

MANAGEMENT AS A TECHNOLOGY?

Nicholas Bloom^a, Raffaella Sadun^b and John Van Reenen^c

December 1st 2013

Abstract

Are some management practices akin to a technology that can explain company and national productivity, or are they simply alternative styles? We collect cross sectional and panel data on core management practices across 8,000 firms in 20 countries in the Americas, Europe and Asia. We find the US has the highest size-weighted average management score and about a quarter of the cross-country “management gap” is due to stronger reallocation effects which rewards better managed firms with greater market share. We present a simple model of management as a technology that predicts: (i) a positive effect of management on firm performance; (ii) a positive effect of product market competition on average management quality; and (iii) that the covariance between management and firm size should be stronger when distortions (such as trade and labor market frictions) are weaker. We find empirical support for all of these predictions. Using this idea we find that the US lead in management can account for up to half of the TFP gap between the US and other nations. In addition to the selection and incentive effects of competition, poor governance, informational frictions and human capital appear to be important in explaining the variance of management practices across firms and countries.

JEL No. L2, M2, O32, O33.

Keywords: management practices, productivity, competition

Acknowledgements:

We would like to thank Marianne Bertrand, Robert Gibbons, John Haltiwanger, Rebecca Henderson and Bengt Holmström for helpful comments as well as participants in seminars at the AEA, Berkeley, Bocconi, Brussels, CEU, Chicago, Dublin, Harvard Labor, LBS, Leuven, LSE, Madrid, MIT ORG, Munich, NBER, the Peterson Institute, Stockholm Toronto and Zurich. The Economic and Social Research Council, the Kauffman Foundation and the Alfred Sloan Foundation have given financial support. We received no funding from the global management consultancy firm (McKinsey) we worked with in developing the survey tool. Our partnership with Pedro Castro, Stephen Dorgan and John Dowdy has been particularly important in the development of the project. We are grateful to Daniela Scur and Renata Lemos for excellent research assistance.

^a Stanford, Centre for Economic Performance and NBER

^b Harvard Business School, Centre for Economic Performance and NBER

^c London School of Economics, Centre for Economic Performance, NBER and CEPR

I. INTRODUCTION

Productivity differences between firms and between countries remain startling. For example, within the average four-digit US manufacturing industries, Syverson (2011) finds that labor productivity for plants at the 90th percentile was four times as high as plants at the 10th 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 they 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).

¹ See, 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 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 20 countries covering over 8,000 firms with up to three 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 US management score (like TFP) is higher than other countries. We find that on average a quarter of the cross-country TFP gap with the US can be accounted for by observed management differences, but this rises to half in some Southern European nations.

We then examine some empirical implications of the model of Management As a Technology (MAT) and find several pieces of supporting evidence. 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. Well managed firms also appear to cope better with rapid change – well managed firms outperformed especially well in industries most heavily hit by the 2008-2009 shock of the Great Recession, consistent with Caballero and Hammour’s (1994) “cleansing effect of recessions”. Second, average management quality is improved by stronger product market competition, both through the extensive margin (competition causes badly managed firms to exit) and the intensive margin (competition causes incumbent firms to improve their management). Third, there is reallocation of economic activity towards better managed firms (in terms of output and inputs like employment), and these reallocation forces are stronger in the US and more generally in countries and industries with lower trade barriers and more flexible labor regulations.

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”.

II. SOME ECONOMIC THEORIES OF MANAGEMENT

II.1 Conventional approaches to productivity heterogeneity

For econometricians, believing that management is a cause of productivity heterogeneity is natural. Since at least Mundlak (1961) the fixed effect in panel data estimates of production functions has been labelled “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 technology a large residual still remains. A response to this is that these differences still reflect some unmeasured 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 definition of technology to incorporate managerial aspects of the firm.⁴ A second problem is that many recent 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.⁵

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.

II.2 Management as Design and Management as Technology (MAT)

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).

⁴ In this sense, management can be seen as part of the firm’s intangible capital stock in Corrado and Hulten (2010).

⁵ In their case study of IT in retail banking, for example, Autor et al (2002) found that banks who failed to re-organise 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 decentralised organisations 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 tougher better “people management” practices (e.g. careful hiring, merit based pay and promotion and vigorously fixing/firing under-performers).

There are a large number of economic theories of management practice. It is useful to analytically distinguish between two broad approaches which we can embed in a simple production function framework where output, Q , is produced as follows:

$$Q = G(A, L, K, M) \quad (1)$$

where A is an efficiency term, labor is L , capital is K , and M is management quality.

