MANAGEMENT AS A TECHNOLOGY?*

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Abstract

Are some management practices akin to a technology that can explain company and national productivity, or are do they simply reflect alternative styles? We collect panel data on core management practices in over 10,000 firms in 30 countries. We find large cross country differences, with the US having the highest size-weighted average management score. About one fifth of these cross-country management differences are due to stronger reallocation effects which rewards better managed firms with greater market share. We present a formal model of management and structurally estimate it on our panel data to recover parameters including the adjustment costs of managerial capital (which are twice those of tangible capital). Our model also predicts (i) a positive effect of management on firm performance; (ii) a positive effect of product market competition on average management quality and its covariance with firm size; and (iii) a rise (fall) in the level (dispersion) of management with firm age. These are not moments we use in the structural estimation and we find empirical support for these predictions in new data. Finally, building on our model we find that differences in management practices explain about one quarter of cross-country productivity differences.

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Keywords: management practices, productivity, competition

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1 Introduction

Productivity differences between firms and between countries remain startling. For example, within the average four-digit US manufacturing industries, Syversson (2011) finds that labor productivity for plants at the 90^{th} percentile was four times as high as plants at the 10^{th} percentile. Even after controlling for other factors, Total Factor Productivity (TFP) is almost twice as high. These differences persist over time and are robust to controlling for plant-specific prices in homogeneous goods industries.[1] Such TFP heterogeneity is evident in all other countries where data is available.[2] One explanation is that these persistent productivity differentials are due to "hard" technological innovations as embodied in patents or adoption of new advanced equipment. Another explanation for this phenomenon is that they reflect variations in management practices and this paper focuses on the latter explanation.

We put forward the idea that some forms of management practices are like a "technology" in the sense that will on average raise TFP. This has a number of empirical implications that we examine and find support for in the data. This perspective on management is distinct from the dominant paradigm in organizational economics that views management as a question of optimal design that depends on the contingent features of a firm's environment (Gibbons and Roberts, 2013). There is no sense in which any management styles are on average better than any others. Our data does show that there is some evidence for the Design perspective, but we show that this gives only a partial explanation of the patterns that we can observe in our data.

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. Different fields have different labels. 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 firm size heterogeneity (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 new focus on how the wage distribution requires an understanding of the heterogeneity of firm productivity (e.g. Card, Heining and Kline, 2013).

To address the lack of management data we have collected original survey data on management practices in 30 countries covering over almost 10,000 firms with up to four waves of panel data. We first present some stylized facts from this database in the cross country and cross firm dimension. One of the striking features of the data is that the average management score, like TFP, is higher

[1] For example, Foster, Haltiwanger and Syverson (2008) show large differences in total factor productivity even within very homogeneous goods industries such as cement and block ice. Hall and Jones (1999) and Jones and Romer (2010) show how the stark differences in productivity across countries account for a substantial fraction of the differences in average income.

[2] Usually productivity dispersion is even greater than in other countries than in the US - see Bartelsman, Haltiwanger and Scarpetta (2013) or Hsieh and Klenow (2009).

in the US than it is in other countries (see Figure 1).

We detail a formal model of Management As a Technology (MAT) which incorporates both the heterogeneous initial draw of managerial ability and the endogenous response of firms to change their level of managerial capital in response to shocks to the environment (modeled as as idiosyncratic TFP shocks). We structurally estimate some key parameters of this model using SMM, such as the depreciation rate and adjustment cost of managerial capital and then derive some additional predictions on moments we did not target in the structural estimation. We find that the data supports the predictions from the model. First, management is associated with improved firm performance (e.g. productivity, profitability, growth and survival) and from experimental evidence this relationship appears to be causal. Second, firm management rises with stronger product market competition, both though reallocating more output to the better managed firms (an Olley-Pakes covariance effect) and also through a higher management level in the unweighted average. Third, older firms will on average have a higher level of management, but lower dispersion due to selection effects. Finally, management falls in its own price as proxied by the presence of universities close to plant's location which increases the supply of managerial talent. We contrast our MAT model to an alternative approach which sees management as a contingent "Design" feature, rather than being an output increasing factor of production. There are some elements consistent with this second approach, but the MAT model seems a better description of our data.

Description of management and productivity results....

The structure of the paper is as follows. We first describe some theories of management (Section II) and how we collect the management data (Section III). We then describe some of the data and stylized facts (Section IV). Section V details our empirical results and Section VI concludes. In short, although there may be other explanations, we provide considerable evidence for our model of management as a technology.

2 Some economic theories of management

2.1 Conventional approaches to productivity heterogeneity

Since at least Mundlak (1961) econometricians have often regarded the fixed effect in panel data estimates of production functions "management ability". For the most part, though, economists have focused on how technological innovations drive economic growth, for example correlating TFP with observable measures of innovation such as R&D, patents or information technology. There is robust evidence of the impact of such "hard" technologies for productivity growth.[3] There are, however, at least two major problems in focusing on these aspects of technical change as the cause of productivity dispersion. First, even after controlling for a wide range of observable measures of

[3] Zvi Griliches pioneered work in this area which motivated the work of the NBER productivity group from the 1980s onwards (e.g. Griliches, 1998).

technology a large residual still remains. A response to this is that these differences still reflect some "hard" technology differences which, if we measured them properly would be properly accounted for. But an alternative view is that we need to widen our notion of technology to incorporate managerial aspects of the firm. A second problem is that many studies of the impact of new technologies on productivity have found that the impact of technologies varies widely across firms and countries. In particular, information technology (IT) has much larger effects on the productivity of firms who have complementary managerial structures which enable IT to be more efficiently exploited.[4]

Given these two issues, we believe that it is worth directly considering management practices as a factor in raising productivity. In addition, there is a huge body of case study work in management science which also suggests a major role for management in raising firm performance.

2.2 Formal models of management

It is useful to analytically distinguish between two broad approaches which we can embed in a simple production function framework where value added Y, is produced as follows:

$$Y = F(\widetilde{A_i}, L, K, M) \tag{1}$$

where $\widetilde{A_i}$ is an efficiency term, labor is L, non-management capital is K, and M is management capital.We label the traditional approach in Organizational Economics (e.g. Gibbons and Roberts, 2013) as the "Design" perspective where differences in practices are styles optimized to a firm's environment. For any indicator of M, such as the measures we gather, the Design approach would not assume that output is monotonically increasing in M. In some circumstances, higher levels of what we would regards as good practices will explicitly reduce output. To take a simple example, consider M as a discrete variable which is unity if promotion takes into account effort and ability and zero otherwise (e.g. purely seniority based promotion). The Design perspective could find that tenure-based promotion reduces output in some sectors, for example by reducing incentives, but increases it in others, for example, by reducing influencing activities (Milgrom and Roberts, 1988).

Under the Design approach the production function can be written as equation (1), but for some firms and practices $F'(M) \leq 0$. Even if M is free and could be costlessly introduced, output would fall if an exogenous shock increased it. The Design approach emphasizes the reason for heterogeneity in the adoption of different practices is due to differences in the environment firms face. This is in the same spirit as the "contingency" paradigm in management science (Woodward, 1958).

[4] In their case study of IT in retail banking, for example, Autor et al (2002) found that banks who failed to re-organize the physical and social relations within the workplace reaped little reward from new ICT (like ATM machines). More systematically, Bresnahan, Brynjolfsson and Hitt (2002) found that decentralized organizations tended to enjoy a higher productivity pay-off from IT. Similarly, Bloom, Sadun and Van Reenen (2012a) found that IT productivity was higher for firms with strounger incentives management (e.g. careful hiring, merit based pay and promotion and vigorously fixing/firing under-performers).

The large dispersion in firm productivity motivates an alternative Technology perspective that some types of management (or bundles of management practices) are better than others for firms in the same environment. There are three types of these "best practices". First, there are some practices that have always been better (e.g. not promoting incompetent employees to senior positions) or collecting some information before making decisions. Second, there may be genuine managerial innovations (e.g. Taylor's Scientific Management; Lean Manufacturing; Deming's Quality movement, etc.) in the same way there are technological innovations. Thirdly, many practices may have become optimal due to changes in the economic environment over time. Incentive pay may be an example of this as the incidence of piece rates declined from the late 19th Century, but today appears to be making a comeback.[5]

We formalize these ideas by treating M as an intangible capital (as in Corrado and Hulten, 2010), which has a market price and also a cost of adjustment. But unlike the conventional intangible capital approach we allow firms to have an exogenous initial draw when they enter the economy. This creates ex ante heterogeneity between firms (generalizing the approach in Hopenhayn, 1992, for TFP). The Design and the Technology perspective can be nested within this set-up but have, as we show, very different theoretical and empirical implications.

The set-up is as follows. Factor inputs and outputs are firm specific (we do not use t subscripts unless needed for simplicity). We consider a single industry so firm-specific values are indicated by an i sub-script

$$Y_i = \widetilde{A_i} K_i^{\alpha} L_i^{\beta} \widetilde{G}(M_i) \tag{2}$$

where $\widetilde{G}(M_i)$ is a management function common to all firms. Demand is assumed to derive from a final good sector (or equivalently a consumer) using a CES aggregator across individual inputs:

$$Y = N^{\frac{1}{1-\rho}} \left(\sum_{i=1}^{N} Y_i^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \tag{3}$$

where $\rho > 1$ is the elasticity of substitution, 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. Our main index of competition will be ρ. Applying the first order conditions gives each firm an inverse demand curve with elasticity ρ where we have normalized the industry price $P = 1$

$$P_i = (\frac{Y}{N})^{\frac{1}{\rho}} Y_i^{\frac{-1}{\rho}} = B Y_i^{-\frac{1}{\rho}}$$

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

$$P_i Y_i = A_i K_i^a L_i^b G(M_i)$$

[5] Lemieux et al (2009) suggest that this may be due to advances in IT. Software companies like SAP have made it much easier to measure output in a timely and robust fashion, making effective incentive pay schemes easier to design and implement.

where for analytical tractability we defined $A_i = \widetilde{A_i}^{1-1/\rho}(\frac{Y}{N})^{\frac{1}{\rho}}$, $a = \alpha(1-1/\rho)$, $b = \beta(1-1/\rho)$ and $G(M_i) = \widetilde{G}(M_i)^{(1-1/\rho)}$. Profits, defined as revenues less capital, labor and management costs ($c(K), c(L)$ and $c(M)$), and fixed costs F are therefore:[6]

$$\Pi_i = A_i K_i^a L_i^b G(M_i) - c(K_i) - c(L_i) - c(M_i) - F$$

2.3 Models of management in production

In terms of the management function$\widetilde{G}(M_i)$ we consider two broad classes of models. First, Management as a Technology (MAT) where management is an intangible capital input in which output is monotonically increasing, and Management as Design (MAD) in which management is a choice of production approach with an optimizing level. We focus on the first as this fits the data substantially better (as we show below) but lay out both approaches here. More technical details are in Appendix A.

2.3.1 Management as a Technology (MAT)

In the Lucas (1978) or Melitz (2003) style models firm performance is increasing continuously in the level of management quality, which is synonymous with productivity. Firms draw a management quality when they are born and this continues with them throughout their lives. Since these types of models assume $G(M_i)$ is increasing in M_i we simplify the revenue function by assuming $G(M_i) = M_i^c$

$$P_i Y_i = A_i K_i^a L_i^b M_i^c$$

Many models assume that management practices are drawn at birth and remain unchanged over the life of firm. But a more general model would allow for the possibility that management can also be improved - for example, by hiring in management consultants, spending employee time developing improved management processes (e.g. Toyota's Kaizen meetings) or paying for a better CEO. Moreover, these improvements may depreciate over time like other tangible and intangible assets such as physical capital, R&D and advertising. Hence, we set up a more general model which still has initial heterogeneous draws of management when firms enter, but treats management as an intangible capital stock with depreciation:

$$M_{it} = (1-\delta_M)M_{it-1} + I_{it}^M \qquad I_{it}^M \geq 0$$

where I_{it}^M reflects (say) "consulting investment" in management practices, which has a non-negativity constraint reflecting the fact that managerial capital cannot be sold. The capital accumulation

[6]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 labor, materials and capital) as constant.

equation is similar except it allows for capital resale with a potential unit resale loss of ϕ_K

$$K_{it} = (1 - \delta_K)K_{it-1} + I_{it}^K - \phi_K I_{it}^K [I_{it}^K < 0]$$

2.3.2 Management as Design (MAD)

An alternative approach is to assume that management practices are contingent on a firm's environment so increases in M do not always increase output. In some 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 with seniority based pay and performance. Likewise, optimal management practices could vary by country if, for example, some cultures are comfortable with firing persistently under-performing employees (e.g. the US) while others emphasize loyalty to long-serving employees (e.g. Japan). We implement the Design model by assuming $\widetilde{G}(M_i) = 1/(1 + \theta|M_i - \overline{M}|)$ where $\widetilde{G}(M_i) \in (0, 1]$ and is decreasing in the absolute deviation of M from its optimal level $\overline{M}$.[7]

2.4 Adjustment costs and dynamics

We also want to allow for management practices to change, but at a cost. This could reflect, for example, the costs of the organizational resistance to new management practices (e.g. March and Simon, 1958; and Cyert and March, 1963). We assume changing management practices involves a quadratic adjustment cost:

$$C_M(M_t, M_{t-1}) = \gamma_M M_{t-1}(\frac{M_t - M_{t-1}}{M_{t-1}} - \delta_M)^2$$

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 similar quadratic adjustment costs for capital:

$$C_K(K_t, K_{t-1}) = \gamma_K K_{t-1}(\frac{K_t - K_{t-1}}{K_{t-1}} - \delta_K)^2$$

To minimize 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

[7]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.

choice of labor by $\frac{\partial PY(A,K,L^*,M)}{\partial L} = w$. Imposing this labor optimality condition and assuming the MAT specification for management in the production function we obtain:

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

where $A^* = b^{\frac{b}{1-b}} A^{\frac{1}{1-b}}$ and we normalize w to unity. Finally, A is assumed to follow a standard AR(1) process so that $\ln(A_{it}) = lnA_0 + \rho_A ln(A_{i,t-1}) + \sigma_A \varepsilon_{i,t}$ where $\varepsilon_{i,t} \sim N(0,1)$, which generates firm-specific dynamics in the model.

2.5 Optimization and equilibrium

Given the firm's three state variables - business conditions A, capital K, and management M - we can write a value function (dropping i-subscripts for brevity)

$$\begin{aligned} V(A_t, K_t, M_t) &= \max[V^c(A_t, K_t, M_t), 0] \\ V^c(A_t, K_t, M_t) &= \max_{K_{t+1}, M_{t+1}} [Y_t^* - C_K(K_{t+1}, K_t) - C_M(M_{t+1}, M_t) - F \\ &\quad + \phi E_t V(A_{t+1}, K_{t+1}, M_{t+1})] \end{aligned}$$

where the first maximum reflects the decision to continue in operation or exit (where exit occurs when $V^c < 0$), and the second (V^c for "continuers") is the optimization of capital and management conditional on operation. The value function depends on our specification for management practices and we use a discount factor, ϕ.

We assume there is a continuum of potential new entrants that would have to pay an entry cost κ to enter. Upon entry they draw their productivity and management values from a joint distribution $H(A, M)$ and start with $K_0 = 0$. Hence, entry occurs until the point that

$$\kappa = \int V(A, K_0, M) dH(A, M)$$

We solve for the steady-state equilibrium 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.

Firms draw stochastically and independently for TFP and management $\{A, M\}$ when they enter from a known distribution. The distribution of lnA is assumed normal, while M is assumed to be drawn from a uniform distribution.[8] We discretize the state space for M, K, A into bins for purposes of the numerical simulation.

[8] Nothing fundamental hinges on the exact distributional assumptions for M and A.

2.6 Numerical Estimation

Solving the model requires finding two nested fixed-points. 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 is from the static first-order condition. Second, we then iterate over the demand curve (3) to satisfy the zero-profit condition. 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. Once both fixed points are satisfied we simulate data for 5,000 firms over 100 years to get to an erogodic steady-state, and then discard the first 90 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 15 parameter values. We predefine nine of these from from the prior literature, normalize two (fixed costs to 100 and log(TFP) to 1) and estimate the remaining four parameters on our management and accounting data panel. The 9 predefined parameters are listed in Table 1 with their rationale alongside, noting that in general these are based on standard values from the literature. The four estimate parameters are the adjustment cost (γ_M) and depreciation rates (δ_K) for management because little is known about them in the prior literature. The sunk cost of entry (κ) is also hard to tie down. Finally, we also estimate the adjustment cost for capital (γ_K) given the complimentarity of this with management.[9]

The four remaining free parameters are estimated using Simulated Method of Moments (SMM). SMM proceeds as follows - a set of four data moments Ψ^A is selected for the model to match. In terms of empirical moments it seemed natural to use the exit rate to help inform the sunk cost entry and the variance of the growth rates of the three state variables (management, capital and TFP) to tie down the adjustment cost and depreciation parameters. For an arbitrary value of the parameter vector θ the dynamic program is solved and the policy functions are generated. These policy functions are used to create a simulated data panel of size $(\mu N, T)$, where μ 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[10] between the simulated moments $\Psi^S(\theta)$ and the actual moments Ψ^A. The parameter estimate $\widehat{\theta}$ is then derived by searching over the parameter space to find the parameter vector which minimizes the criterion function:

$$\widehat{\theta} = \arg\min_{\theta \in \Theta} [\Psi^A - \Psi^S(\theta)]'W[\Psi^A - \Psi^S(\theta)] \tag{4}$$

Given the potential for discontinuities in the model and the discretization of the state space we use

[9] While prior papers have estimated labor and capital adjustment costs (see, for example, Bloom (2009) and the survey therein) they ignore management as an input so it is not clear these parameters are transferable to this set-up

[10] 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.

an annealing algorithm for the parameter search (see Appendix A). Different initial values of θ are selected to ensure the solution converges to the global minimum.

