as those with over 50 and under 5000 employees. This was in order to compare firms of a broadly similar size. However, it could potentially cause bias in our comparisons of management levels across countries as the size distribution is different across nations (e.g. Garicano, Lelarge and Van Reenen, 2013, and Table A3). Obviously we do not know the exact distribution of management scores in these very large and very small firms, but we can estimate with additional assumptions what the potential biases could be.

From the census manufacturing population databases of firm demographics, in most countries we know the number of firms above and below 50 employees, and the total number of workers employed across firms of different sizes (see Table A3). We need to then make an assumption about the relationship between firm size and management for the very large and very small firms, which we extrapolate off the size-management relationship over the part of the distribution that we observe (50 to 5,000 employees). We checked that the extrapolated size-management relationship holds for firms below 50 and above 5,000 using the MOPs dataset which asks management questions to firms from all parts of the U.S. size distribution.<sup>65</sup>

We then use this information to estimate the weighted average management score across the entire distribution. Our preferred method exploits the fact that the firm size distribution in each country follows a power law (Axtell, 2001). Using results from this literature we can approximate the employment weighted mean management score in the sub-population under 50 workers and the sub-population with over 5,000 workers.<sup>66</sup> We then use the information in Table A3 to calculate the mean management score across the entire size distribution. Results of this exercise are in rows 8 and 9 of Table 8. We first reproduce the baseline results on the smaller sample of countries in row 8 of Table 8. In this sub-sample of 14 countries (13 differences as the U.S. is the base) we account for a higher fraction of TFP (41%) since these are OECD countries. We then implement

<sup>65</sup>The coefficient on  $\ln(\text{employment size})$  in the management regression is 0.25. We considered imposing a common constant on each country (-1.46) or adjusting this to be consistent with the country-mean management score in the 50 to 5,000 range. Both methods lead to similar results.

<sup>66</sup>First, we consider the approximation in Johnson et al (1994) showing that the number of employees in each size “bin” is equal when the bins are logarithmically sized if firm size is distributed according to Zipf’s Law (which is approximately true in the data). We predict management in each bin and then employment weight the bin to obtain mean management for the below 50 and above 5,000 firms. We also considered the continuous version of the power law which lead to similar results.

the size correction. The correlation between our baseline management scores and the new “size corrected” management scores is very high (0.925), as is the correlation of the fraction of TFP explained (0.968). If anything, we account for an even higher fraction of the TFP gap (just under 50%) when making this correction.

### B.3.3 Manufacturing TFP vs. Whole Economy TFP

The management scores are derived from manufacturing firms, but the decompositions in Table 7 use economy wide TFP. This is purely due to data restrictions - there are few countries in the world for which it is possible to construct reliable measures of manufacturing TFP that are comparable across countries. Our assumption is that countries with high economy wide TFP also have high manufacturing TFP. To test whether this might bias our results, we draw on estimates of manufacturing specific TFP levels (Citino, Haskel and Van Reenen, 2016). This is based primarily on the KLEMs data and constructs TFP in the same way as the Penn World Tables, correcting for capital services and skills. There are only seven countries that overlap between the two exercises where data is sufficiently rich: Australia, Germany, Italy, Spain, Sweden, the U.K. and U.S. The correlation of manufacturing TFP (relative to the U.S.) for these countries with economy TFP is reassuringly high: 0.938. The average proportion of the TFP gap accounted for by management is 35%, similar to the overall mean (but smaller than the proportion for just the seven countries in the baseline which is 43%).<sup>67</sup>