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 increases in M . In some circumstances, higher levels of what we would regard 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). MAT would see output increasing in M (i.e. higher for performance based promotion), whereas the Design perspective would find that tenure-based promotion could lead to output falls in some or even all sectors. The latter could be the case if, for example, reports on employee effort/ability were subject to costly influence activities (Milgrom and Roberts, 1988).

Under the Design approach the production function can be written as equation (1), but for some firms and practices $G'(M) < 0$. Even if M is free and could be costlessly introduced, output would fall if an exogenous force increased it. The Design approach puts the reason for heterogeneity in the adoption of different practices as mainly due to the different environments firms face – say in the industry’s technology, rather than inefficiencies. This is in the same spirit as the “contingency” paradigm in management science (Woodward, 1958).

The large dispersion in firm productivity motivates an alternative perspective that some types of management (or bundles of management practices) are strictly 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 throughout time and space (e.g. not promoting incompetent employees to senior positions) or collecting some information before making decisions. Second, there may be genuine managerial innovations (Taylor’s Scientific Management; Lean Manufacturing; Demming’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, as the design perspective highlights. Incentive pay may be an example of this: the proportion of firms using piece rates declined from the late 19th Century, but today incentive pay appears to be making somewhat of a comeback.⁶

So we can think of MAT as either being a key factor shifting TFP (i.e. $A(M)$) or management as being another factor of production alongside X , a form of intangible capital that raises output (as in Corrado and Hulten, 2010), has a price and costs of adjustment. The next section formalizing these ideas.

II.3 A Formal Model of Management as a Technology (MAT)

In Appendix A we consider a version of MAT where following Melitz (2003) and Hopenhayn (1992) we assume firms do not know their management quality/productivity before they pay a sunk cost to enter an industry, but when they enter they receive a draw from a known distribution. We present a fairly general model in Appendix A1 that does not have closed form solutions so much be numerically simulated in order to consider comparative statics and dynamics. In Appendix A2 we consider a simplified version of the model (similar to Bartelsman, Haltiwanger and Scarpetta, 2013) where we can obtain closed form solutions for some of the predictions we shall test. The main difference between the two models is that we allow firms to endogenously change their level of managerial capital over time in the more general model, which requires solving the stochastic dynamic programming problem for the optimal path of investment in management (and of capital).

The set-up is as follows. Firms produce intermediate goods under conditions of monopolistic competition. Entrepreneurs decide whether to enter at stage zero on the basis of a sunk entry cost (κ) compared to the expected value of being in the economy. If they enter they draw a triple of management (M_i), TFP (A_i) and distortions, (τ_i). These distortions, τ_i which “tax” the firm (a share of revenue is lost) and could be due to corruption, arbitrary enforcement of taxes, size-contingent regulations, etc. This triple defines the initial conditions of the firm and then in every period a firm

⁶ Lemieux et al (2009) suggest that this may be due to advances in IT – companies like SAP make it much easier to measure output in a timely and robust fashion, making effective incentive pay schemes easier to design.

draws an i.i.d. shock, ε_{it} , to business conditions (a combination of TFP and demand) which is the fundamental external dynamic driving force of the economy. Firm i 's revenue is:

$$PY_i = A_i(1 - \tau_i)K_i^a L_i^b M_i^c$$

The firm has fixed costs F and there are quadratic adjustment costs for capital and management. Labor is assumed to be completely flexible.

Firms who draw a very low level of productivity will tend to exit immediately as there is some fixed cost of production they cannot profitably cover. Those who produce will have a mixture of productivity levels, however. Over time, the low productivity firms are selected out and the better ones survive and gain higher market shares.⁷ There is some stochastic element to this, however, so in the steady state there will always be some dispersion of productivity.

We simulate data under this model examine the long-run steady states of the key moments in the simulated data. The key predictions we look at are (proofs in Appendix A):

1. *Performance. Firm performance is increasing with management quality*

There is a positive correlation between management quality and firm size as measured by sales, employment or capital. More formally, define M_i as the management score for firm i , s_i as the firm's market share (e.g. firm sales/total sales or firm employment/total employment) relative to the economy and \bar{M} as the unweighted average management score across firms. The "Olley Pakes" covariance term, is $\sum_i [(M_i - \bar{M})(s_i - \bar{s})]$ and this will be positive. Further, there is a positive correlation between management quality and labor productivity, measured total factor productivity (TFPQ and TFPR), profitability, firm survival and growth.