To generate our SMM moments we take the panel dataset of management surveys on the populations of public and private manufacturing companies for all countries from 2004 to 2014, covering 13,944 firm-year observations. This data is then matched to firm-level panel accounting data since 2004 where available. We describe the data in more detail in the next section. To fill holes in the matched management-accounting panel dataset we interpolate (but do not extrapolate) missing years, which is important for the management data where we interview firms on a rotating panel rather than every single year. We then generate 5-year growth rates for sales, capital and management, and 5-year exit (bankruptcy/liquidation) rates, and use as moments the standard-deviation of the growth rates and the absolute value of the exit rates. Finally, we block-bootstrap over firms the entire process 1000 times to generate the variance-covariance matrix for the moments, which is used in weighting the SMM criterion function.

The top panel of Table 2 contains the SMM estimates and standard errors values for the four estimated parameters, and in bottom panel the moments from the data used to estimate these. Because we are exactly identified we can precisely match the moments within numerical rounding errors.[11] We obtain a high level of adjustment costs for management of 0.387 (approximately double the level of capital 0.150) which seems plausible, as managerial capital is likely to be much harder to change than plant or equipment. Depreciation of management capital is is 8.2%, similar to the level of the depreciation of capital (10% - see Table 1). We obtain a sunk cost of entry which is 87% of the ongoing fixed cost of running a plant.

2.7 Simulation results

Having defined and estimated the main MAT model we can proceed to examine covariances of various moments that we have not targeted in the structural estimation to later compare these with actual data. Figures 2 through 5 show some predictions arising from the simulation. Using the data from the last ten years of the simulation we simply plot the local linear regressions of firm ln(sales) against firm management (Figure 2). We use size (sales) as our performance measure, but we obtain similar results for TFPQ, TFPR, labor productivity and profits. There is a positive and monotonic relationship as we expect. The second prediction relates to product market competition as indexed by changes in the elasticity of demand (ρ,consumers' sensitivity to price). We run all the simulations 10 times for increasingly high levels of the absolute price elasticity of demand between 3 and 15 (recall that our baseline is elasticity = 5). This represents economies with increasingly high levels of competition. Figure 3 shows that average management scores are higher when competition is stronger. The darker bars from are the unweighted means of firms management and rise because under higher competition poorly managed firms will tend to exit because they cannot cover their

[11]The grid-point set-up for the value function and the data simulation means the relationship between parameter values and the criterion function has some slight noise.

fixed cost of production. Figure 2 also shows that the management scores weighted by firm size (employment) increase with competition, and that this is an even stronger relationship than the unweighted scores. This is because greater competition causes the covariance between firm size and management to become stronger (an "Olley Pakes reallocation" term), as better managed firms will acquire larger market shares (and therefore need more inputs).

Figure 4 examines the relationship between management and firm age. Firms over five years old appear to have higher management scores than those who are younger, and there is less dispersion of management. This is because of selection effects with the worst managed firms exiting. Interestingly, this seems to happen relatively rapidly: within about the first five years of life. Finally in Figure 5 we confirm the obvious, namely that management falls as it's own price increases.

Figure A1 is the analog to Figures 2 to 5 for the Management as Design model. In Panel A performance is an inverted U in management, declining as firms are above and below around a threshold. This is expected - in the design view of the world firms should all be at the same level of M. The reason that there are firms away from this point is that in their early years they generally will have drawn a level of management that is too high or too low compared to the optimal point (since there are always firms entering and exiting there are always firms in this adjustment path even in the steady state). In Panel B we show the relationship between management and competition. There is no correlation at all, as there is no sense in which high levels of M are better and therefore positively selected as competition increases. Likewise in Panel C there is very little relationship be.... In Panel D...

3 Data

3.1 Survey method

To measure management practices we developed a new "double blind" survey methodology in Bloom and Van Reenen (2007). This uses an interview-based evaluation tool that defines and scores from one ("worst practice") to five ("best practice") across 18 basic management practices on a scoring grid. This evaluation tool was first developed by an international consulting firm, and scores these practices in three broad areas.[12] First, *Monitoring*: how well do companies track what goes on inside their firms, and use this for continuous improvement? Second, *Target setting*: do companies set the right targets, track the right outcomes and take appropriate action if the two are inconsistent? Third, *Incentives/people management*[13]: are companies promoting and rewarding employees based on performance, and systematically trying to hire and keep their best employees?

[12] Bertrand and Schoar (2003) focus on the characteristics and style of the CEO and CFO. This captures differences in management strategy (say over mergers and acquisitions) rather than management practices *per se*.

[13] These practices are similar to those emphasized in earlier work on management practices, by for example Ichniowski, Prennushi and Shaw (1997) and Black and Lynch (2001).

To obtain accurate responses from firms we interview production plant managers using a 'double-blind' technique. One part of this double-blind technique is that managers are not told in advance they are being scored or shown the scoring grid. They are only told 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 used open questions. For example, on the first monitoring question we start by asking the open question "tell me how your monitor your production process", rather than closed questions such as "do you monitor your production daily [yes/no]". We continue with open questions focusing 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 round your factory could I tell how each person was performing?". The full list of questions for the grid with examples is available at http://worldmanagementsurvey.org/wp-content/images/2010/09/Manufacturing-Survey-Instrument.pdf.

The other side of the double-blind technique is that interviewers are not told in advance anything about the firm's performance. 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 generally have not heard of these firms before, so should have no preconceptions. By contrast, it would be hard to do this if an interviewer knew they were talking to an employee of Microsoft, General Electric or Boeing. Focusing on firms over a size threshold is important as the formal management practices we consider will not be so important for smaller firms. Since we only interviewed one or two plant managers in a firm, we would only have an inaccurate picture of very large firms.

The survey was 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 collected 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.

To ensure high sample response rates and skilled interviewers we hired MBA students to run interviews because they generally had some business experience and training. We also obtained Government endorsements for the surveys in each country covered. We positioned it as a "piece of work on Lean manufacturing", never using the word "survey" or "research". We also never ask interviewees for financial data obtaining this from independent sources on company accounts. Finally, the interviewers were encouraged to be persistent - so they ran about two interviews a day lasting 45 minutes each on average, with the rest of the time spent repeatedly contacting managers to schedule interviews. These steps helped to yield a 44% response rate which was uncorrelated with the (independently collected) performance measures.

3.2 Survey waves

We have administered the survey in several waves since 2004. There were five major waves in 2004, 2006, 2009, 2013 and 2014. In 2004 we surveyed four countries (France, Germany, the UK and the US). In 2006 we expanded this to twelve countries (including Brazil, China, India and Japan) continuing random sampling, but also re-contacting all of the 2004 firms to establish a panel. In 2009 we re-contacted all the firms surveyed in 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 US and some EU countries. The final sample includes 26 countries and a short panel of up to four different years for some firms. In the full dataset we have 10,953 firms and 13,617 interviews where we have usable management information. We have smaller samples depending on the type of analysis undertaken - for example, most firms in Africa do not have accounting data for example as this depends on the different disclosure rules across countries.

3.3 Internal validation

We re-surveyed 5% of the sample using a second interviewer to independently survey a second plant manager in the same firm. The idea is the two independent management interviews on different plants within the same firms reveal where how consistently we are measuring management practices. We found that in the 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 firms is likely to be real internal variations 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

The bar chart in Figure 1 plots the average (unweighted) management practice score across countries. This shows that the US has the highest management practice scores on average, with the Germans, Japanese, Swedes and Canadians below, followed by a block of mid-European countries (e.g. France, Italy, Ireland, UK and Poland), with Southern Europe next (e.g. Portugal and Greece). Emerging economies (e.g. Brazil, China and India) are next and low income countries (mainly in Africa) at the bottom. In one sense this cross-country ranking is not surprising since it approximates the cross-country productivity ranking. But the correlation is far from perfect - Southern European countries do a lot worse than expected and other nations - like Poland - do better.

A key question is whether management practices are uniformly better in some countries like the US 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 selected countries, and shows that management practices display tremendous variation within countries. Of the total firm-level variation in management only 13% is explained by country of location, a further 10% by four digit industry with the remaining 77% being within a country and industry. Interestingly, countries like Brazil, China and India have a far larger left tail of badly run firms than the US (e.g. scores of 2 or less). This immediately suggests that one reason for the better average performance in the US is that the American economy is more ruthless at selecting out the badly managed firms. We pursue this idea that the US advantage may be linked to stronger forces of competition below.

Figure A3 shows average management scores in domestic firms compared to plants belonging to foreign subsidiaries. The means across domestic plants look similar to those in Figure 1, which is unsurprising as most of our firms are domestic. More interesting is that multinationals appear to score highly in almost every country, suggesting that such firms are able to "transport" their management internationally. This is consistent with the idea of a subset of globally productivity enhancing practices and is robust to controlling for many other factors (such as firm size, age and industry). We could extend our model to allow for this type of cross-plant transfer of management practices, but for parsimony in the current model have not done so.

4 Implications of Management as a Technology

4.1 Management and firm performance

Basic results

The most obvious implication of seeing management as a technology is that it should raise firm performance monotonically. Figure 6 plots firm Sales (left axis) and TFP (right axis) on firm management scores using local linear regression and shows a positive and monotonic relationship. To probe the bivariate relationship more formally we run some simple regressions. To compare the association of management with outcomes we z-score each individual practice, averaged across all 18 questions and z-scored the average so the management index has a standard deviation of unity. Table 3 examines the correlation between different measures of firm performance and management. To measure firm performance we used company accounts data[14], estimating production functions where Q_{it} is proxied by the real sales of firm i at time t:

$$lnQ_{it} = \alpha_M M_{it} + \alpha_L lnL_{it} + \alpha_K lnK_{it} + \alpha_X x_{it} + u_{it} \tag{5}$$

[14]Our sampling frame contained 90% private firms and 10% publicly listed firms. In most countries around the world both public and private firms publish basic accounts. In the US, 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 US, Canada and India.

Here x is a vector of other controls (such as the proportion of employees with college degrees, hours per worker, noise controls like interviewer dummies, country and three digit industry dummies) and u is an error term. In column (1) of Table 3 we regress ln(sales) against ln(employment) and the management score finding a highly significant coefficient of 0.330. This suggests that firms with one standard deviation of the management score are associated with 33 log points higher labor productivity (i.e. about 39%). In column (2) we add the capital stock and other controls which cause the coefficient on management to drop to 0.150 and it remains highly significant. Column (3) conditions on a sub-sample where we observe each firm in at least two years to show the effects are stable and estimates again by OLS whereas column (4) implements the Olley-Pakes method. Column (5) re-estimates the specification but includes a full set of firm fixed effects, a very tough test given the likelihood of attenuation bias. The coefficient on management does fall, but remains positive and significant.[15]

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 3 shows that better managed firms are significantly larger than poorly managed firms with a one standard deviation of management associated with 34 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 again see a positive and significant association with this stock market based measure.[16] Finally, column (10) examines bankruptcy/death and finds that better managed firms are significantly less likely to die, and since the mean of exit to bankruptcy is only 4.4%, the point estimate suggests a substantial 10% reduction in the probability of exit from a one-standard deviation increase in the management score.

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 evidence in Indian textile firms (Bloom et al, 2013) showed that a one standard deviation in management caused a 10% increase of TFP. This estimate lies between the fixed effect estimates of column (5) and the cross sectional and Olley-Pakes estimates of columns (3) and (4).

[15]Note that these correlations are not simply driven by the "Anglo-Saxon" countries, as one might suspect if the 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 only 0.790 (0.642).

[16]The association of management practices with performance is also clear in other sectors outside manufacturing. In Bloom, Propper, Seiler and Van Reenen (2014) we interviewed 181 managers and physicians in the orthopedic and cardiology departments of English acute care hospitals. We also found that management scores were significantly associated with better performance as indicated by improved survival rates from emergency heart attack admissions and other forms of surgery, lower in-hospital infection rates and shorter waiting lists. In Bloom, Genakos, Sadun, and Van Reenen (2012) we show similar strong correlations in a larger sample of hospitals across seven countries. We also found that pupil performance (as measured by test score value added for example) was significantly higher in better managed schools and performance was higher in retail firms with better management scores.

4.2 Product Market Competition

4.2.1 Competition and management

Another implication of the management as technology model is that tougher competition is likely to improve average management scores. Table 4 presents the management practice score regressed on three alternative competition measures. We use the four countries that we have the most extensive panel data (France, Germany, the UK and the US). We pool data from the 2006 and 2004 waves in order to look at changes over time. The first three columns use the inverse industry Lerner index. We include a full set of industry dummies and country dummies as well as the general and noise controls. Column (1) simply reports the pooled OLS results. Higher competition as proxied by the inverse of the Lerner index[17] is associated with significantly higher average management scores. Column (2) includes industry by country fixed effects so that the competition effect is only identified from changes over time in the degree of competition within an industry by country cell. The coefficient on the inverse Lerner actually increases in the within dimension, suggesting industries that grew more competitive also significantly increased their management scores. Column (3) conditions on the balanced panel of the 429 firms who we have full data on in both 2004 and 2006 and runs the same specification as column (1), producing again a positive and significant correlation with a similar coefficient, implying that there is little bias associated with the firms in the balanced sub-sample.

The next three columns of Table 4 repeat the same specifications, but use (lagged) trade openness as a competition measure defined as the (natural logarithm of) imports divided by home production in the plant's industry by country cell. Imports are also positively associated with improved management practices across all specifications, with the marginal effects for the specifications that include industry by country fixed effects (column (5) having the larger coefficients. The next three columns use the survey measure, the plant manager's stated number of rivals as the competition measure. Significant positive effects are evident in all columns with and without fixed effects. The final three columns show the results are robust when using the panel. All of these results are consistent with the Management as a Technology model.

4.2.2 Competition and reallocation towards better managed firms

If management is a technology, then better managed firms should also have more market share. If management is purely a matter of design or a productive factor it is not obvious why firms which score more highly on our generic management index should be systematically larger. We investigate this in a regression framework by considering the equation:

[17]The Lerner index is a classic measure of competition (e.g. as in Aghion et al, 2005). The Lerner is calculated as the median price cost margin using all firms in the accounting population database (except the firm itself), and we can confirm in the simulations that this is closely related to consumer price sensitivity, ρ.

$$Y_{it} = \gamma \left(M_{it} * RL\right)_{it} + \delta_1 M_{it} + \delta_2 RL_{it} + \delta_3 x_{ijt} + \nu_{ijt} \tag{6}$$

Where Y is firm size and RL is a measure of the degree of "competitive pressure for reallocation" in firm i's environment. The model of management as a technology implies that the covariance between firm size and management should be stronger when reallocation forces are stronger, so $\gamma > 0$. The simplest method of testing this idea is to use a set of country dummies to proxy reallocation as we know that it is much more likely that reallocation will be stronger in some countries (like the US) than others (like Greece). Firm employment is a good volume measure of size and Table 3 showed that better managed firms tend to be larger, so we begin with using employment (L) to proxy firm size.

Column (1) of Table 5 reports the results of a regression of firm employment on the average management score and a set of industry, year and country dummies.[18] The results indicate that firms with one unit (a standard deviation) higher management practices tend to have an extra 185 workers. In column (2) we allow the management coefficient to vary with country with the US as the omitted base. The significance of the coefficient on linear management indicates that there is a very strong relationship between size and management in the US compared to other countries, with an extra point on the management index being associated with 360 extra workers. With only one exception (out of twenty countries)[19], every other country interaction with management has a negative coefficient indicating that reallocation is weaker than in the US. For example, a standard deviation improvement in management is associated with only 235 (= 359.7 - 125) extra workers in the UK, 76 extra workers in Italy and essentially zero extra workers in Greece. In column (3) we control for capital and find our results appear robust. Finally, in column (4) we to dynamic selection using the annual average firm sales growth as the dependent variable (Y). The sample is smaller here because sales are not a mandatory reporting item in the accounts for all countries for all firms (e.g. some countries like the US do not require reporting of sales for smaller and/or privately listed firms). Column (4) shows that in the US (which is the base country) firms with higher management scores tend to grow faster, as we would expect. As before, the management coefficient is allowed to vary by country and almost all significant interactions are negative, indicating that the relationship between management and reallocation is stronger for the US than for any other country.[20]

The results in Tables 5 suggest that reallocation is stronger in the US than for the other countries which are consistent with the findings on productivity in Bartelsman, Haltiwanger and Scarpetta

[18]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 6 drops multinationals and their subsidiaries, but we show robustness of this procedure below.

[19]The Chinese interaction is positive which is surprising, but it is insignificant. We suspect this may be related to the unusual size distribution and sampling in China.

[20]We also investigated the survival equation of the column (9) of Table 2. The coefficient on the US interaction was 0.001, suggesting that death rates were 20% more likely for a badly managed firm in the US compared to a badly managed firm in another country. Although this corroborates the patterns found in the sales growth and size equations, the interaction was insignificant. This is probably because of the low mean exit rate in the data.

(2013) and Hsieh and Klenow (2009). But an alternative approach is to use explicit policy-relevant variables that could shift the degree of competition. We investigated some of the country-level policy variables that have been developed by the World Bank. We illustrate these in Table 6. We again use employment as the dependent variable as in Table 5. In column (1) we use the World Bank's trade-cost measure (the costs to export in a country) and find find a negative significant interaction suggesting higher trade costs impede reallocation to better managed firms. Countries with higher trade costs often have higher employment protection, so in column (2) we include both measures and find empirically that trade restrictions were more important.