## C CALIBRATION AND SIMULATION

### C.1 Calibration Values

The calibration values in Table 1 are conventional, but the presence of management in the production function generates some additional considerations. Conventional measures of the auto-correlation coefficient on TFPR ( $\rho_A$ ) assume that we have measured all factor inputs, but since managerial capital is a missing variable, it will implicitly show up in estimated TFPR. For example, consider the value added production function in Section 2,  $(PY)_i = A_i K_i^a L_i^b M_i^c$ . TFPR will be  $\ln A_i = \ln(PY)_i - a \ln K_i - b \ln L_i - c \ln M_i$ . A standard way to measure TFP is replace the parameters with cost shares. This has the problem that management shows up in the residual so we actually have  $\ln A_i + c \ln M_i$ . This implies that we probably overestimate the auto-correlation of “true TFPR” by using existing measures as  $M$  and  $A$  will co-vary together. We can assess this by examining how our estimates of TFPR in the data compare with those from conventional measures. We find that the estimated coefficient is, in fact, not much less than the calibrated value

<sup>67</sup>We performed a similar exercise for the market sector (i.e. dropping health, education and public administration). For this sample we do not have Australia, but we do can add France. Again the correlation of TFP between this sector (market sector) and total economy is high at 0.844. We could account for 43.6% of the cross country TFP gaps, very similar to the fraction for these seven countries in Table 7 (44.7%).

from Cooper and Haltiwanger (2006) of 0.885. For example, using the productivity equation of column (2) in Table 3, we can calculate the (net-of-management) TFPR residual and then estimate an AR(1) regression which generates  $\hat{\rho}_A = 0.867$  (standard error = 0.009; observations=7,463). This is close to the 0.871 if we do not control for management in our data. The similarity reflects the fact that management capital is a relatively small share of total value added.

An alternative approach is to use the implied values in the dynamic version of the revenue function. Under the assumptions in our model we can write  $\ln(PY)_{it} = \rho_A \ln(PY)_{it} + a \ln K_{it} - a \rho_A \ln K_{it} + b \ln L_{it} - b \rho_A \ln L_{it} + c \ln M_{it} - c \rho_A \ln M_{it} + e_{it}$  where  $e_{it} = \ln A_0 + \rho_A \varepsilon_{it}$  which is serially uncorrelated. This is the same specification as Cooper and Haltiwanger (2006) and Blundell and Bond (2000) and, like them, we estimate the equation by system GMM and impose the common factor restrictions (COMFAC) to recover the structural parameters (see Table A5 column (2)). Our estimate of  $(\rho_A)$  is 0.854 (standard error = 0.013) which is again, very close to the calibrated value used in Table 1.<sup>68</sup>

As noted in the text we use labor's factor share in GDP to guide the calibration of the output elasticities. It seems reasonable to assume that the cost of managerial capital shows up as payments to labor (e.g. executive time and consultancy wages). Recall that our model implies that the labor share of GDP is  $\beta = wL\rho/PY(\rho - 1)$ . Following Corrado, Hulten and Sichel (2005, 2009) we assume that a fraction  $\varsigma$  of total compensation is the investment in building managerial capital. From the US NIPA labor share is about 50% (see Autor et al, 2018, Table 1). Using our estimates of the share of management costs in total compensation from subsection 4.4 of  $\varsigma = 0.07$  we obtain  $\beta = (1 - \varsigma) * 0.5\rho/(\rho - 1) = 0.93 * (0.5 * 5)/(5 - 1) = 0.6$  given the calibrated assumptions on the demand elasticity (Bartelsman et al, 2013;  $\rho = 5$ ). Given our assumption on the output elasticity of management (Bloom et al, 2013;  $\gamma = 0.1$ ) we can then derive the output elasticity of capital from our assumption of constant returns to scale in production as  $\alpha = 1 - \beta - \gamma = 1 - 0.6 - 0.1 = 0.3$ .

## C.2 Details of Simulated Method of Moments (SMM) Approach

SMM starts by selecting an arbitrary starting value of the parameter vector to be estimated ( $\theta$ ). The dynamic program is then solved and the policy functions are generated. These policy functions are used to create a simulated data panel of size  $(\mu N, T)$ , where  $\mu$  is a strictly positive integer,  $N$  is the number of firms in the actual data, and  $T$  is the time dimension of the actual data. The simulated moments  $\Psi^S(\theta)$  are calculated on the simulated data panel, along with an associated criterion function  $\Gamma(\theta)$ , where  $\Gamma(\theta) = [\Psi^A - \Psi^S(\theta)]'W[\Psi^A - \Psi^S(\theta)]$ , which is a weighted distance<sup>69</sup>

<sup>68</sup>A similar exercise for the standard deviation of TFPR ( $\sigma_A$ ) generates a value of 0.62 which is higher than the calibrated value of 0.453 in Cooper and Haltiwanger (2006). In our view, these higher order moments are better estimated from near population Census data, so we prefer to use these external measures than our more specific sample.