We illustrate this with results from the numerical simulation in Figure 1. The simpler analytical model for MAT had three empirical implications that we can now examine in the richer numerical model. We look at the results for the MAT model (left hand side panel) and the MAD model (right hand side

⁷ There is an offsetting force. Managerial capital depreciates and TFP has an AR(1) component which means that over time older firms will tend to revert to the mean.

panel). Using the data from the last 5 years of the simulation we simply plot the local linear regression (Lowess) of firm $\ln(\text{sales}/\text{capital})$ against management. Figure 1 shows the first result, the correlation between performance and management. Although we used productivity as our performance measure, we obtained similar results using TFPQ, TFPR, sales, employment, exit rates and profits.

2. Competition. *There will be higher average management quality with higher competition*

We run all the simulations five times for increasingly high levels of the absolute price elasticity of demand between 2 and 10 (our baseline is elasticity = 6). Figure 2 shows that average management scores are higher when competition is higher. This is because with more price-sensitive consumers there will be lower price cost margins for any given number of firms. In order to make sufficient profits to cover the fixed costs and entry costs fewer firms will stay in the market. Equivalently the cut-off threshold for managerial quality (productivity) will rise, so that the lower number of incumbents will be, on average, of higher managerial quality.

3. Distortions. *The management and firm size covariance is stronger with less distortions*

Finally we examine the covariance between management and size as the variance of distortions increase. We implement this by increasing the upper support of the uniform distribution of distortions (note distortions are modeled as a tax on revenue) from 2% to 50% (recall that the baseline uses an upper support of 10% and lower support of 0). To do this we plot out the covariance between employment and management for different levels of distortions in Figure 3. The covariance between management and size declines as the spread of distortions increases. Highly distorted economies reward well managed firms with lower market shares than less distorted economies. In other words, the Olley-Pakes covariance term is higher when the variance of distortions is lower. This translates into a lower size-weighted management score in more distorted economies (e.g. US vs. India).

Results 1 (*performance*) and 2 (*competition*) can be proven analytically, whereas Result 3 has to be shown through numerically through the simulation. We will show that all three predictions receive strong support from the data.

III. DATA

III.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 developed by an international consulting firm, and scores these practices in three broad areas.⁸ 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*⁹: are companies promoting and rewarding employees based on performance, and systematically trying to hire and keep their best employees?

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”.

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 you 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 are in Appendix D.

⁸ Bertrand and Schoar (2003) focus on another important managerial angle - CEO and CFO management style - which will capture differences in management strategy (say over mergers and acquisitions) rather than practices *per se*.

⁹ These practices are similar to those emphasized in earlier work on management practices, by for example Ichinowski, Prennushi and Shaw (1997) and Black and Lynch (2001).

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 to 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. We did not focus on smaller firms where more formal management practices may not be necessary. 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 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. Most importantly 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.

III.2 Survey Waves

We have administered the survey in several waves since 2004. There were three large waves in 2004, 2006 and 2009, but we also collected some data for a smaller number of firms/countries in the years

in between. In summer 2004 wave we surveyed four countries (France, Germany, the UK and the US). In summer 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 winter 2009/10 we re-contacted all the firms surveyed in 2006, but did not do a refreshment sample (due to budgetary constraints). The final sample includes 20 countries and a short panel of up to three years for some firms. In the full dataset we have 8,117 firms and 10,161 interviews where we have usable management information. We have smaller samples depending on the type of analysis undertaken – many firms do not have accounting data for example as this depends on disclosure rules.

III.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.

III.4 Panel Data: Change in Management Practices over time

In the 2006 survey wave we followed up all of the firms surveyed in 2004 and in the 2009 survey wave we followed up all of the firms surveyed in 2006. Because we sampled a much wider number of countries in 2006 the 2006-2009 panel (1600 firms) is much larger than the 2004-2006 panel (396 firms). These are balanced panels, but are not random as better managed firms were significantly less likely to exit. We were concerned that response to the survey may not be random with respect to management. The fact that productivity and profitability were uncorrelated with response probability in the cross section was reassuring (see Appendix B) as was the fact that the 2009 response rate of survivors was uncorrelated with the 2006 management score.

Table C1 shows the transition matrices for management quality where we divide the firms into quintiles of the management scores. Panel A does this for the 2004-2006 sample where we only have four countries (France, Germany, the UK and the US). It is clear that there is persistence in management quality. 42% of the worst managed quintile of firms in 2004 was also in the same quintile in 2006. Similarly, 44% of firms who were in the top 20% of the management score in 2004 stayed in this top quintile in 2006. Panel B replicates this analysis for the same four countries over 2006-2009 and shows a very similar picture: 47% of the bottom quintile remained where they did in 2006 as did 43% of the top quintile. In the middle quintiles there was substantial churn in all years. Panel C replicates this analysis for all the countries we surveyed in 2006. The picture is very similar, although there is greater persistence in this larger sample – now 52% of the worst managed firms stay in the same quintile. This persistence is comparable with the persistence performance differentials when looking at TFP. For example, Panel D reproduces the Bailey et al (1992) analysis of TFP dynamics. Despite the different years, time frame and measure, the degree of persistence is strikingly similar.