A problem with these regressions, of course, is that we are relying on cross-country variation and we have, at best, only 20 countries (and therefore 20 values of the policy variables). There could be many other correlates with these country-level policy variables we cannot control for. Hence, in columns (3) and (4) we use a measure of tariffs - a trade measure that varies at the industry by country level (see Feenstra and Romalis, 2012). We express this variable in deviations from the industry and country average in the regressions to take out global industry and country-specific effects. Column (3) first presents a regression where we use management as the dependent variable. As we might expect higher tariffs are associated with poorer management practices. Column (4) returns to the reallocation analysis. We regress firm employment on a linear tariff, the management variable and a management*tariff interaction. We find, first a negative (although not significant) effect of tariffs on firm size as the Melitz (2003) model would suggest, and second a significant interaction effect consistent with our earlier interpretation that higher tariffs depress reallocation, even after removing country and industry effects.

To give some quantitative guide to this effect, the results in column (4) of Table 6 imply that a one standard deviation increase in the management score is associated with 110 extra employees if a country has no tariff barriers. If this country increased tariff barriers to 4 percentage points (roughly the difference in tariff levels between the US and Greece), the increase in employment would be only 65 workers, almost one-third lower (= (8.25*4)/110).

4.3 Firm Age

Examining the relationship between firm age and management is complicated by the fact that the "date of incorporation" information in company accounts is problematic. The date that is given in accounts is when the company is formed, even if this is due to a merger or acquisition.[21] Consequently, we turn to complementary management database, the MOPs survey (Bloom et al, 2014). This is plant-level survey with management questions that we designed with very similar questions those in our standard telephone survey. We implemented this together with the US Census to generate data in 2010 on about 35,000 manufacturing plants.

[21] 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 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).

Figure 7 shows in the Census data we found strong evidence that as plants age their average management scores rises and their variance of management scores falls, particularly within the first 5 years of existence. This matches the predictions from the simulation model, in which the exit of firms with low management draws after birth increases the average management score and reduces the management variation. These management questions were also linked to the Annual Survey of Manufacturers and Census of Manufacturing, and also generate similar results on the positive connection between higher plant level management scores and performance as shown in Table 2.

4.4 The price of management

There is no good proxy of the price of management, but it is plausible that the supply of highly educated workers is a complement to managerial ability, especially from institutions that supply managerial education. To examine this idea we used GIS software to geocode the latitude and longitude of every plant in our database and performed a similar exercise for every college and Business School using the UNESCO Higher Education database (See Feng, 2013 and Valero and Van Reenen, 2014) which has the location of every university and business school in the world down to the zipcode. We then used Googlemaps to calculate the drive-times to the nearest university/B-School for each of our plants.

Table 7 column (1) regresses the management score on the distance from the nearest university or business school. Plants located nearer one of these institutions were significantly more likely to obtain a higher management score. Since there may be many other factors causing this correlation, we also conditioned on population density, regional dummies, weather conditions, distance the coast and a host of other confounders. Column (2) shows that the proportion of more educated employees in the plant is also increasing with proximity to a university, as one would expect if there are mobility frictions and graduates are more likely to find employment in a nearby firm. Column (3) shows that high skilled firms also have higher management practice scores and column (4) instruments the skills measure with distance to college and again finds a positive and significant coefficient.

The IV estimate in column (4) is only valid under the exclusion restriction that the only way universities affect management is through the supply of skills. This is obviously suspect as universities could, for example, supply consultancy services. even in the presence of these effects, however, the reduced form results in column (1) are still of interest as they are broadly consistent with the fourth prediction of the model that management is falling in it's skill price. The usual caveat holds, of course that these are only cross sectional correlations and there may be many other omitted variables causing this correlation (there is not enough changes in the number of universities).

4.5 Management contingency

So, as we have seen our MAT model's predictions on performance, competition, age and price are all consistent with the results from our telephone and Census management datasets. Examining the predictions for the MAD model in Appendix A1 we see these are rejected on all these tests. As such we conclude the MAT model provides the best fit for modeling management practices, at least in terms of their relationship to firm performance, competition and age. However, before completing our discussion of management models we present one set of results on contingency.

The Design approach suggests we might expect fixed capital intensive sectors to specialize more in monitoring and targets, whereas human capital intensive sectors focus more on people management. Further, intensive monitoring and target setting may be counterproductive in industries that rely a lot on creativity and innovation where there is more need for experimentation. This is indeed what we tend to observe. We matched in four digit US industry data on the capital-labor ratio (NBER) and R&D per employee (NSF) and present some results in Panel A of Table 9. Although both people management (column (1)) and monitoring/targets management (column (2) are increasing in capital intensity, the relationship is much stronger for the latter, as shown when we regress relative people management on capital intensity in column (3). The opposite is true for R&D intensity as shown in the next three columns: in high tech industries people management is much 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, we matched in country and 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.

So in summary MAT appears to provide the best all round fit for the data, particularly in terms of firm performance, and we will use 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 MAD model in terms of contingent management styles, suggesting a hybrid model could offer a slightly better fit but at the expense of greater complexity.

5 Accounting for cross-country TFP differences with Management

We can define an "aggregate management index" following Olley and Pakes (1996) as:

$$M = \sum_i M_i s_i = \sum_i \left[\left(M_i - \overline{M_i} \right) (s_i - \overline{s_i}) \right] + \overline{M} = OP + \overline{M}$$

Where, as before, $M_i$is the management score for firm i, s_i.is a size-weight (such as the firm's share of employment or share of output), $\overline{M}$ is the unweighted average management score across firms and

OP indicates the "Olley Pakes" covariance term, $\sum_i \left[\left(M_i - \overline{M_i}\right)\left(s_i - \overline{s_i}\right)\right]$. The OP term simply divides management into a within and between/reallocation term. Comparing any two countries k and k', the difference in weighted scores is decomposed into the difference in reallocation and unweighted management scores:

$$M^k - M^{k'} = \left(OP^k - OP^{k'}\right) + \left(\overline{M}^k - \overline{M}^{k'}\right)$$

A deficit in aggregate management is composed of a difference in average (unweighted) firm management scores (as analyzed in e.g. Bloom and Van Reenen, 2007) and the reallocation effect $\left(OP^k - OP^{k'}\right)$ as focused on in Hsieh and Klenow (2009), for example. Note that one could replace Management, M, by TFP or labor productivity for a more conventional analysis.

Table 9 contains the results of this analysis with more details in Appendix C. In column (1) we present the employment share-weighted management scores (M) in z-scores, so all differences can be read in standard deviations. In column (2) we show the Olley Pakes covariance term (OP) and in column (3) the unweighted management score $\left(\overline{M_i}\right)$. From this we can see that, for example, the leading country of the US has a score of 0.80 which is split almost half and half between a reallocation effect (0.37) and a within firm effect (0.43). The US not only has the highest unweighted management score but it also has a high degree of reallocation. Singapore, Germany and Canada also have high degrees of reallocation. By contrast, Southern European countries have relatively low reallocation (in fact it is negative in Greece). 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 US at the top with Germany second and then France.[22]

Perhaps a more revealing way to illustrate these results is to calculate each country's management gap with the US. Column (4) does this for the overall gap. and column (5) reports the share of this gap arising from differences in reallocation (covariance). These results are also shown graphically in Figure 8, which highlights that reallocation accounts for up to half of the management gap with the US, with an average of 20%.

We can push this analysis further by examining how much management could explain cross country differences in TFP. Column (6) contains the country's TFP gap with the US from Jones and Romer (2010) available for a sub-set of our countries. Following the randomized control trial and non-experimental evidence presented above we assume that a one standard deviation increase in management causes a 10% increase in TFP. Thus, we can estimate that improving Greece's weighted average management score to that of the US would increase Greek TFP by 16.5%, about a third of the total TFP gap between Greece and the US. Column (7) contains similar calculations for

[22] Britain does somewhat better in our analysis, being above France, but our data is more recent (2006 compared to 1992-2001) and Bartelsman et al (2013) note that Britain's reallocation position improved in the 2000s (see their footnote 9).

the other countries implying that although management accounts for between only 10% of Japan's TFP gap with the US, it accounts for almost half of the gap between the US and countries like Portugal or Italy. Across countries, management accounts for an average of 23% of the TFP gap with the US.

In Appendix C we consider a wide variety of robustness tests of this basic finding. For example we consider alternative sampling re-weighting schemes (by conditioning on other variables in determining the propensity scores used for weighting the data), using other inputs like capital as firm size measures, including multinationals and also controlling for the fact that we do not run our survey on very small and very large firms. Although the exact quantitative findings change, the qualitative results are very robust to all these alternative modeling details.

We can also look at the within country/cross-firm dimension for those countries where we have detailed productivity data. The average industry TFPR spread between the 90^{th} and 10^{th} percentiles is 90% in US manufacturing, so with our spread of management (2.7 standard deviations between the 90-10) we can account for 30% of the TFP spread (=(2.7*0.1)/0.9). In the UK the TFPR spread is wider (110%) as is management (the 90-10 is 3 standard deviations) so we account for 38% of this.

6 Conclusions

Economists and the public have long believed that management practices are an important element in productivity. We collect original cross sectional and panel data on over 10,000 firms across 30 countries to provide robust firm-level measures of management in an internationally comparable way. We detail a formal model where our management measures have "technological" elements. In the model, management enters as another capital stock in the production function and raises output It raises output. 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 show how the qualitative predictions of this 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).

First, firms who scored more highly in our management quality index improved firm performance in both non-experimental and experimental settings. Second, in the cross section and panel dimension firms in sectors facing greater competition were more likely to have better management practices. Part of this competition effect is due to stronger reallocation effects whereby the better managed firms are rewarded with more market share in some countries compared to others. Third, as cohorts of firms age, the average level of management increases and dispersion decreases (due to selection). Fourthly, the falls in the price of management as proxied by increases in the supply the skills (e.g. through universities and business schools) are associated with higher management scores.

Finally, we use the model to show that estimate that across countries that management accounts for about 22% of a nation's TFP deficit with the US.

There are many directions to take this work. It would be useful to examine the role of co-ordination in determining the heterogeneity of management practices. Gibbons and Henderson (2012) make a persuasive case that the issues of information and motivation that we focus on here may be less important than the need to co-ordinate a multitude of powerful agents within this firm. In other words, a CEO may know the firm is has management problems, know in principle how to fix it and be well incentivized to change but he cannot persuade other senior managers (or other agents) to go along with him.

A further implication of the view of management as a technology is that it will be partly non-rival and so should exhibit spillovers as firms learn from each other. Thus, there will be positive effects of management on those neighbors who can learn best practice. This is analogous to the R&D or peer effects literature and techniques can be borrowed from this body of work (e.g. Bloom, Schankerman and Van Reenen, 2013) as a test of the alternative model, which we leave this for future work.

We hope our work opens up research agenda on why there appear to be so many very badly managed firms and what factors can help improve management and so the aggregate wealth of nations.

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A APPENDIX: DATA

We overview the dataset in this Appendix. More information on an earlier version of the dataset can be found in Bloom, Sadun and Van Reenen (2012b). More information on the management survey in general (including datasets, methods and an on-line benchmarking tool) is available on http://worldmanagementsurvey.org/.

A.1 Firm-level Accounting Databases

Our sampling frame was based on the Bureau van Dijk (BVD) Amadeus dataset for Europe (France, Germany, Greece, Italy, Ireland, Poland, Portugal and the U.K.), on BVD Icarus for the US, on CMIE Firstsource dataset for India, on the BVD Oriana dataset for China and Japan, on BVD Orbis for Argentina, Brazil, Canada, Mexico, on BVD Orbis and Duns & Bradstreet for Australia and New Zealand, and on the Industrial Annual Survey Sample of Firms (Encuesta Nacional Industrial Annual - ENIA) for Chile. These databases all provide sufficient information on companies to conduct a stratified telephone survey (company name, address and a size indicator). These databases also typically have accounting information on employment, sales and capital. Apart from size, we did not insist on having accounting information to form the sampling population, however.

Amadeus, Firstsource, and Orbis are constructed from a range of sources, primarily the National registries of companies (such as Companies House in the UK and the Registry of Companies in India). Icarus is constructed from the Dun & Bradstreet 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. ENIA, collected by the Chilean Statistic Agency, covers all the manufacturing plants that employ at least 10 individuals.

Census data do not report firm sizes on a consistent basis across different countries which is why we use the BVD and CMIE datasets. We discuss issues of representativeness below in sub-section A2.

A.2 The Management Survey

In every country the sampling frame for the management survey was all firms with a manufacturing primary industry code with between 50 and 5,000 employees on average over the most recent three years of data prior to the survey.[23] In Japan and China we used all manufacturing firms with 150 to

[23] In the US 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(employees) on log (assets) for public firms.

5000 employees since Oriana only samples firms with over 150 employees.[24] We checked the results by conditioning on common size bands (above 150 in all countries) to ensure that the results were robust.

Interviewers were each given a randomly selected list of firms from the sampling frame. This should therefore be representative of medium sized manufacturing firms. The size of this sampling frame by country is shown in Table B1, together with information on firm size. Looking at Table B1 two points are worth highlighting on the sampling frame. First, the size of the sampling frame appears broadly proportional to the absolute size of each country's manufacturing base, with China, the US and India having the most firms and Sweden, Greece and Portugal the least.[25]Second, China has the largest firms on average, presumably reflecting both the higher size cut-off for its sampling frame (150 employees versus 100 employees for other countries) and also the presence of many current and ex state-owned enterprises (11% in the survey are still Government owned). When we condition on the sample of firms with more than 150 employees in all countries, median employment for Chinese firms is still relatively high, but lower than the Argentina, Canada, Mexico, US, UK and Sweden. Third, Greece and India have a much higher share of publicly quoted firms then the other countries, with this presumably reflecting their more limited provision of data on privately held firms. Because of this potential bias across countries will control for firm size and listing status in all the main regressions.

In addition to randomly surveying from the sampling frame described above we also resurveyed in 2006 and 2009 that we interviewed in the 2004 survey wave used in Bloom and Van Reenen (2007). This was a sample of 732 firms from France, Germany, the UK and the US, with a manufacturing primary industry code and 50 to 10,000 employees (on average between 2000 and 2003). This sample was drawn from the Amadeus dataset for Europe and the Compustat dataset for the U.S. Only companies with accounting data were selected. So, for the UK 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 do not report balance sheet information. For the US it comprised only publicly quoted firms. As a robustness test we drop the firms that were resurveyed from 2004. In 2009 we also resurveyed all firms interviewed in 2006. This was a sample of 4,145 firms from China, France, Germany, Greece, India, Italy, Japan, Poland, Portugal, the UK, the US, and Sweden.

The Representativeness of the Sampling Frame

The accounting databases are used to generate our management survey. How does this compare to Census data? In Bloom, Sadun and Van Reenen (2012) we analyze this in more detail. For example, we compare the number of employees for different size bands from our sample with the figures for

[24]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.

[25]The size of the manufacturing sector can be obtained from http://laborsta.ilo.org/, a database maintained by ILO. Indian data can be obtained from Indiastat, from the "Employment in Industry" table.

the corresponding manufacturing populations obtained from national Census Bureau data from each of the countries. There are several reasons for mismatch between Census data and firm level accounts.[26] Despite these potential differences, the broad picture is that the sample matches up reasonably with the population of medium sized manufacturing firms (being within 17% above or below the Census total employment number). This suggests our sampling frame covers near to the population of all firms for most countries. 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. In the US and Japan the accounting databases appears to overestimate the employment of manufacturing firms compared to Census data, by about a third, due to some double counting of the employment of subsidiaries and imperfect recording of the consolidation markers in Japanese and US accounts.

These issues will be a problem if our sampling frame is non-randomly omitting firms - for example under-representing smaller firms - because it would bias our cross-country comparisons. We try a couple of approaches to try and address this. First, in almost all the tables of results we include country fixed-effects to try to control for any differences across countries in sample selection bias. Hence, our key results are identified by within country variation. Second, in our quantification analysis when we compare across countries we control for size, public listing status and industry. This should help to condition on the types of factors that lead to under/over sampling of firms. Since these factors explain only a limited share of cross country variation in decentralization this suggests this differential sampling bias is not likely to be particularly severe. Finally, we also present experiments where we drop the four possibly problematic countries (Japan, Portugal, Sweden and the US) from the analysis to show that the results are robust.

One further concern that is that the proportion of employment covered by medium sized firms differs systematically across countries. Using mainly Census Bureau sources on firm populations Table B2 shows the employment distribution for the countries where it is available. Firms between 50 and 5,000 employed 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 in very large firms does vary more between nations. It is highest in the US (34%) and lowest in Ireland, Portugal and Greece (under 5%), which is consistent with the fact that we find reallocation forces are stronger in the US. We correct for the fact that the support of the sampling frame covers a different fraction of firms in each country below in Appendix C.

A caveat to Table B2 is that the population employment in firms with over 5,000 workers is not

[26]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 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 in a sales regression.

disclosed in all countries. In the US and Japan we have the exact Census numbers from public use table and in the UK we had access to the confidential micro-data to do this ourselves. In the other countries we used accounting data from ORBIS and other sources to estimate employment for the mega-firms. Since these firms are so large, data is relatively plentiful as they are almost all publicly listed and followed closely. Corrections have to be made to estimate the number of domestic employees (which is the Census concept) if this is not revealed directly.[27]

The Survey Response Rate

As shown in Table B3 of the firms we contacted 42.2% took part in the survey: a high success rate given the voluntary nature of participation. Of the remaining firms 14.7% refused to be surveyed, while the remaining 42.9% were in the process of being scheduled when the survey ended.