<sup>69</sup>The efficient choice for  $W$  is the inverse of the variance-covariance matrix of  $[\Psi^A - \Psi^S(\theta)]$ , which Lee and Ingram (1991) show under the null can be calculated from the variance-covariance of the empirical moments.

between the simulated moments  $\Psi^S(\theta)$  and the actual moments  $\Psi^A$ .

$$\hat{\theta} = \arg \min_{\theta \in \Theta} [\Psi^A - \Psi^S(\theta)]' W [\Psi^A - \Psi^S(\theta)] \quad (18)$$

A second parameter value is then drawn by taking a random jump from the first value, and the third parameter value onwards is drawn by taking a random jump away from the best prior guess (the parameter value that has delivered the lowest criterion function up to that point). This way, the parameter estimate  $\hat{\theta}$  derived by randomly searching over the parameter space to find the parameter vector, which minimizes the criterion function. This simulated annealing random jumping approach is used because of the potential for discontinuities in the model and the discretization of the state space (so a gradient minimization approach may simply find a local rather than a global minimum). Finally, different initial values of  $\theta$  are selected to ensure the solution converges to the global minimum.

## D EXECUTIVE PAY AND MANAGEMENT

We discussed the relationship between payments to senior management and management practices in the main text in sub-section 4.4. This Appendix gives more details on the data collection and analysis.

Compensation data was collected for executives in publicly listed firms in four countries: the US, UK, India, and China. There is an overall measure of CEO Compensation as well as a disaggregation into salary, bonus and equity. In some cases, an executive’s total compensation exceeds the sum of the components—e.g. in cases where the executive received separate perquisites such as retirement benefits. Stock options are valued using the Black-Scholes formula. Data on equity compensation is not available for executives in Indian firms, and data on bonus compensation are not available for executives in Chinese firms. Due to these data limitations for Indian and Chinese firms, regressions that use the total compensation measure include only executives from firms the US and UK. Executive Compensation in the US is from S&P Capital IQ’s ExecuComp and the UK the data is taken from BoardEx. For India we use Prowess, and for China we use the China Stock Market & Accounting Research database. For comparability across time and across countries, all compensation values are converted to 2006 PPP-adjusted dollars.

We focus on the relationship between a firm’s managerial quality and the compensation of its top executive. In American firms, the top executive is typically the Chief Executive Officer. In other countries, the exact title of the top executive varies. We use “CEO” to refer to each firm’s top executive. After merging these data with the WMS we have a sample of 532 firms: 242 in the US, 107 in the UK, 132 in India, and 51 in China. Unless otherwise specified, we use each firm’s management score and compensation data from the year in which the management survey was conducted for the firm.

Table A6 shows the results of regressing  $\ln(\text{CEO salary})$  on our management score and country dummies in all four countries. There a positive and significant association between higher management scores and higher CEO pay. Column (2) controls for a number of other variables such as firm size, age and skills. This reduced the coefficient on management from 0.309 to 0.189, but it remains significant. The final two columns repeat these specifications but use a measure of total compensation that includes stock options, long-term incentive plans and bonuses. This data is only available in the UK and US. Despite the loss of sample, the management remains positively and significantly associated with CEO compensation with a similar pattern of coefficients to the earlier columns

The Social Security Data comes directly from Song et al (2017), which in turn is obtained from the Master Earnings File in the Social Security Earnings, which contains the labor (W2) earnings (uncapped) of all employees in the US from 1978 to 2013. The values provided in text are for 2013 for all firms defined as a single Employee Identification Number in a given year.

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