Although there is some persistence, Table C1 also highlights that there is substantial movement over years even at extremes of the management distribution. For example, 54% of firms in the top quintile of management in 2006 fell out of this quintile after three years. Of course, there is likely to be a role for measurement error here, but when we look at the correlation of changes of management with changes in productivity, we continue to find a significant positive correlation, which suggests that there is some information in the change of the management scores. We exploit both cross section and panel in the empirical work below.

IV. MANAGEMENT PRACTICES OVER FIRMS AND COUNTRIES: SOME STYLIZED FACTS

In this section we describe some of the stylized facts in the management data both across firms and across countries.

IV.1 Cross Country patterns

The bar chart in Figure 4 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 (Portugal and Greece) and developing countries (Brazil, China and India) 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 5 plots the firm-level histogram of management practices (solid bars) by country, and shows that management practices display tremendous within country variation. Of the total firm-level variation in management only 11.7% is explained by country of location, with the remaining 88.3% within country heterogeneity. 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 reallocation forces below.

IV.2 Accounting for Differences in aggregate management scores across countries

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

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

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), \bar{M} is the unweighted average management score across firms and OP indicates the “Olley Pakes” covariance term, $\sum_i [(M_i - \bar{M}_i)(s_i - \bar{s}_i)]$. The OP term simply divides management into a within and 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:

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

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 ($OP^k - OP^{k'}$) 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 1 and Figures 6 and 7 contain the results of this analysis with more details are in Appendix C. In column (1) of Table 1 we present the employment share-weighted management scores (M) in z-scores, so all differences can be read in standard deviations. This is illustrated in Figure 6 which has a broadly similar ranking to Figure 4 even though the methodology is different in several respects.¹⁰ In column (2) we show the Olley Pakes reallocation term (OP) and in column (3) the unweighted management score (\bar{M}_i). From this we can see that, for example, the leading country of the US has a score of 0.67 which is split almost half and half between a reallocation effect (0.36) and a within firm effect (0.31). The US not only has the highest unweighted management score but it also has the highest degree of reallocation. Germany and Canada also have a high degree of reallocation (0.26). By contrast, Southern European countries have little reallocation and Greece stands out uniquely as having no positive reallocation at all. Interestingly, these results are 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. This is identical to our ranking.¹¹

Perhaps a more revealing way to illustrate these results is to calculate each country's management gap with the US. Column (4) of Table 1 does this for the overall gap and column (5) for the reallocation component and this is illustrated in Figure 7. Reallocation accounts for between 12% and

¹⁰ Apart from Figure 1 being unweighted and Figure 6 weighted, we use data from only the 2006 wave and include only domestic firms. The results are robust to including multinationals (see below) but we were concerned that management would be more influenced by overseas headquarters and measurement error in employment measure. Another difference is that we correct for non-random sampling responses rates through a propensity score method to re-weight the data. We run a country specific response rate regression on the sampling frame where the controls are firm employment, listing status, age and industry dummies. We then construct weights based on the inverse sampling probability (see Appendix C).

¹¹ 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).

56% of the management gap with the US, with an average of 23%. To put it another way, the weighted average difference between the US and Greece's management is 1.65 (= 0.67 + 0.98) standard deviations and 30% or 0.49 of a standard deviation (= 0.13 + 0.36) of this difference is due to worse relocation in Greece than the US.

We can push this analysis further by examining how much management could explain cross country differences in TFP. Column (7) of Table 3 contains the country's TFP gap with the US from Jones and Romer (2010, Table 5, <http://www.stanford.edu/~chadj/tfpdata2000.txt>) available for a sub-set of our countries. Following the randomized control trial and non-experimental evidence presented in section V below 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 (8) contains similar calculations for 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 25% 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.