The reason for this high share of 'scheduling in progress' firms was the need for interviewers to keep a portfolio of firms who they cycle though when trying to set up interviews. Since interviewers only ran an average of 2.8 interviews a day the majority of their time was spent trying to contact managers to schedule future interviews. For scheduling it was efficient for interviewers to keep a stock of between 100 to 500 firms to cycle through. The optimal level of this stock varied by the country - in the US and UK many managers operated voicemail, so that large stocks of firms were needed. In Japan after two weeks the team switched from working Japanese hours (midnight to 8am) to Japanese afternoons and UK morning (4am till midday), which left large stocks of contacted firms in Japan.[28] In Continental Europe, in contrast, managers typically had personnel assistants rather than voicemail, who wanted to see government endorsement materials before connecting with the managers. So each approach was more time consuming, requiring a smaller stock of firms.

The ratio of successful interviews to rejections (ignoring "scheduling in progress") is above 1 in every country. Hence, managers typically agreed to the survey proposition when interviewers were able to connect with them. This agreement ratio is lowest in Japan. There were two reasons for this: first, the Japanese firms were less willing to refuse to be interviewed; and second, the time-zone meant that our interviewers could not run talk during the Japanese morning; which sometimes led to rejections if managers were too busy to talk in the afternoon.

Table B4 analyses the probability of being interviewed[29]. In all columns, we compare the probability of running an interview conditional on contacting the firm, so including rejections and 'scheduling in progress' firms in the baseline. In column (1) we analyze the differences in sample response rates across countries and find that compared to the US, China, France, Germany, Greece, India,

[27]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.

[28]After two weeks of the Japanese team working midnight to 8am it became clear this schedule was not sustainable due to the unsociability of the hours, with one of the Japanese interviewers quitting. The rest of the team then switched to working 4am until noon.

[29]Note this sample is smaller than the total survey sample because some firms do not report data for certain explanatory variables, for example US private firms do not report sales.

Italy, Poland, Portugal and Sweden had significantly higher conditional acceptance rate – while Australia, Canada, Ireland, Japan and Mexico had a significantly lower acceptance rate.

In column (2) we add in firm size and find that larger firms are significantly more likely to agree to be interviewed, although the size of this effect if not large - firms were about 4 percentage points more likely for a doubling in size. However, we see in column (3) of Table A4 that the decision to accept is uncorrelated with revenues per worker, a basic productivity measure. This is an important result as it suggests we are not interviewing particularly high or low performing firms. In column (4) we find that firm age, listed and multinational status are also all uncorrelated with response rates. Finally, Column (5) shows that the likelihood of a contacted firm eventually being interviewed is also uncorrelated with return on capital employed, a basic profits measure.

So, in summary, respondents were not significantly more productive or profitable than nonresponders. Respondents did tend to be slightly larger, but were not more likely to be stock-market listed, older or multinationals. There was also some response differences across countries. Note, however, that we address this potential source of bias including in all regressions controls for size and country dummies.

Firm-level variables

We have firm accounting data on sales, employment, capital, profits, shareholder equity, long-term debt, market values (for quoted firms) and wages (where available). BVD and CMIE also have extensive information on ownership structure, so we can use this to identify whether the firm was part of a multinational enterprise. We also asked specific questions on the multinational status of the firm (whether it owned plants aboard 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 size, skills, organization, etc. as described in the main text. We asked the manager to estimate how many competitors he thought he faced (top-coded at 10 or more) which was used to construct the firm level competition variable (see next sub-section for the other industry-level competition measures).

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. 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 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 again this average.

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. 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" constructed, as in Aghion et al. (2005), as the mean of (1 -profit/sales) in the entire database (excluding the surveyed firms themselves) for every country industry pair. 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 five year period 2000 to 2004 is used in every country to ensure comparability across countries (since earlier data is not available in Oriana). In the US and India private firms do not provide profits data so the index was constructed from the population of all publicly listed firms, obtained from Compustat for the US and the CMIE Prowess dataset for India.

B APPENDIX: FURTHER RESULTS

In the section on decomposing share-weighted management into reallocation and unweighted average components (equations (4) and (5)) we made a variety of assumptions and modeling decisions that we now relax to see how they alter our results. Note that the sample we used in the analysis is a sub-sample of that underlying Figure 1 as we focus on the survey wave in 2006, drop multinationals and drop countries were we have poor employment data. The methodology differs from Figure 1 as we weight the management data according to a firm's country-specific market share and adjust for non-random selection.

B.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 B has examined the overall evidence on sampling bias and argued that these were relatively small both on the observable and unobservable dimensions. Nevertheless, the baseline results in attempted to 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 employment size, firm age, whether the firm was publicly listed and industry dummies. We then calculate the weights as the inverse of the probability of response. We chose these controls as they are available for responders and non-responders and there was some evidence that larger firms were more likely to respond (see Appendix B). We experimented with an alternative first stage probit for sample response based on just using employment rather than the richer set of controls. The results are in Table C2 and Figure B1 which mirror Table 1 and Figure 7. Although there are a few minor changes, the results appear very stable.

B.2 Non-labor inputs

We have focused on employment as our key measure of size as it is simple, a volume and broadly 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*ln(labor) + 0.3*ln(capital)]. The results are in Figure C3 and again are similar to the baseline.

B.3 Multinationals

In Table 1 we dropped multinationals because of the difficulty of measuring group size appropriately for such entities. To check robustness we included them, but included multinational status into the selection equation used to calculate the sample response rate weights (multinationals were more likely to participate in the survey: see Table B2). The results of repeating the decomposition are in Figure C4. The broad qualitative picture is the same as the baseline with the US still having the highest weighted and unweighted management scores and the greatest degree of reallocation. Further, there are a group of countries just behind the US who do very well: Japan, Sweden and Germany. There are a few differences, however. Greece's gap with the US shrinks to -1.29 from -1.65 and Portugal's improves to -0.89 from -1.2. This is because multinationals tend have high management scores and both countries have a good fraction of foreign multinationals. France also improves its position (-0.51 behind the US instead of -0.98), moving ahead of the UK with a larger reallocation term of 0.24, closer to that in Bartelsman et al (2013).

B.4 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 comparable 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, 2012). 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 we know the number of firms and workers above and below 50 employees in most countries (see Table B2). 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 corroborate 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 US size distribution (Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten and Van Reenen, 2014).[30]

We then use this information to estimate what 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 under 50 and over 5,000 populations.[31] We then use the information in Table B2 to calculate the mean management score across the entire size distribution. Results of this exercise are in Figure C5. The correlation between our baseline management scores and the new corrected management scores is very high (0.95). There are a

[30] The coefficient on ln(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. Figure C5 does the latter, but both methods lead to similar results.

[31] 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 Zipf distributed (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 5000 firms. This "discrete" method is used in Figure B4. We also considered the continuous version of the power law which lead to similar results.

couple of differences though. France does better on the corrected numbers because it has relatively more employment in large firms. Italy and Portugal do relatively worse because of a very high proportion of small firms.

TABLE 1: CALIBRATED PARAMETERS FROM THE LITERATURE

Parameter	**Symbol**	**value**	**Rationale**
Capital – output elasticity	α	0.3	NIPA factor share
Labor – output elasticity	β	0.6	NIPA factor share
Management – output elasticity	γ	0.1	Bloom et al (2013)
Demand elasticity	e	5	Bartelsman et al (2013)
Standard deviation of ln(TFP)	σ_A	0.31	Bloom (2009)
AR(1) parameter on ln(TFP)	ρ	0.885	Cooper and Haltiwanger(2006)
Discount Factor	ϕ	0.9	Standard 10% interest rate
Capital depreciation rate	δ_K	10%	Bond and Van Reenen (2007)
Capital resale loss	ϕ_K	50%	Ramey and Shapiro (2001)

Notes: Fixed cost of production is normalized to 100 and mean of ln(TFP) is normalized to 1.

TABLE 2: ESTIMATED PARAMETERS USING SIMULATED METHOD OF MOMENTS

PANEL A: PARAMETER ESTIMATES FROM SMM

Parameter	Symbol	Value
Depreciation rate of management	δ_M	0.082(X)
Adjustment cost parameter for management	γ_M	0.387(X)
Adjustment cost parameter for capital	γ_K	0.150(X)
Sunk cost of entry	κ	86.9(X)

PANEL B: MOMENTS USED IN SMM ESTIMATES

Parameter	Data Value	Estimated value
Standard deviation of 5 year management growth	0.564	0.560
Standard deviation of 5 year sales growth	0.980	0.980
Standard deviation of 5 year capital growth	0.887	0.888
Annual Exit rate	4.43%	4.44%

Notes: These are the parameters we estimate using the model (see text). Calibrated parameters from Table 1. Estimation by SMM on the management- accounting panel dataset of XXX firm-year observations. Standard errors generated by block-bootstrap.

TABLE 3: PERFORMANCE REGRESSIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	**Ln (Sales)**	**Ln (Sales)**	**Ln (Sales)**	**Ln (Sales)**	**Ln (Sales)**	**Ln (Employees)**	**Profitability (ROCE, %)**	**5 year Sales growth**	**Ln(Tobin Q)**	**Death (%)**
Method	**OLS**	**OLS**	**OLS**	**Olley-Pakes**	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**	**OLS**
Management	0.330***	0.150***	0.142***	0.134***	0.033**	0.338***	1.202***	0.039***	0.082**	-0.006***
(z-score)	(0.018)	(0.016)	(0.019)	(0.020)	(0.013)	(0.015)	(0.264)	(0.013)	(0.031)	(0.002)
Ln(Employees)	0.905***	0.645***	0.632***	0.621***	0.374***					
	(0.018)	(0.024)	(0.030)	(0.050)	(0.096)					
Ln(Capital)		0.307***	0.305***	0.333***	0.237***					
		(0.019)	(0.024)	(0.034)	(0.078)					
General controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Firm FE	No	No	No	No	Yes	No	No	No	No	No
Firms	4,265	3,493	1,543	1,543	1,543	7,519	3,917	3,606	657	7,532
Observations	9,352	8,314	6,364	6,364	6,364	15,608	9,163	8,365	1,743	7,532

Note: All columns estimated by OLS with standard errors are in parentheses under coefficient estimates clustered by firm. *** denotes 1% significant, ** denotes 5% significance and * denotes 10% significance. For sample comparability columns (1) to (7) are run on the same sample of firms with sales, employment, capital, ROCE and 5 years of sales data. Columns (8) and (9) are run on the sample of firms with exit data and which are publicly listed respectively. We condition on a sample with non-missing values on the accounting variables for sales, employment, capital, ROCE and 5-year sales growth data. Column (3) also restricts to firms with two or more surveys and drops the noise controls (which have little time series variation). "**Management"** is the firm's normalized z-score of management (the average of the z-scores across all 18 questions, normalized to then have itself a mean of 0 and standard-deviation of 1). **"Profitability"** is "Return on Capital Employed" (ROCE) and "**5 year Sales growth"** is the 5-year growth of sales defined as the difference of current and 5-year lagged logged sales. All columns include a full set of country, three digit industry and time dummies. "**Death**" is the probability of exit by 2010 (sample mean is 2.4%). "**Tobin's Q**" is the stock-market equity and book value of debt value of the firm normalized by the book value of the firm, available for the publicly listed firms only. "**General controls**" comprise of firm-level controls for average hours worked and the proportion of employees with college degrees (from the survey), plus a set of survey noise controls which are interviewer dummies, the seniority and tenure of the manager who responded, the day of the week the interview was conducted, the time of the day the interview was conducted, the duration of the interviews and an indicator of the reliability of the information as coded by the interviewer, and a full set of 3-digit SIC industry controls except for columns (8) and (9) where the number of exits is too small for industry controls ."**Competition**" is the perceived number of competitors on a 0 to 10 scale (where 10 is 10+ competitors and 0 is no competitors), with both coefficients and standard-errors scaled by 100 for ease of presentation.

TABLE 4: COMPETITION AND MANAGEMENT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1 – Lerner)	0.025**	0.019**					
	(0.012)	(0.009)					
Ln(Import Pen.)			0.086**	0.065*			
			(0.035)	(0.035)			
Number of Rivals					0.041***	0.043***	0.085**
					(0.013)	(0.012)	(0.041)
General Controls	No	Yes	No	Yes	No	Yes	Yes
Firm fixed effects	No	No	No	No	No	No	Yes
Observations	4905	4905	4361	4361	8744	8744	8744
Number of clusters	876	876	187	187	6480	6480	6480

Notes: ** indicates significance at 5% level and * at the 10%. OLS estimates with clustered standard errors in parentheses below coefficients. Clustering is at the level where competition is measured so the industry by country cell for columns (1)-(4) and firm level for columns (5)-(7). All columns include a full set of linear country, industry dummies and noise controls. **Lerner** is the (lagged) median gross price-cost margin across all firms (from ORBIS population) in the plant's three-digit industry by country cell; **Import penetration** is the (lagged) log of the value of all imports normalized divided by domestic production in the plant's two-digit industry by country cell; "**Number of rivals**" is the perceived number of competitors coded as 1 (none), 2 (2 to 5 competitors) and 3 (5 or more competitors). Columns (1) to (4) are on OECD countries (where the industry by country competition measures are well measured) and columns (5)-(7) are on all countries. General controls are the proportion of employees with a college degree, ln(firm size) and ln(plant size). Data from 2004-2010 waves pooled. Number of rivals changes over time whereas other measures are time-averaged.

TABLE 5: MANAGEMENT, FIRM SIZE AND GROWTH ACROSS COUNTRIES

	(1)	(2)	(3)	(4)
Dep. Variable:	**Employees**	**Employees**	**Employees**	**Sales Growth**
Management (MNG)	201.9***	359.7***	284.9**	0.092***
(US is the omitted base)	(38.0)	(99.6)	(129.9)	(0.035)
MNG*Argentina		-270.9**	-329.7*	-0.134***
		(109.8)	(197.2)	(0.051)
MNG*Australia		-258.3*	-249.0	-0.145**
		(145.8)	(244.0)	(0.072)
MNG*Brazil		-211.7*	-325.8*	-0.101**
		(108.4)	(168.7)	(0.040)
MNG*Canada		-169.3		-0.131**
		(104.1)		(0.066)
MNG*Chile		-92.6		-0.150
		(120.2)		(0.128)
MNG*China		84.9	-68.1	-0.060
		(113.7)	(172.2)	(0.047)
MNG*France		-489.5**	-386.1**	-0.085*
		(214.4)	(188.1)	(0.044)
MNG*Germany		-9.0	-209.7	-0.080*
		(131.6)	(184.0)	(0.047)
MNG*Greece		-355.9***	-434.6***	-0.089**
		(105.6)	(155.6)	(0.041)
MNG*India		-145.4	-42.0	-0.066
		(119.5)	(175.7)	(0.051)
MNG*Ireland		-258.8**	-250.7	-0.085
		(108.1)	(156.8)	(0.090)
MNG*Italy		-283.1***	-256.0*	-0.092**
		(106.0)	(144.3)	(0.044)
MNG*Mexico		-250.1**	-137.6	-0.075*
		(124.8)	(167.9)	(0.043)
MNG*NZ		-375.7*		0.718**
		(219.5)		(0.307)
MNG*Japan		-297.3**	-294.8	-0.099**
		(142.7)	(187.8)	(0.040)
MNG*Poland		-308.1***	-221.3*	-0.058
		(106.0)	(132.9)	(0.042)
MNG*Portugal		-308.9***	-301.5**	-0.109**
		(102.1)	(147.4)	(0.047)
MNG*Sweden		-228.7*	-246.0	-0.068
		(134.3)	(153.6)	(0.054)
MNG*UK		-125.1	-224.5	-0.054
		(180.0)	(165.0)	(0.053)
Capital			8.4***	
			(1.7)	
Observations	5,842	5,842	3,858	2,756

Notes: Management*US is the omitted base. *** significance at the 1%, 5% (**) or 10% (*) level. OLS with standard errors clustered by firm. All columns include year, country, three digit industry dummies, # management questions missing, firm age, skills and noise controls (interviewer dummies, reliability score, the manager's seniority and tenure and the duration of the interview). Domestic firms only (i.e. no multinationals). *MNG* is z-score of the average z-scores of the 18 management questions. Sales growth is logarithmic change between 2007 and 2006 where available.

TABLE 6: FIRM SIZE AND MANAGEMENT ACROSS COUNTRIES – IMPACT OF POLICY VARIABLES

	(1)	(2)	(3)	(4)
Dependent variable:	**Employment**	**Employment**	**Management**	**Employment**
Management	356.73***	381.84***		110.970*
	(55.89)	(62.88)		(66.302)
Management*Employment Protection		-1.16		
		(0.75)		
Management *Trade costs	-0.18***	-0.18***		
	(0.05)	(0.05)		
Tariff Levels			-0.007***	-4.961
			(0.002)	(4.122)
Management *Tariff Levels				-8.249**
				(3.349)
Management *country interactions	No	No	No	Yes
Observations	5,017	5,017	1,559	1,559

Notes: *** significance at the 1%, 5% (**) or 10% (*) level. OLS with standard errors clustered by firm below coefficients. All columns include full set of three digit industry dummies, year dummies, # management questions missing and a full set of country dummies. Firm size taken from survey. Multinationals dropped because of the difficulty of defining size. Management is a z-score of the average z-scores of the 18 management questions. "General" controls include firm age, skills and noise (interviewer dummies, reliability score, the manager's seniority and tenure and the duration of the interview). EPL (WB) is the "Difficulty of Hiring" index is from World Bank (from 1 to 100). "Trade Cost" is World Bank measure of the costs to export in the country (in US$). Tariffs are specific to the industry and country (MFN rates) kindly supplied by John Romalis (see Feenstra and Romalis, 2012).

TABLE 7: MANAGEMENT AND SUPPLY OF SKILLS

	(1)	(2)	(3)	(4)
Dependent variable:	**Management**	**% Employees with college**	**Management**	**Management**
Method	**OLS**	**OLS**	**OLS**	**IV**
Drive time to nearest University/B-School	-0.044***	-1.634***		
	(0.016)	(0.359)		
% Employees with college in the firm			0.008***	0.027***
			(0.001)	(0.008)
Observations	6,406	6,406	6,406	6,406

Notes: *** significance at the 1%, 5% (**) or 10% (*) level. Clustered by region (313). All columns include local population density, distance to coast, weather, firm age, skills, noise controls (interviewer dummies, reliability score, the manager's seniority and tenure and the duration of the interview), a full set of three digit industry dummies, regional and year dummies, and a full set of country dummies. Management is a z-score of the average z-scores of the 18 management questions. See Feng (2013) for more details on distance measures. IV in column (4) is the drive time to nearest university.

TABLE 8: MANAGEMENT BY DESIGN - STYLES DIFFER DEPENDING ON ENVIRONMENT

	(1) People Management (P)	(2) Monitoring & Targets (MT)	(3) Relative People (P-MT)	(4) People Management (P)	(5) Monitoring &Targets (MT)	(6) Relative People (P-MT)	(7) People Management (P)	(8) Monitoring &Targets (MT)	(9) Relative People (P-MT)
				Panel A: Using US Four digit industry (NBER, NSF)					
ln(K/L)	0.054***	0.128***	-0.097***				0.027	0.108***	-0.106***
	(0.020)	(0.026)	(0.022)				(0.018)	(0.023)	(0.022)
R&D Intensity				0.174**	-0.040	0.261**	-0.002	-0.247**	0.312***
				(0.077)	(0.140)	(0.115)	(0.057)	(0.097)	(0.091)
ln(%degree)							0.197***	0.174***	0.016
							(0.010)	(0.011)	(0.014)
Observations	9,545	9,545	9,545	9,545	9,545	9,545	9,545	9,545	9,545
				Panel B: Two-Digit industry by county specific value (KLEMS, OECD)					
ln(K/L)	-0.003	0.044	-0.060				-0.020	0.044	-0.080*
	(0.046)	(0.033)	(0.043)				(0.044)	(0.034)	(0.042)
R&D Intensity				0.461	0.017	0.535**	0.372	-0.142	0.630***
				(0.340)	(0.344)	(0.221)	(0.356)	(0.340)	(0.218)
ln(%degree)							0.206***	0.136***	0.076***
							(0.017)	(0.019)	(0.020)
Observations	4,550	4,550	4,550	4,550	4,550	4,550	4,550	4,550	4,550

***Note*:** All dependent variables are z-scores of average z-scores of the underlying questions. "People management" is the index for all questions in questions 13 – 18 (i.e. take the average of these z-scores and then z-score this index) and "Monitoring and targets" are all the remaining questions. All columns estimated by OLS with standard errors in parentheses under coefficients. *** denotes 1% significant, ** denotes 5% significance and * denotes 10% significance. All columns control for two-digit industry dummies, country by year dummies, ln(firm employment), ln(plant employment), ln(firm age) and number of competitors. In Panel A the capital-labor ratio is taken from the NBER Bartelsman-Grey dataset and R&D intensity is business R&D divided by employment from NSF. Both capital-labor and R&D intensity are at the four digit level for the US and used across all countries (so no country-specific variation). In Panel B the capital-labor ratio is measured at the two digit by country level from the EU KLEMs dataset and R&D/Value added is from the OECD STAN/ANBERD. EU-KLEMS is only available for a restricted set of countries (Australia, Germany, Italy, Japan, Sweden, UK and US) hence the smaller sample size. Standard errors are clustered at the four digit level in Panel A and two-digit industry by country level in Panel B.

TABLE 9: DECOMPOSITION OF SHARE WEIGHTED AVERAGE MANAGEMENT SCORE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Share-weighted Management	Covariance	Unweighted management	Management Deficit with US	% due to covariance	TFP Deficit With US	% accounted for by management
US	0.80	0.37	0.43	0			
Sweden	0.53	0.22	0.30	-0.27	55.56	0.32	0.04
Japan	0.46	0.20	0.26	-0.34	50.00	0.34	0.05
Germany	0.35	0.26	0.09	-0.45	24.44	0.18	0.19
Canada	0.31	0.26	0.05	-0.49	22.45	0.22	0.17
Singapore	0.24	0.43	-0.18	-0.56	-10.71	0.08	0.76
Britain	0.05	0.17	-0.11	-0.75	26.67	0.20	0.27
Australia	0.04	0.20	-0.15	-0.76	22.37	0.23	0.25
Mexico	0.03	0.32	-0.29	-0.77	6.49	0.60	0.12
Poland	-0.01	0.19	-0.20	-0.81	22.22	0.20	0.32
Italy	-0.02	0.07	-0.10	-0.82	36.59	0.17	0.31
Spain	-0.13	0.35	-0.49	-0.93	2.15	0.31	0.30
NZ	-0.14	0.27	-0.41	-0.94	10.64	0.47	0.18
France	-0.22	0.08	-0.30	-1.02	28.43	0.25	0.29
Brazil	-0.22	0.26	-0.48	-1.02	10.78	0.60	0.15
Chile	-0.22	0.34	-0.56	-1.02	2.94	0.54	0.18
India	-0.29	0.23	-0.52	-1.09	12.84	0.81	0.12
Kenya	-0.34	0.21	-0.56	-1.14	14.04	0.98	0.10
China	-0.39	0.12	-0.52	-1.19	21.01	0.78	0.12
Argentina	-0.40	0.14	-0.55	-1.20	19.17	0.57	0.17
Portugal	-0.42	0.08	-0.51	-1.22	23.77	0.25	0.38
Greece	-0.87	-0.12	-0.74	-1.67	29.34	0.51	0.23
Ghana	-1.00	0.02	-1.03	-1.80	19.44	0.87	0.17
Zambia	-1.29	-0.05	-1.23	-2.09	20.10	0.95	0.17
Mozambique	-1.37	0.15	-1.53	-2.17	10.14	0.79	0.25
Mean					20%		22%

Notes: Colum (1) is the employment share weighted management score in the country. Management scores have standard deviation 1, so Greece is 1.67 (0.87 + 0.74) standard deviations lower than the US. Column (2) is the Olley-Pakes covariance/reallocation term, the sum of all the management-employment share covariance in the country. Column (3) is the raw unweighted average management score. The sum of columns (2) and (3) equal column (1). Columns (4) and (5) deduct the value in column (1) from the US level to show relative country positions. Column (6) calculates the proportion of a country's management deficit with the US that is due to reallocation. TFP gap in column (7) is from Jones and Romer (2010). Column (8) = α_M *(4)/ (7) where α_M =0.10 the effect of a one standard deviation increase in the management score on TFP (Table 2 and Bloom et al, 2013). All scores are adjusted for nonrandom selection into the management survey through the propensity score method (selection equation uses country-specific coefficients on employment, listing status, age, SIC1). Only domestic firms used in these calculations (i.e. multinationals and their subsidiaries are dropped).

APPENDIX A1: MANAGEMENT PRACTICES QUESTIONNAIRE

Any score from 1 to 5 can be given, but the scoring guide and examples are only provided for scores of 1, 3 and 5. The survey also includes a set of Questions that are asked to score each dimension, which are included in Bloom and Van Reenen (2007).

(1) Modern manufacturing, introduction

	Score 1	Score 3	Score 5
Scoring grid:	Other than Just-In-Time (JIT) delivery from suppliers few modern manufacturing techniques have been introduced, (or have been introduced in an ad-hoc manner)	Some aspects of modern manufacturing techniques have been introduced, through informal/isolated change programs	All major aspects of modern manufacturing have been introduced (Just-In-Time, autonomation, flexible manpower, support systems, attitudes and behaviour) in a formal way

(2) Modern manufacturing, rationale

	Score 1	Score 3	Score 5
Scoring grid:	Modern manufacturing techniques were introduced because others were using them.	Modern manufacturing techniques were introduced to reduce costs	Modern manufacturing techniques were introduced to enable us to meet our business objectives (including costs)

(3) Process problem documentation

	Score 1	Score 3	Score 5
Scoring grid:	No, process improvements are made when problems occur.	Improvements are made in one week workshops involving all staff, to improve performance in their area of the plant	Exposing problems in a structured way is integral to individuals' responsibilities and resolution occurs as a part of normal business processes rather than by extraordinary effort/teams

(4) Performance tracking

	Score 1	Score 3	Score 5
Scoring grid:	Measures tracked do not indicate directly if overall business objectives are being met. Tracking is an ad-hoc process (certain processes aren't tracked at all)	Most key performance indicators are tracked formally. Tracking is overseen by senior management.	Performance is continuously tracked and communicated, both formally and informally, to all staff using a range of visual management tools.

(5) Performance review

	Score 1	Score 3	Score 5

	Score 1	Score 3	Score 5
Scoring grid:	Performance is reviewed infrequently or in an un-meaningful way, e.g. only success or failure is noted.	Performance is reviewed periodically with successes and failures identified. Results are communicated to senior management. No clear follow-up plan is adopted.	Performance is continually reviewed, based on indicators tracked. All aspects are followed up ensure continuous improvement. Results are communicated to all staff

(6) Performance dialogue

	Score 1	Score 3	Score 5
Scoring grid:	The right data or information for a constructive discussion is often not present or conversations overly focus on data that is not meaningful. Clear agenda is not known and purpose is not stated explicitly	Review conversations are held with the appropriate data and information present. Objectives of meetings are clear to all participating and a clear agenda is present. Conversations do not, as a matter of course, drive to the root causes of the problems.	Regular review/performance conversations focus on problem solving and addressing root causes. Purpose, agenda and follow-up steps are clear to all. Meetings are an opportunity for constructive feedback and coaching.

(7) Consequence management

	Score 1	Score 3	Score 5
Scoring grid:	Failure to achieve agreed objectives does not carry any consequences	Failure to achieve agreed results is tolerated for a period before action is taken.	A failure to achieve agreed targets drives retraining in identified areas of weakness or moving individuals to where their skills are appropriate

(8) Target balance

	Score 1	Score 3	Score 5
Scoring grid:	Goals are exclusively financial or operational	Goals include non-financial targets, which form part of the performance appraisal of top management only (they are not reinforced throughout the rest of organization)	Goals are a balance of financial and non-financial targets. Senior managers believe the non-financial targets are often more inspiring and challenging than financials alone.

(9) Target interconnection

	Score 1	Score 3	Score 5
Scoring grid:	Goals are based purely on accounting figures (with no clear connection to shareholder value)	Corporate goals are based on shareholder value but are not clearly communicated down to individuals	Corporate goals focus on shareholder value. They increase in specificity as they cascade through business units ultimately defining individual performance expectations.

(10) Target time horizon

	Score 1	Score 3	Score 5

Scoring grid:	Top management's main focus is on short term targets	There are short and long-term goals for all levels of the organization. As they are set independently, they are not necessarily linked to each other	Long term goals are translated into specific short term targets so that short term targets become a "staircase" to reach long term goals
(11) Targets are stretching			
	Score 1	**Score 3**	**Score 5**
Scoring grid:	Goals are either too easy or impossible to achieve; managers provide low estimates to ensure easy goals	In most areas, top management pushes for aggressive goals based on solid economic rationale. There are a few "sacred cows" that are not held to the same rigorous standard	Goals are genuinely demanding for all divisions. They are grounded in solid, solid economic rationale
(12) Performance clarity			
	Score 1	**Score 3**	**Score 5**
Scoring grid:	Performance measures are complex and not clearly understood. Individual performance is not made public	Performance measures are well defined and communicated; performance is public in all levels but comparisons are discouraged	Performance measures are well defined, strongly communicated and reinforced at all reviews; performance and rankings are made public to induce competition
(13) Managing human capital			
	Score 1	**Score 3**	**Score 5**
Scoring grid:	Senior management **do not** communicate that attracting, retaining and developing talent throughout the organization is a top priority	Senior management believe and communicate that having top talent throughout the organization is a key way to win	Senior managers are evaluated and held accountable on the strength of the talent pool they actively build
(14) Rewarding high-performance			
	Score 1	**Score 3**	**Score 5**
Scoring grid:	People within our firm are rewarded equally irrespective of performance level	Our company has an evaluation system for the awarding of performance related rewards	We strive to outperform the competitors by providing ambitious stretch targets with clear performance related accountability and rewards
(15) Removing poor performers			
	Score 1	**Score 3**	**Score 5**
Scoring grid:	Poor performers are rarely removed from their positions	Suspected poor performers stay in a position for a few years before action is taken	We move poor performers out of the company or to less critical roles as soon as a weakness is identified
(16) Promoting high performers			
	Score 1	**Score 3**	**Score 5**

	Score 1	Score 3	Score 5
Scoring grid:	People are promoted primarily upon the basis of tenure	People are promoted upon the basis of performance	We actively identify, develop and promote our top performers
(17) Attracting human capital			
	Score 1	**Score 3**	**Score 5**
Scoring grid:	Our competitors offer stronger reasons for talented people to join their companies	Our value proposition to those joining our company is comparable to those offered by others in the sector.	We provide a unique value proposition to encourage talented people join our company above our competitors
(18) Retaining human capital			
	Score 1	**Score 3**	**Score 5**
Scoring grid:	We do little to try to keep our top talent.	We usually work hard to keep our top talent.	We do whatever it takes to retain our top talent.

Source: Bloom and Van Reenen (2007)

TABLE A1

The 2006/2007 Sampling Frame

	CN	FR	GE	GR	IN	IT	JP	PO	PT	SW	UK	US
Sampling frame, number of firms (#)	86,733	4,683	9,722	522	31,699	5,182	3,546	3,684	1,687	1,034	5,953	27,795
Employees (median, sampling frame)	290	201	198	180	175	183	240	200	127	206	219	200
Employees (median, conditioning on firms with 150+ employees)	290	291	285	269	229	262	240	260	239	315	311	300
Publicly listed (%)	1	4	1	17	11	1	1	3	1	6	4	4

The 2008/2009/2010 Sampling Frame

	AR	AU	BR	CA	CL	IR	MX	NI	NZ
Sampling frame, number of firms (#)	1,000	492	5,617	5,215	1,516	596	4,662	203	67
Employees (median, sampling frame)	200	533	191	185	200-499	85	250	109	321
Employees (median, conditioning on firms with 150+ employees)	292	639	294	300	200-499	255	344	276	390
Publicly listed (%)	0.13		0.09	0.42	4.08	1.85	0.08	0	

Notes: AR=Argentina, AU=Australia, BR=Brazil, CA=Canada, CL=Chile, CN=China, FR=France, GE=Germany, GR=Greece, IN=India, IT=Italy, IR=Republic of Ireland, JP=Japan, MX=Mexico, NI=Northern Ireland, NZ=New Zealand, PO=Poland, PT=Portugal, SW=Sweden, UK=United Kingdom, US=United States. **Sampling frame** is the total number of eligible firms for the survey. The sampling frame includes all firms between 100 and 5,000 employees in the population accounting databases for all countries, excluding China and Japan (for which the employment bracket is 150 to 5,000 employees) and Portugal (for which the employment bracket is 75 to 5,000 employees). **Employees** are the median number of employees in the firm. **Publicly listed** is the percentage of firms which are directly publicly listed (note that some firms may be privately incorporate subsidiaries of publicly listed parents). Indian and Japanese employment numbers are predicted from balance sheet information for privately held firms (India) and unconsolidated accounts (Japan).

TABLE A2: DISTRIBUTION OF WORKERS IN DIFFERENT FIRM SIZE CLASSES ACROSS COUNTRIES

% workers in firms with:	France	Germany	Greece	Ireland	Italy	Japan	Poland	Portugal	Sweden	UK	US
Under 50 employees	30.1%	17.8%	41.4%	28.3%	45.2%	23.9%	27.2%	51.4%	23.8%	36.2%	16.2%
Between 50 and 5,000 employees	48.6%	52.8%	53.9%	71.7%	48.6%	58.6%	71.0%	47.8%	54.4%	49.3%	49.1%
Over 5,000 employees	21.3%	29.4%	4.6%	0.0%	6.2%	17.5%	1.8%	0.7%	21.9%	14.5%	34.7%

Notes: This table displays estimates of the distribution of employment in manufacturing across firms in different size classes. The WMS sampling frame covers medium sized firms (between 50 and 5,000 workers) which usually covers half or more of total workers. The US (2006) and Japanese (2007) data are from published Census Bureau data and UK data (2010) is from unpublished Census data. For the other countries we use Eurostat data (which is based on Census) for the proportion of employment in firms with under 50 employees. For disclosure reasons, the proportion of employees in firms in over 5,000 employees is not reported in public use tables, however. Consequently, we used other data sources to estimate this fraction since we know the total manufacturing employment and we have access to the employment of the largest firms in every country from ORBIS company accounts data. Details are in Appendix B.