V. IMPLICATIONS OF MANAGEMENT AS A TECHNOLOGY

V.1 Management and Firm Performance

Basic Results

The most obvious implication of seeing management as a technology is that it should raise firm performance. So we can compare the association of management with outcomes easily 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 2 examines the correlation between different measures of firm performance and management (M). To measure firm performance we used company accounts data and found higher management scores are robustly associated with better performance.¹² For example, we estimated production functions where Q_{it} is proxied by the real sales of firm i at time t :

$$\ln Q_{it} = \alpha_M M_{it} + \alpha_L \ln L_{it} + \alpha_K \ln K_{it} + \alpha_X x_{it} + u_{it} \quad (2)$$

Where 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), u is an error term In column (1) we regress $\ln(\text{sales})$ against $\ln(\text{employment})$ and the management score finding a highly significant coefficient of 0.355. This suggests that firms with one standard deviation of the management score are associated with 35.5 log points higher labor productivity (i.e. about 43%). In column (2) we add the capital stock and other controls which cause the coefficient on management to drop to 0.158 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. Column (4) 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 substantially, but remains positive and significant at conventional levels.¹³

As discussed in Section II one of the most basic predictions is that better managed firms should be larger than poorly managed firms. Column (5) shows that better managed firms are significantly larger than poorly managed firms with a one standard deviation of management associated with 28.7 log point increase in size.¹⁴ In column (6) 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, columns (7) uses sales growth as a dependent variable, revealing that better managed firms are significantly more likely to grow. Column (8) estimates a

¹² 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.

¹³ 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).

¹⁴ If we used the manager’s declared firm employment the coefficient is almost identical: 0.284 with a standard error of 0.023.

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 of firm performance and management.¹⁵

Finally, columns (9) to (11) examine bankruptcy, finding three results. First, better managed firms are significantly less likely to die, and since the mean of exit to bankruptcy is only 2.2%, the point estimate suggests a substantial 20% reduction in the probability of exit from a one-standard deviation increase in the management score. Second, in column (10) we also include competition – as proxied by the number of competitors the firms reported facing – and find unsurprisingly a significant positive effect. More revealingly in column (11) we include the interaction of management and competition and find that management practices are particularly important in more competitive markets, exactly as predicted by our management as a technology model (see Figure 2). This suggests one way competition improves management practices (which we examine further in the next section) is through the extensive margin, by increasing the exit of badly managed firms.

The Great Recession and Field Experiments on Management

The performance evidence from Table 2 reported management-performance associations with extensive controls, but no clear evidence on causality. One piece of more causal evidence we have is exploiting the natural experiment of the 2008-2009 Great Recession. Over this period many firms faced a large unexpected and exogenous negative shock after the credit crunch and collapse of Lehman's in 2008. This enables us to investigate if well managed firms are more resilient to major shocks, a dynamic version of the Management as a Technology theory.

To examine this idea we run regressions of the form:

¹⁵ The association of management practices with performance is also clear in other sectors outside manufacturing. In Bloom, Propper, Seiler and Van Reenen (2010) 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.

$$\Delta \ln Q_{ijkt} = \beta_1 (SHOCK_{jkt} * M_{ijkt-1}) + \beta_2 (SHOCK_{jkt}) + \beta_3 M_{ijkt-1} + \beta_4 x_{ijkt} + \varepsilon_{ijkt}$$

where *SHOCK* is an indicator of the negative shock which we define in an industry-country (*jk*) cell: we would expect to be associated with a fall in firm sales all else equal. Our key hypothesis is that $\beta_1 > 0$, i.e. firms with better management (in the pre-crisis period) will not perform better than poorly managed firms. The control variables, *x*, include industry dummies and country dummies.

We build several measures of the *SHOCK*. First, we aggregate all information on exports in the UN COMTRADE database in the three digit industry by country cell. Trade fell more than GDP during the crisis and is more likely to be determined by factors exogenous to the firm's behavior. We then calculate the change in (real) exports between the average of 2006 and 2007 ("pre crisis") to the average of 2008 and 2009 ("crisis"). *SHOCK* is defined as all cells which had a negative fall in this industry trade measure. Second, we calculated aggregate sales at the same country by three digit industry level (from ORBIS) and deducted the firm's own sale to avoid the most obvious form of feedback. *SHOCK (ORBIS)* is defined as all cells which had a negative fall in this industry sales measure. Our third measure uses the NBER value added data defined solely from the US.

Table 3 presents the results, with the findings consistent with better managed firms faring better in response to the shock. Column (1) confirms, unsurprisingly those firms in industry by country pairs that experienced a greater negative export shock were more likely to shrink. Column (2) is of more interest as it shows that firms who were better managed in the pre-shock period (2006) were significantly less likely to shrink in the face of a negative export demand shock than those who were poorly managed. A one standard deviation increase in the management score implies a 1.8 percentage point slower loss of sales in response to a negative shock (i.e. a 3.4% loss of sales rather than 5.2%). This result is robust whether we define the shock in terms of sales (rather than exports) in the industry by country pair in columns (4) and (5) or by US value added in columns (5) and (6). Note that these results are all conditional on survival, but if we repeat this specification but use survival as the dependent variable the interaction with the industry shock is also positive and weakly significant.¹⁶

¹⁶ In a specification analogous to column (2) the marginal effect of the interaction in a probit is -0.234 with a standard error of 0.138.

Overall then, the experience of the Great Recession confirms the notion that management is particularly important in sectors which experienced a large and arguably more exogenous demand shock, echoing the “cleansing effect of recessions” (Caballero and Hammour, 1994).

The most causal results on management and performance are the randomized control trials in Indian textile firms carried out by Bloom, Eifert, Mahajan, McKenzie and Roberts (2013). They introduced intensive management consultancy to treatment plants and compared these to control plants who receive a light consultancy treatment (just sufficient to obtain data). The management consultancy implemented the type of practices surveyed here, especially the monitoring and targets questions. They find significant increases in productivity as a result of these interventions. The intervention raised TFP by 10% for a one standard deviation increase in the management score, somewhere between columns (2) and (3). Even more pertinently to the management as a technology model, they find significant effects on profitability as the interventions would have repaid themselves (at full market rates) in less than a year. This is not consistent with the perspective of management as design as forcing firms to use different practices should have lowered performance.

Symmetry of the effects of management on performance

Under the Design perspective, we would expect worse performance from firms who are either a lot below or a lot above the average practice mix in their country by industry cell, assuming that the average firm gets this mix approximately right. That is, if we consider that the mean management score within a three digit by country cell as an estimate of the optimal management style, then this idea can be tested by allowing the coefficient on management to be different above or below this cell average.

As shown in Table 4 in fact we cannot reject that the coefficients are equal and opposite from being above and below the cell average as would be predicted by the MAT model, but not by the management as design approach. As shown in Table 4 this is true whether we define optimal management as the cell mean at the country-industry level (column (1)), country level (column (2)) or industry level (column (3)). Furthermore it is true not only for TFP but also for profitability (column (4)), sales growth (column (5)) and Tobin’s Q (column (7)). This result also holds if we repeat the specifications but use each of the 18 questions separately. In fact the only evidence we find

for any difference above vs below the industry by country mean is for exit (column (6)), and this is not robust to defining the cell as the country or industry (rather than country-by-industry).¹⁷

Thus, in summary we find no robust evidence for a significantly different association of management practices with performance above vs below the average score for the industry and/or country mean. This suggests that differences in the optimal management practices across country and/or industry groupings are unlikely to be large – best practices for our list of basic management practices does not appear to be contingent by industry and/or country.

Summary on management and performance

Taking the non-experimental evidence from Tables 2, 3 and 4, together with the field experiment evidence, leads us to conclude that the performance-management relationship offers some support for the management as a technology model.

V.2 Competition

A second implication of the management technology model is that tougher competition is likely to improve average management scores. One route is the extensive margin - badly run firms exit more speedily, particularly in competitive markets, which we saw in columns (9) to (11) of Table 2. Another route may be through the intensive margin – improvements in management practices within existing firms - if competition increases the incentives for good management by “raising the stakes”. In the Management as a Technology model this naturally arises because efficiency improvements have a larger impact on shifting market share in more competitive market, so the returns to good management increase as shown in Figure 2.¹⁸

Table 5 presents the management practice score regressed on three competition measures. We use the four countries that we have the most extensive panel data (France, Germany, the UK and the US). Since we do not yet have full industry data for 2009/10 we pool data from the 2006 and 2004 waves

¹⁷ If we re-estimate all the specifications from columns (4) to (7) using deviations from the country or industry average (rather than deviations from the country-by-industry average) none of the differences between the management coefficients below vs above the cell mean are significant.

¹⁸ Another mechanism outside of the model is that managers are more fearful of losing their jobs in more competitive markets to try harder. Theoretically competition has ambiguous effects on incentives of course. Tougher competition means lower profit margins and therefore less of an upside for improving efficiency as Schumpeter emphasised.

in order to look at changes over time. The first four columns use the inverse industry Lerner index as a measure of competition (as in Aghion, Bloom, Blundell, Griffith and Howitt, 2005). This is calculated as the median price cost margin using all firms in the accounting population database (except the firm itself). We lag this variable by two years to reduce feedback effects. 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 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. Column (4) estimates the regression in differences for this subsample and produces a similar coefficient to column (2).