TABLE A3

The Survey Response Rate

	CN	**FR**	**GE**	**GR**	**IN**	**IT**	**JP**	**PO**	**PT**	**SW**	**UK**	**US**
Interviews completed (%)	43.9	59.3	58.6	53.4	61.4	68.2	21.5	37.5	60.5	68.2	32.9	37.2
Interviews refused (%)	13.7	13.7	27.2	10.7	13.7	20	20.1	16.5	15.8	16.9	19.6	13.7
Scheduling in progress (%)	40.1	27	14.2	35.9	25	11.8	58.4	46	23.7	14.9	47.4	49.1
Survey sample, number of firms (#)	727	528	526	350	761	304	563	637	293	380	1,851	1,833
Interviews completed (#)	319	313	308	187	467	207	121	239	177	259	609	682

	AR	**AU**	**BR**	**CA**	**CL**	**IR**	**MX**	**NZ**	**NI**
Interviews completed (%)	42.4	32.8	43.3	33.2	42.7	43.2	41.4	44.1	53.7
Interviews refused (%)	14.3	11.0	9.3	10.4	22.8	10.6	17.8	8.4	6.4
Scheduling in progress (%)	43.3	56.2	47.4	56.4	34.5	46.3	40.8	47.5	39.9
Survey sample, number of firms (#)	589	1,355	1,381	1,246	663	387	461	345	203
Interviews completed (#)	250	445	598	423	283	167	191	152	109

Notes: AR=Argentina, AU=Australia, BR=Brazil, CA=Canada, CL=Chile, CN=China, FR=France, GE=Germany, GR=Greece, IN=India, IT=Italy, IR=Republic of Ireland, JP=Japan, MX=Mexico, NI=Northern Ireland, NZ=New Zealand, PO=Poland, PT=Portugal, SW=Sweden, UK=United Kingdom, US=United States. **Interviews completed** reports the percentage of companies contacted for which a management interview was completed. **Interviews refused** reports the percentage of companies contacted in which the manager contacted refused to take part in the interview. **Scheduling in progress** reports the percentage of companies contacted for which the scheduling was still in progress at the end of the survey period (so the firm had been contacted, with no interview run nor any manager refusing to be interviewed). **Survey sample** is the total number of firms that were randomly selected from the complete sampling frame.

TABLE A4: RESPONSE RATES TO THE SURVEY

	(1)	(2)	(3)	(4)	(5)
Ln(employment)		0.039***	0.023***	0.023***	0.044***
		(0.004)	(0.007)	(0.007)	(0.011)
Ln (Sales/employee)			0.005	0.005	
			(0.007)	(0.007)	
Age of firm (in years) §				-0.003	0.021
				(0.014)	(0.020)
Publicly listed				-0.009	-0.031
				(0.024)	(0.033)
Multinational subsidiary				0.003	0.023
				(0.022)	(0.036)
Return on Capital Employed §					-0.012
					(0.047)
Country is Argentina	0.003	0.032	0.085***	0.086***	
	(0.023)	(0.023)	(0.030)	(0.031)	
Country is Australia	-0.156***	-0.132***			
	(0.014)	(0.015)			
Country is Brazil	0.007	0.036**	0.129***	0.129***	
	(0.017)	(0.018)	(0.028)	(0.029)	
Country is Canada	-0.087***	-0.042**	-0.003	-0.003	
	(0.017)	(0.018)	(0.025)	(0.026)	
Country is Chile	-0.015	0.594***			
	(0.021)	(0.008)			
Country is China	0.089***	0.070***	0.074**	0.072**	
	(0.019)	(0.019)	(0.030)	(0.031)	
Country is France	0.222***	0.247***	0.277***	0.278***	-0.074
	(0.024)	(0.024)	(0.026)	(0.026)	(0.046)
Country is Germany	0.204***	0.220***	0.248***	0.249***	
	(0.024)	(0.024)	(0.026)	(0.026)	
Country is Greece	0.159***	0.193***	0.234***	0.234***	-0.108**
	(0.029)	(0.029)	(0.031)	(0.031)	(0.049)
Country is India	0.259***	0.270***	0.309***	0.306***	
	(0.021)	(0.021)	(0.032)	(0.032)	
Country is Ireland	-0.102***	-0.045*	0.119***	0.120***	
	(0.022)	(0.024)	(0.040)	(0.041)	
Country is Italy	0.314***	0.341***	0.357***	0.356***	0.046
	(0.028)	(0.027)	(0.028)	(0.028)	(0.052)
Country is Japan	-0.175***	-0.176***	-0.163***	-0.162***	
	(0.024)	(0.025)	(0.030)	(0.031)	
Country is Mexico	-0.091***	-0.066***	0.072**	0.073**	
	(0.021)	(0.022)	(0.035)	(0.036)	
Country is New Zealand	-0.028	0.023			
	(0.026)	(0.027)			
Country is Poland	-0.000	0.024	0.069**	0.071**	-0.273***
	(0.023)	(0.023)	(0.028)	(0.028)	(0.039)
Country is Portugal	0.237***	0.279***	0.316***	0.316***	0.006
	(0.030)	(0.029)	(0.029)	(0.029)	(0.053)
Country is Sweden	0.286***	0.310***	0.333***	0.334***	0.007
	(0.026)	(0.025)	(0.026)	(0.026)	(0.049)
Country is UK	0.019	0.032*	0.061***	0.063***	-0.296***
	(0.017)	(0.018)	(0.023)	(0.023)	(0.039)
Country is US	Baseline	Baseline	Baseline	Baseline	Baseline
Industry dummies (SIC 3-digit)	No	No	Yes	Yes	Yes
Number of firms	17877	17137	10216	10216	4654

Notes: All columns estimated by probit with standard errors clustered by firm and marginal effects reported. The dependent variable takes value one if the firm was interviewed, and zero if the interview was refused, or if scheduling was still in progress as the end of the project (mean value for the US baseline is 0.381). § denotes the coefficient and standard-errors have been multiplied by 100.

TABLE B1: DECOMPOSITION OF WEIGHTED AVERAGE MANAGEMENT SCORE (EMPLOYMENT ONLY IN SELECTION EQUATION)

	(1)	(2)	(3)	(4)	(5)	(6)
Country	Share-Weighted Average Management Score (1)=(2)+(3)	Reallocation effect (Olley-Pakes)	Unweighted Average Management Score	"Deficit" in Share-weighted Management Score relative to US	"Deficit" in Reallocation relative to US	% of deficit in management score due to worse reallocation (6)=(5)/(4)
US	0.62	0.31	0.31	0	0	n/a
Sweden	0.42	0.22	0.20	-0.2	-0.09	45%
Japan	0.36	0.19	0.16	-0.26	-0.12	46%
Germany	0.29	0.26	0.03	-0.33	-0.05	15%
Great Britain	-0.06	0.17	-0.24	-0.68	-0.14	21%
Italy	-0.07	0.13	-0.20	-0.69	-0.18	26%
Poland	-0.16	0.17	-0.33	-0.78	-0.14	18%
France	-0.30	0.09	-0.40	-0.92	-0.22	24%
China	-0.49	0.12	-0.61	-1.11	-0.19	17%
Portugal	-0.52	0.11	-0.63	-1.14	-0.20	18%
Greece	-0.92	-0.08	-0.84	-1.54	-0.39	25%
Unweighted Average		0.20		-0.76	-0.17	25.5%

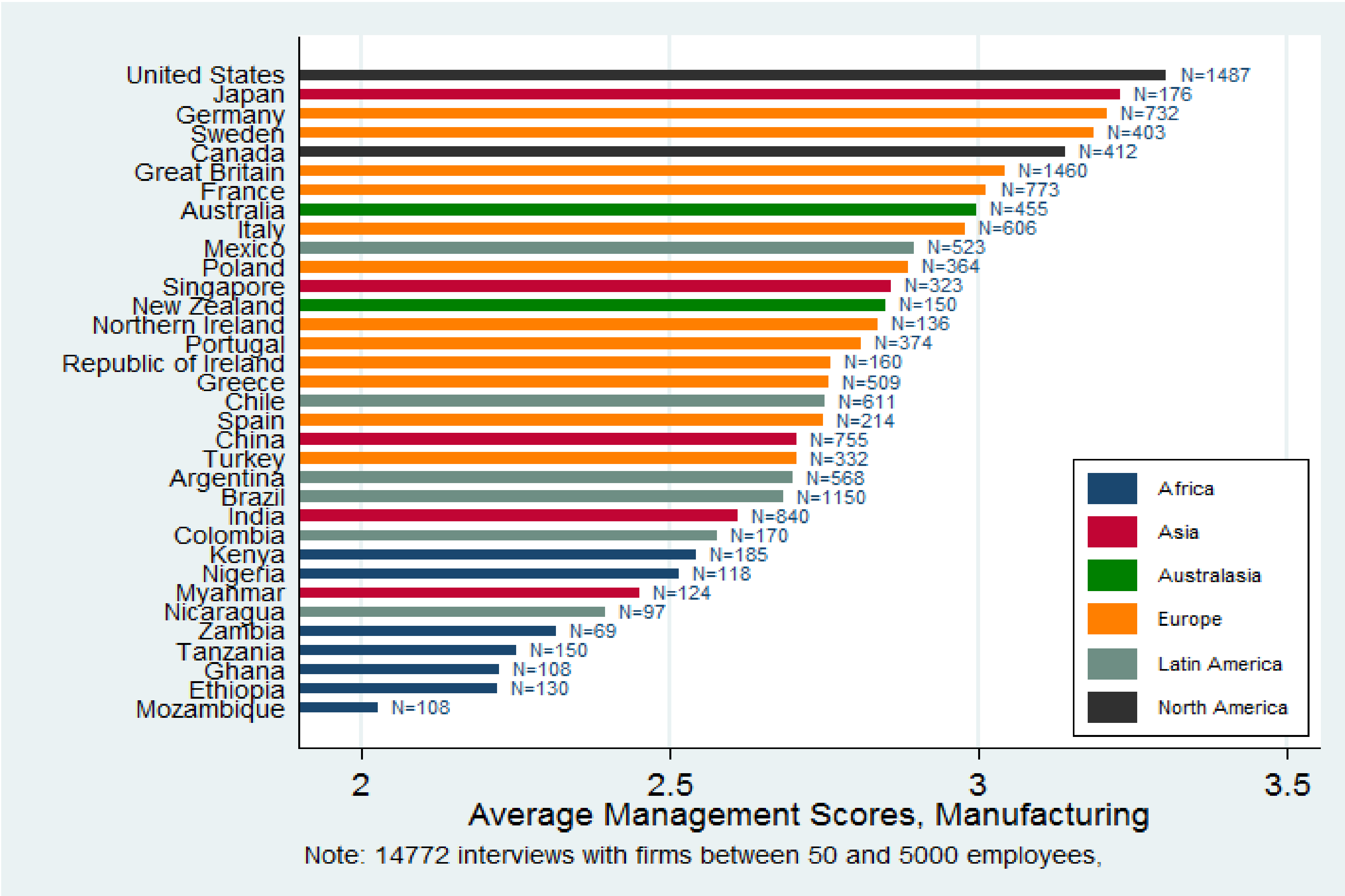
Notes: Colum (1) is the employment share weighted management score in the country. Management scores have standard deviation 1, so Greece is 1.54 (0.62 + 0.92) SD lower than the US. Using column (2) of Table 3 this implies that Greece's TFP would be 23% = 1 - exp(0.14*1.5)) higher if it had US levels of management, which would account for about half the total US-Greece TFP gap. Column (2) is the Olley-Pakes reallocation term, the sum of all the management-employment share covariance in the country. Column (3) is the raw unweighted average management score. The sum of columns (2) and (3) equal column (1). Columns (4) and (5) deduct the value in column (1) from the US level to show relative country positions. Column (6) calculates the proportion of a country's management deficit with the US that is due to reallocation. All scores are adjusted for nonrandom selection into the management survey through the propensity score method (selection equation uses country-specific coefficients on employment only instead of firm age, publicly listing status and industry dummies as in baseline). Only domestic firms used in these calculations (i.e. multinationals and their subsidiaries are dropped).

TABLE B2: CORRECTING FOR CHOOSING A SAMPLING FRAME OF MEDIUM SIZED FIRMS IN MANUFACTURING

	US	Japan	Germany	France	GB	Greece	Italy	Poland	Portugal	Sweden
Proportion of employees in firms of Different sizes:										
Under 50 employee firms	0.162	0.239	0.165	0.294	0.229	0.413	0.451	0.272	0.514	0.233
Greater or equal to 50 and less than or equal to 5000	0.491	0.586	0.486	0.476	0.573	0.525	0.485	0.710	0.479	0.533
Greater than 5000 employees	0.347	0.175	0.349	0.230	0.198	0.062	0.064	0.018	0.007	0.234
Total employment	14,743,400	8,836,150	8,669,054	3,639,907	3,868,718	345,558	4,172,679	2,097,196	802,243	754,976
Total firms	267,999	258,648	199,119	257,048	150,481	94,346	512,879	195,909	96,289	61,129

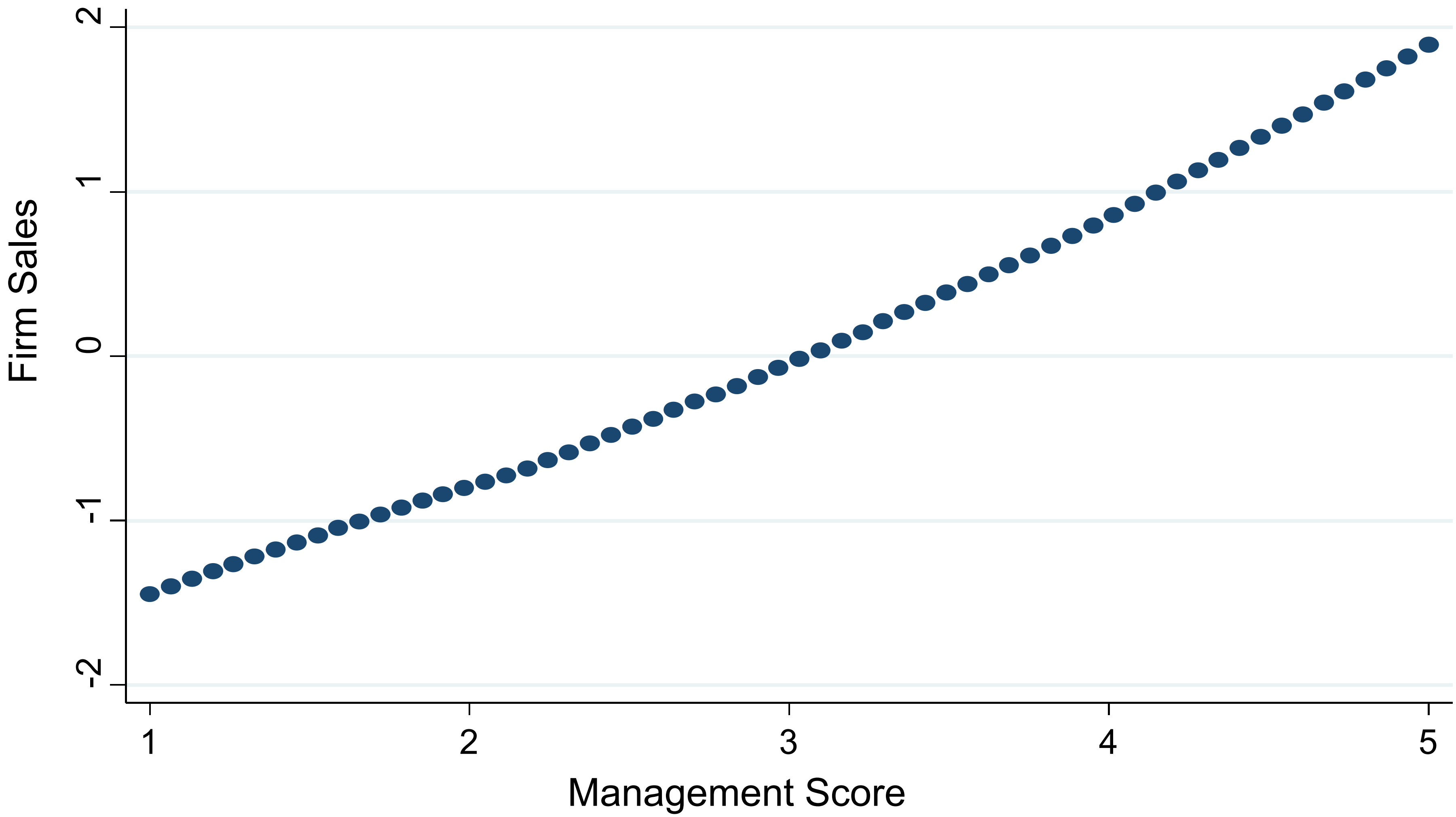
Notes: These numbers are based on various sources. Census data for US, GB and Japan. Eurostat firm demographics files for France, Germany, Ireland, Italy, Poland, Portugal and Spain. Although firms with under 50 are always given firms with over 5000 employees are generally not given in Eurostat because of confidentiality reasons. We use Orbis to estimate the numbers for the large firms combined with manual inspection of the published company accounts to obtain a breakdown between domestic and overseas employment (we use domestic employment).