The next four columns of Table 5 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)) or firm effects (column (9)) having the larger coefficients. The final four columns use the survey measure from Table 2, 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. All of these results are of course consistent with the Management as a Technology theory but not the basic version of Management as Design outlined in Section III and in Figure 2.

V.3 Reallocation effects

If management is a technology, then better managed firms should 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:

$$Y_{it} = \gamma(M_{it} * RL)_{it} + \delta_1 M_{it} + \delta_2 RL_{it} + \delta_3 x_{ijt} + v_{ijt} \quad (3)$$

Where Y is firm size and RL is a measure of the degree of “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 6 reports the results of a regression of firm employment on the average management score and a set of industry, year and country dummies.¹⁹ 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)²⁰, 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

¹⁹ 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.

²⁰ 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.

significant interactions are negative, indicating that the relationship between management and reallocation is stronger for the US than for any other country.²¹

The results in Tables 6 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 (2013) and Hsieh and Klenow (2009). This could explain why there is such a thin tail of very badly managed firms in the US (recall Figure 2). It is also consistent with the model of management as a technology.

Policy variables explaining reallocation

There are a large number of possible policy-relevant variables that could account for the greater degree of reallocation in the US than in other nations. We investigated some of the country-level policy variables that have been developed by the World Bank. Two groups of variables consistently stood out as being important in accounting for reallocation: labor and trade-related product market regulations. We illustrate these in Table 7. We again use employment as the dependent variable as in Table 6. However, instead of country dummies to indicate the pressure for reallocation (*RL*) we include explicit policy indicators. In column (1) we use the World Bank's latest Employment Protection Law ("EPL") index for 2008. The interaction between EPL and management is significantly negative, indicating that a country with higher EPL has significantly less reallocation towards better managed firms. Column (2) uses a World Bank trade-cost measure (the costs to export in a country) again finding a negative significant interaction suggesting higher trade costs impeded reallocation. In column (3) 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 (4) and (5) we use a measure of tariffs – a trade measure that varies at the industry by country level

²¹ 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.

(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 (4) 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 (5) 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 (5) of Table 7 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 ($= (8.25*4)/110$).

Summary

As Figure 3 shows the Management as a Technology model implies that better managed firm should enjoy higher market shares and this should be stronger in environments where selection/reallocation is expected to be stronger. We find evidence to support this proposition in Tables 6 and 7. First, better managed firms are larger (and grow more swiftly) and this effect is stronger in the US than in other countries. The greater reallocation in the US accounts for on average about 30% of the overall higher US management advantage over other nations. Second, this appears to be related to more competitive labor and product markets.

V.4 Contingency and Management As Design

Contingency: Management As Design

The predictions of the formal model of MAT are quite intuitive. It is unclear why for example, if all practices were contingent, exogenously increasing M in an experiment (as in Bloom et al, 2013) should lead to higher productivity and profits. Nevertheless, to test or intuition also formalized a Management as Design model using the same set-up as MAT (see Appendix A1). The only change

we make is to adopt a functional form $G(M_i) = [1 + |M - \bar{M}|]^{-1}$ in the production function so that firm output is maximized when $M = \bar{M}$. We assume that \bar{M} is the same for all firms in an industry. Unsurprisingly (see Figure A1), in such a model there is no relationship between management and the level of competition and distortions. There is an inverse U shaped relationship between performance and management, with the peak at the industry average. This is again as 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 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).

Although more sophisticated versions of MAD may be able to rationalize the relationships we observe in the data, it is not clear how they would drop cleanly out of a simple model such as MAT.

Contingency in sub-components of the management score

While the evidence so far on performance, competition and reallocation all appear to support the Management as Technology model there is some evidence in the data for contingent management practices. Intuitively, 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 8. 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. Column (9), for example, shows that relative people management is significantly higher when industry-country cells are more R&D or skills intensive, but lower when the environment is more capital intensive.

So although MAT does a reasonable job at accounting for the variation in overall management, there does appear to be evidence in favor of firms choosing management styles that fit their environment as in the Design perspective.

V.5 Information

Having some market imperfection is a necessary condition for persistent performance differences. But what could account for heterogeneity in management? These do not seem to be purely permanent differences as firms change their management practices over time: this was clear from Table 2 and the evidence from experimental interventions.