Figure 1: Average Management Scores by Country



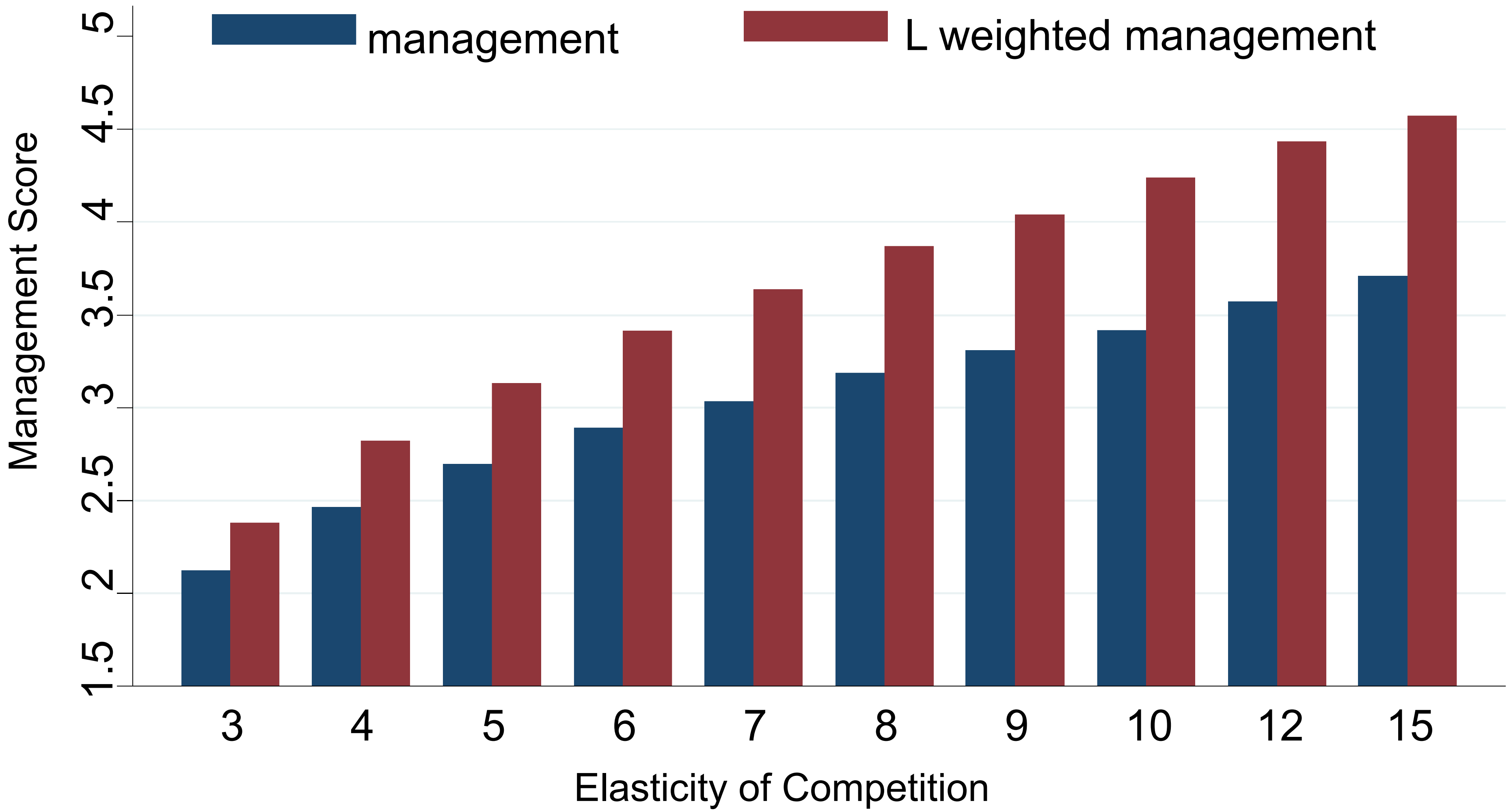
Note: Unweighted average management scores (raw data) with number of observations. All waves pooled (2004-2014)

Figure 2: Performance and management - Simulations



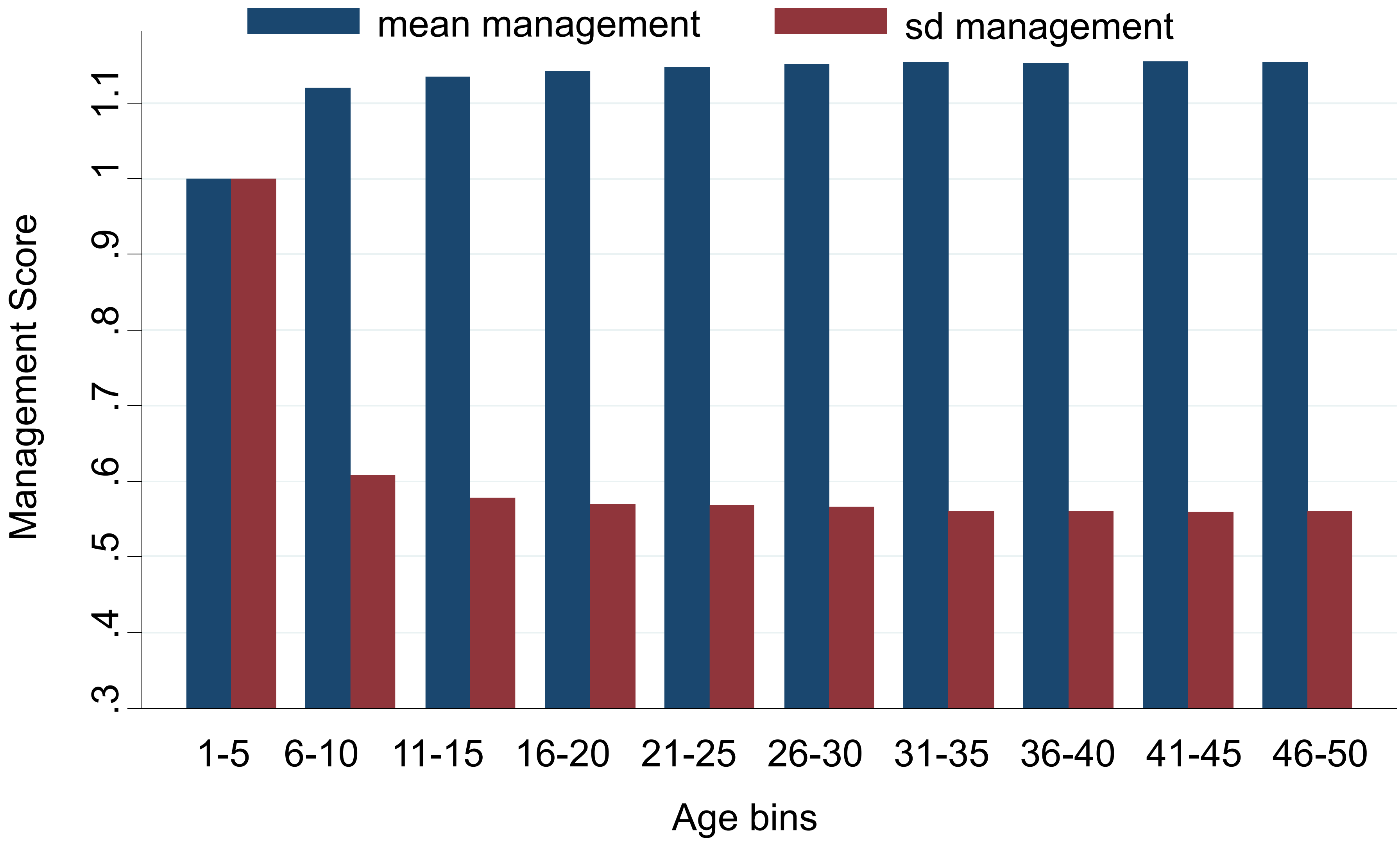
Notes: Results from using our estimated MAT model to simulate 5,000 firms per year in the steady state taking the last 10 years of data. Plots log(management) in the simulation data normalized onto a 1 to 5 scale, and log(sales). Lowess plots shown with Stata defaults (bandwidth of 0.8 and tricube weighting). See text for more details.

Figure 3: Management and competition - Simulations



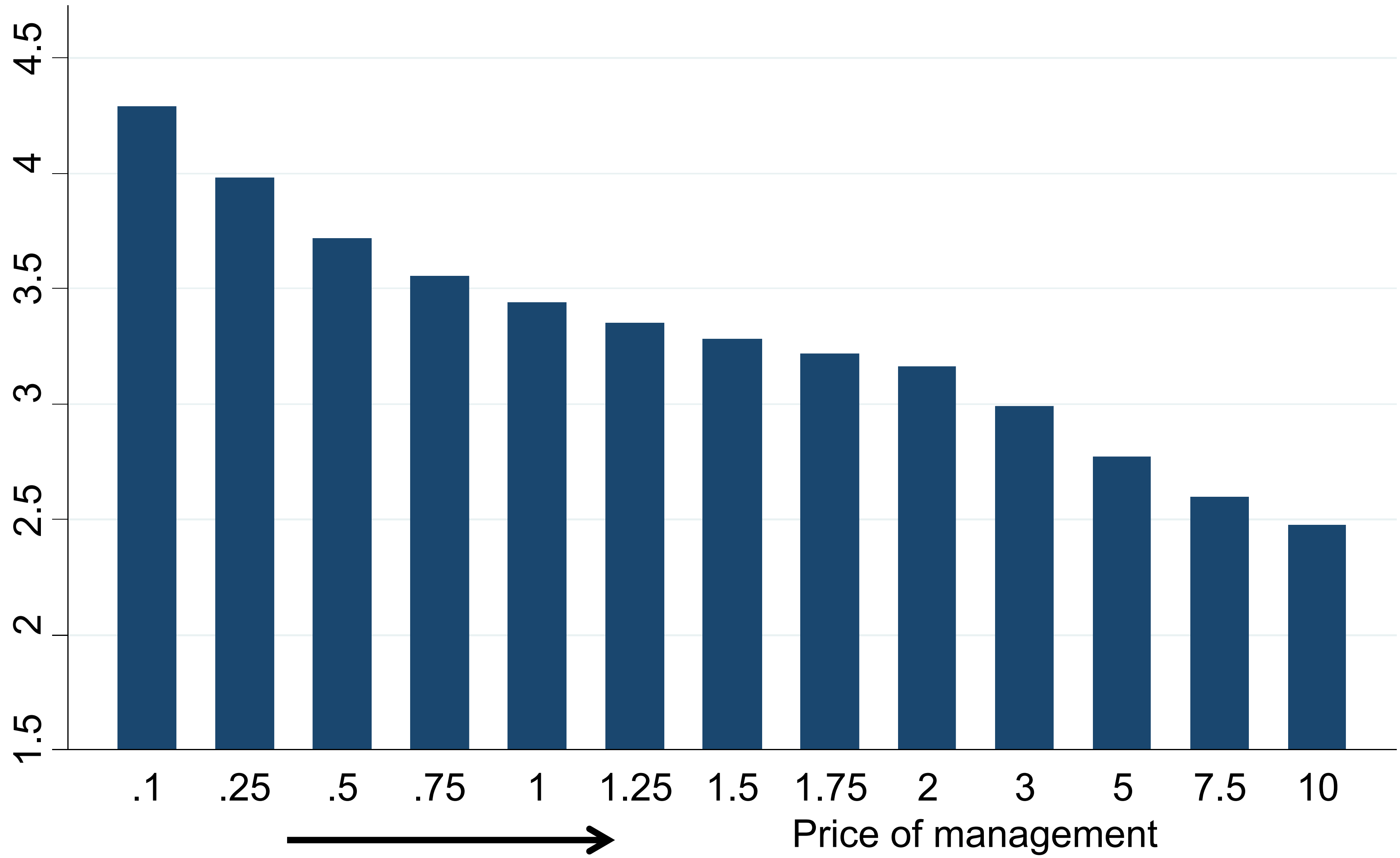
Notes: Results from using our estimated MAT model to simulate 5,000 firms per year in the steady state taking the last 10 years of data. Plots log(management) in the simulation data normalized onto a 1 to 5 scale, and log(sales). Lowess plots shown with Stata defaults (bandwidth of 0.8 and tricube weighting). See text for more details. Competition is index by demand elasticity (e=5) in baseline. Blue bar is unweighted mean across firms, red bar is weighted by firm size (employees).

Figure 4: Management and age - Simulations



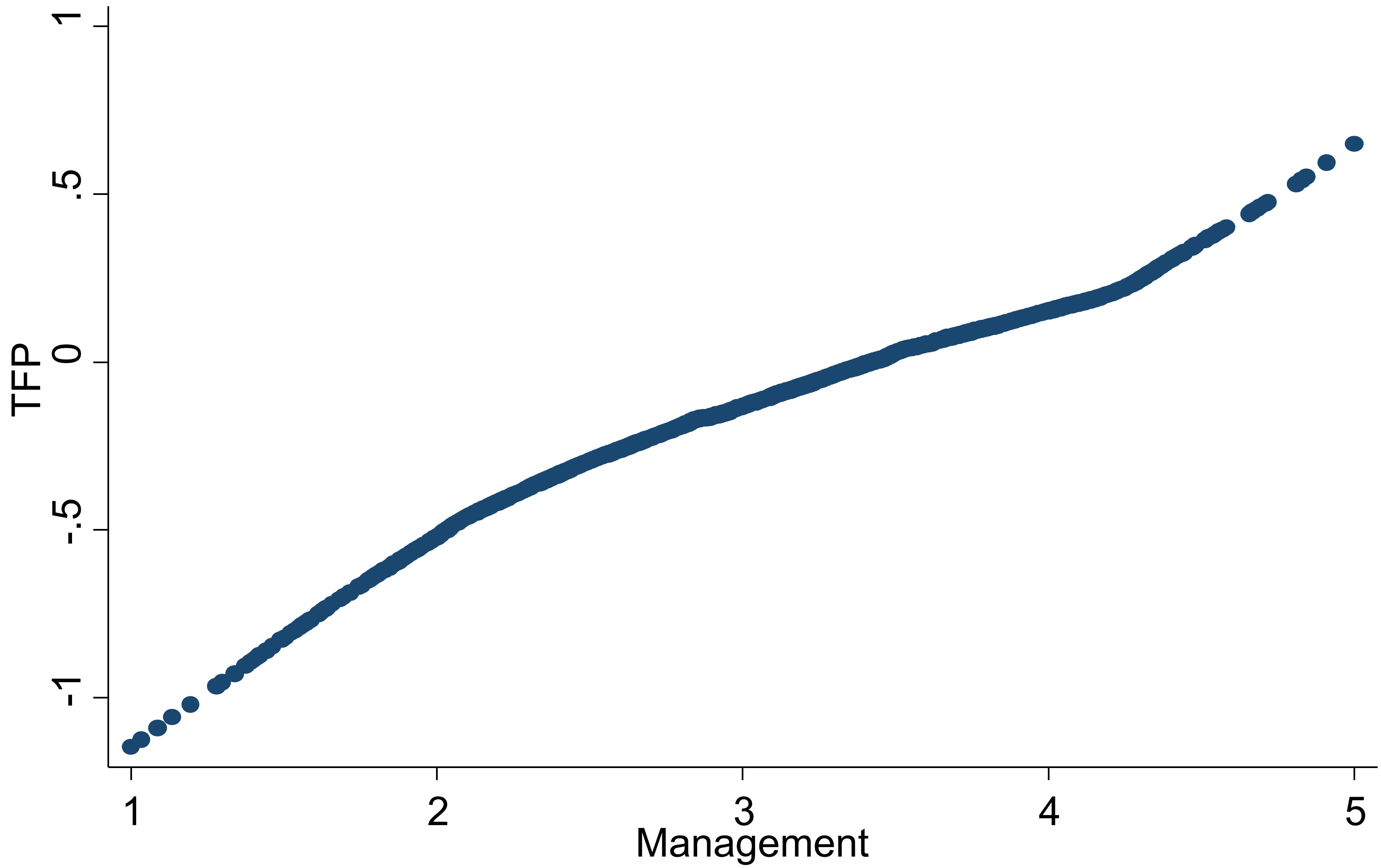
Notes: Plots ln(management) scores weighted by firm sales. Results from simulating 5,000 firms per year in the steady state taking the last 5 years of data for each level of (upper bound) of the distortion distribution (from 2% to 50%, baseline case is 10%). ln(management) in the simulation data is normalized onto a 1 to 5 scale.

Figure 5. Management and its own price - Simulations



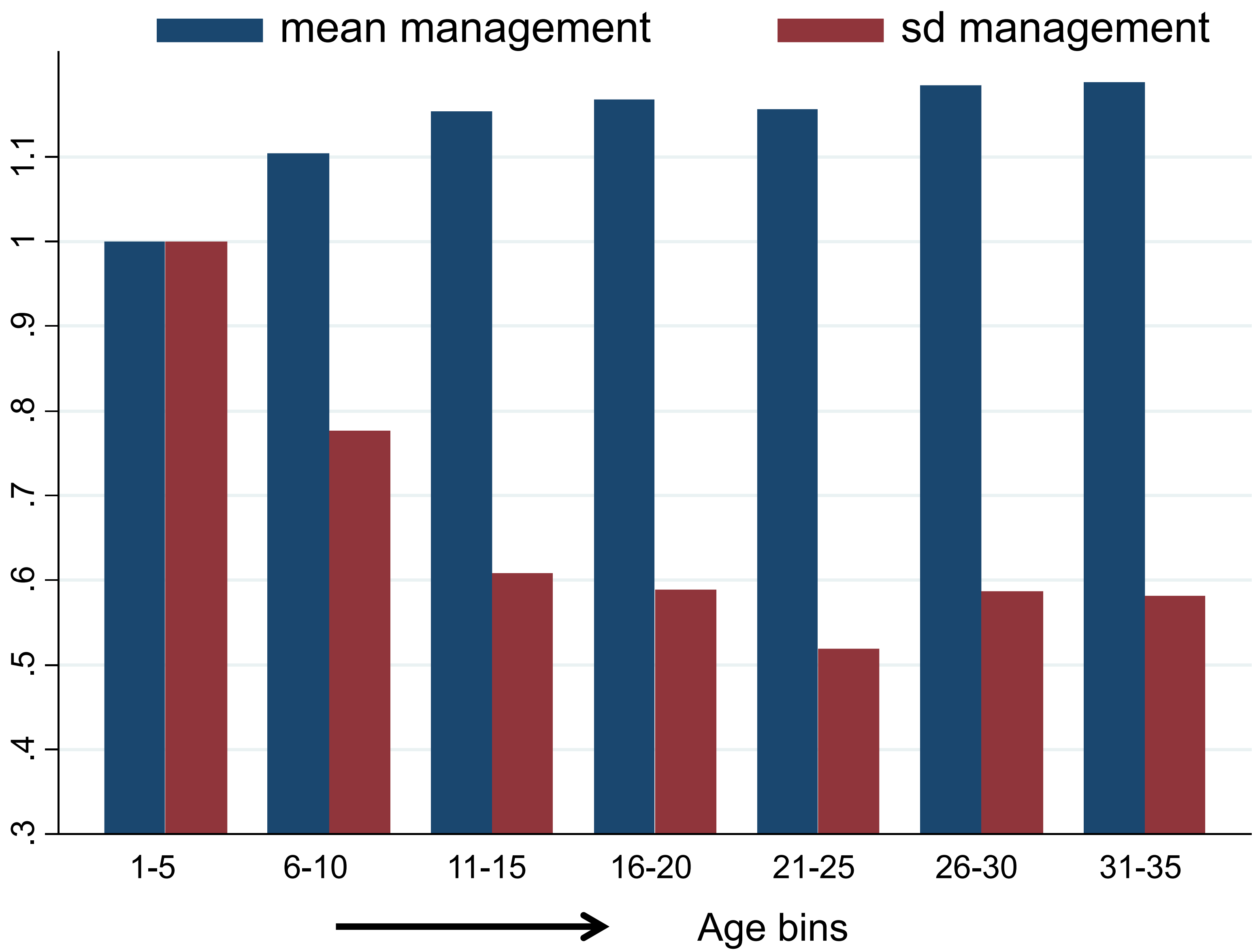
Notes: Results from using our estimated MAT model to simulate 5,000 firms per year in the steady state taking the last 10 years of data. Plots log(management) on y-axis in the simulation data normalized onto a 1 to 5 scale, and log(price) on the x-axis. normalized onto a 0.1 to 10 scale. See text for more details.

Figure 6. Management and TFP - Data



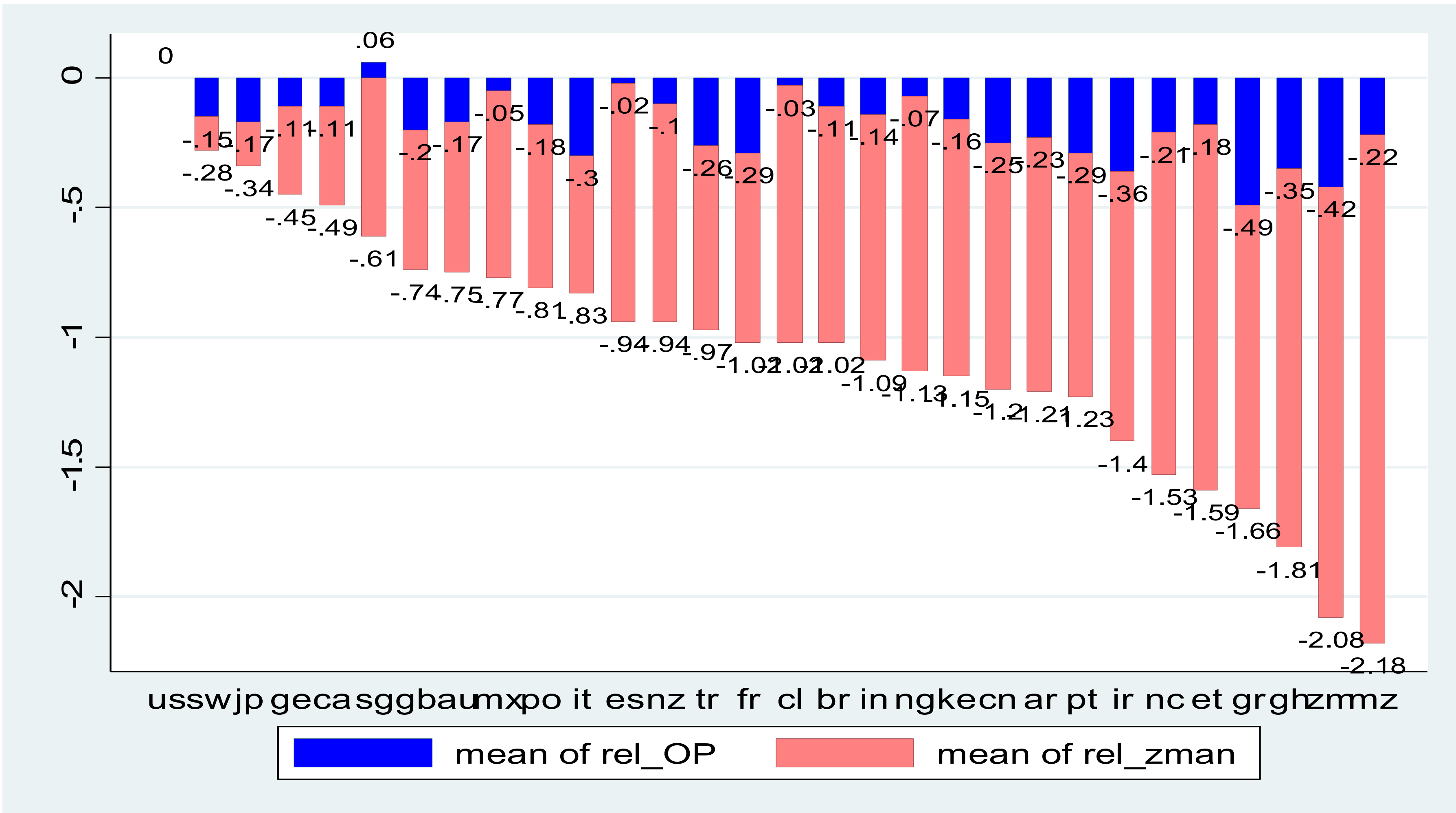
Notes: Management is an average of all 18 questions (set to sd=1). TFP residuals of sales on capital, labor, skills controls plus a full set of SIC-3 industry, country and year dummies controls. N=8314

Figure 7. Management and Age - Data



Notes: Data from 31,793 plants from the Management and Organizational Practices supplement to the 2010 Annual Survey of Manufacturing, run by the US Census.

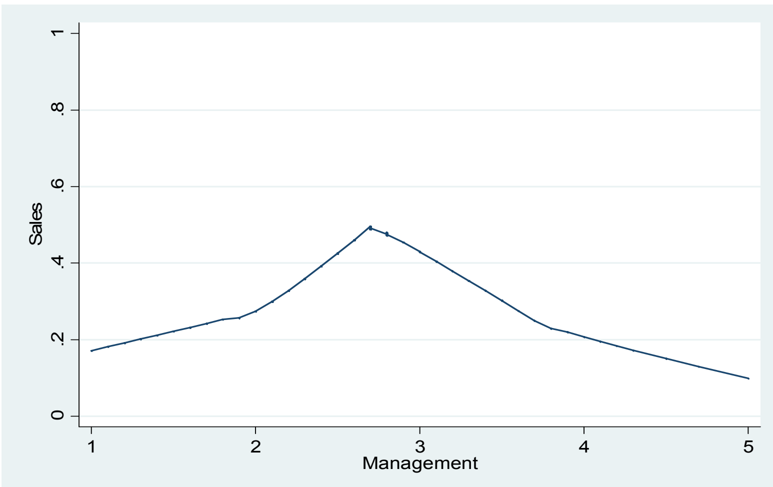
Figure 8: Management Scores and Reallocation across countries relative to the US level



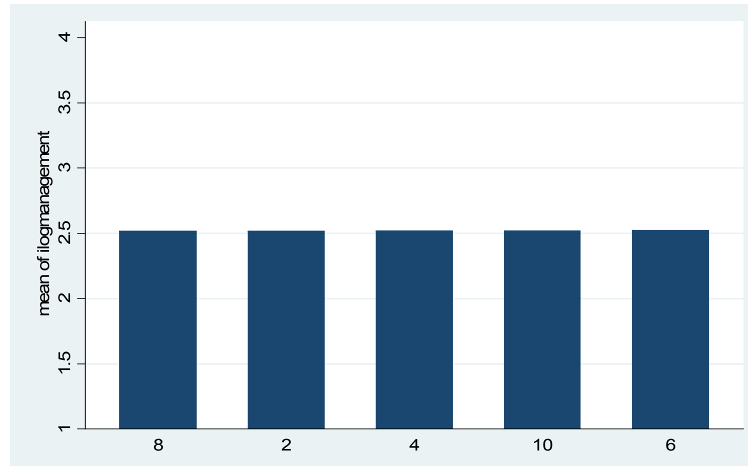
Notes: Share-weighted management score differences relative to the US (sd=1) . Length of bar shows total deficit, composed of (i) the unweighted average management scores ("rel_zman", light red bar) and reallocation effect ("rel_OP" blue bar) . Domestic firms only with management scores corrected for sampling selection bias

Figure A1: Management as Design

Panel A: Management & Performance



Panel B: Management & Competition



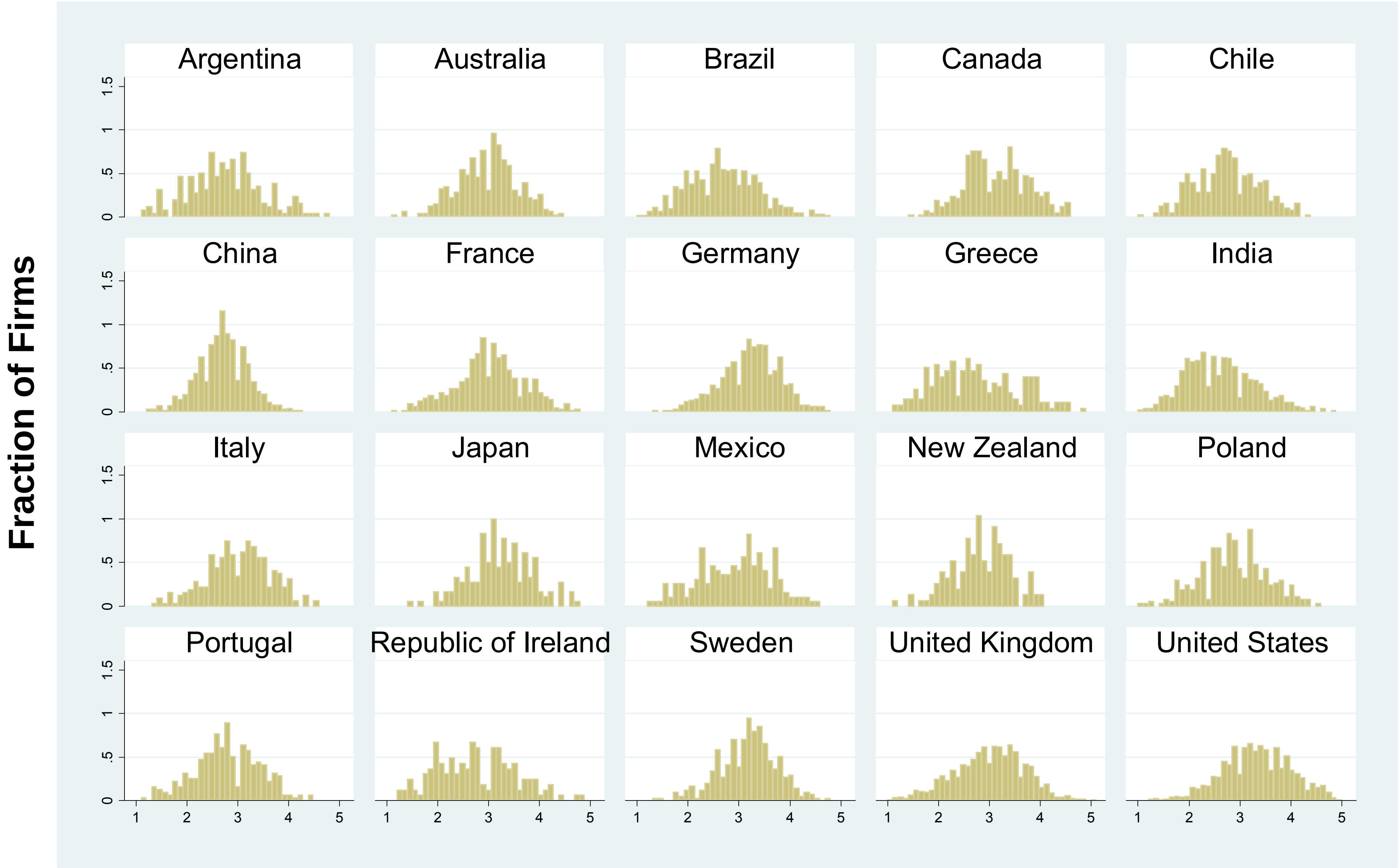
Comp increasing

Panel C: Management & Age

Panel D: Management & its own price

Notes: Results from using our estimated Design model to simulate 5,000 firms per year in the steady state taking the last 10 years of data. Plots log(management) in the simulation data normalized onto a 1 to 5 scale, and log(sales). Lowess plots shown with Stata defaults (bandwidth of 0.8 and tricube weighting). See text for more details. Production function is $Y=AK^{\alpha}L^{\beta}/(1+|M-M^*|)$

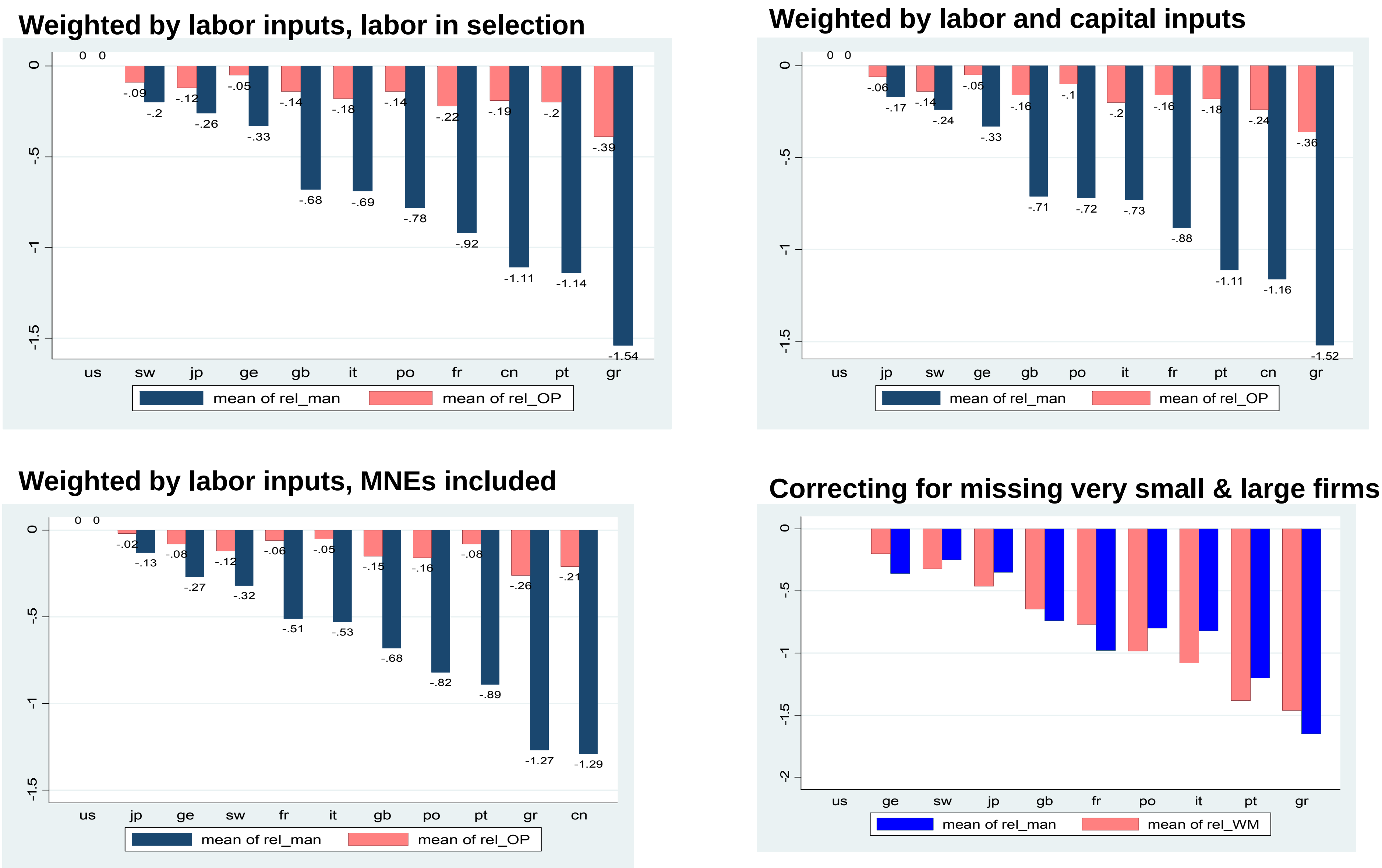
Figure A2: Management Practice Scores Across Firms



Firm level average management scores, 1 (worst practice) to 5 (best practice)

Note: Bars are the histogram of the actual density.

Figure B1: Robustness of weighted management results



Notes: Differences relative to the US of (i) the weighted average management scores (sd=1, blue bar) and (ii) reallocation effect (OP, light red bar). Domestic firms,.2006 wave. Response bias corrections use country-specific employment only