Poor incentives arising from lack of competition or non-value maximizing owners (e.g. family or governments) could be reasons for the failure of firms to adopt best practice. But aside from incentives, information could be another reason for the heterogeneity. Part of the problem may simply be that managers do not realize how bad they actually are (or they may know this, but not know what to do about it). Some indication on this is available from our survey since at the end of our survey we asked “*Excluding yourself, how well managed would you say your firm is on a scale of 1 to 10, where 1 is worst practice, 5 is average and 10 is best practice*”. The distribution of answers to this question is in Figure 9. Unsurprisingly the vast majority of managers believe their firms to be better managed than average (this managerial overconfidence is shared in many areas such as driving ability). There is no significant correlation of perceptions with performance, though.

Table 9 examines whether competition influences managerial self-perception. We begin by repeating the analysis of Table 5 regressing our measures of management on competition. Because this is available from the survey we have it for all years and can use the full sample of data. Column (1) includes all observations, column (2) conditions on those firms where we have at least two time series observations (in order to be comparable with the later specifications that include fixed effects). Column (3) includes fixed effects and the full set of controls from columns (1) and (2). Throughout

all the specifications there is a strong and significant association between better management and tougher competition. This is all consistent with the previous Table using a larger sample. The last three columns repeat the same specifications but the dependent variable is now the perceptions of managerial quality. The coefficients are the opposite sign, although the standard errors are also larger. Tougher competition appears to make managers judge themselves more harshly and this could be a reason why it invigorates firms to work harder to improve their practices. It may also help to overcome some of the organizational resistance to changing management practices highlighted in Gibbons and Henderson (2012).

VI. CONCLUSIONS

Economists and the public have long believed that management practices are an important element in productivity. We collect original panel data on over 10,000 interviews on over 8,000 firms across 20 countries to provide robust firm-level measures of management in an internationally comparable way. We estimated that across countries that management accounts for on average 25% of a country's TFP deficit with the US ranging from 8% in Sweden to 48% in Portugal.

We contrast different economic theories of management and argued for a “management as technology” (MAT) model. This has at least three empirical implications: (i) management should improve firm performance; (ii) competition should improve average management quality; and (iii) better managed firms should have higher market shares (reallocation), and this covariance should be systematically greater in countries like the US where barriers to reallocation are likely to be weaker.

The data appears to support these three broad predictions. 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. Third, reallocation effects are present and stronger in the US than other countries - better managed firms are able to attain greater scale than other countries. This is related to policies over labor regulation and trade barriers.

In future work we are planning to examine many other factors that influence management such as the supply the skills (e.g. through universities and business schools), information and co-ordination.

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.

One other important difference is that under the transferable version of MAT, management 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.

Despite these caveats, 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 aggregate productivity.

Bibliography

- Aghion, Philippe, Bloom, Nick, Blundell, Richard, Griffith, Rachel, and Howitt, Peter, (2005) “Competition and Innovation: An inverted U relationship”, *Quarterly Journal of Economics*, 120(2) 701-728
- Autor, David, Frank Levy and Richard Murnane (2002) “Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank” *Industrial and Labor Relations Review*, 55 (3)
- Axtell, Robert (2001) “Zipf Distribution of US firm sizes”, *Science*, 293 (5536), 1818-20.
- Baily, Martin, Charles Hulten and David Campbell “Productivity Dynamics in Manufacturing Plants” (1992), *Brookings Papers on Economic Activity: Microeconomics*, 187-267
- Bartelsman, Erik, Haltiwanger, John and Scarpetta, Stefano (2013) “Cross Country Differences in Productivity: The Role of Allocation and Selection” *American Economic Review*, 103(1) 305-334
- Bertrand, Marianne and Antoinette Schoar (2003), “Managing with Style: The Effect of Managers on Firm Policies”, *Quarterly Journal of Economics*, CXVIII (4), 1169-1208.
- Black, Sandra and Lisa Lynch (2001) ‘How to Compete: The Impact of Workplace Practices and Information Technology on Productivity’, *Review of Economics and Statistics*, 83(3), 434–445.
- Bloom, Nicholas, and John Van Reenen (2007) “Measuring and Explaining Management Practices across Firms and Countries”, *Quarterly Journal of Economics*, 122(4), 1341-1408.
- Bloom, Nicholas, Eifert, Ben, Mahajan, Abarjit, McKenzie, David and John Roberts (2013) “Does management matter? Evidence from India” *Quarterly Journal of Economics* 128 (1) 1-51
- Bloom, Nicholas, Raffaella Sadun, and John Van Reenen (2012a) “Americans do IT Better: American Multinationals and the Productivity Miracle”, *American Economic Review* 102 (1), 167-201
- Bloom, Nicholas, Raffaella Sadun, and John Van Reenen (2012b) “The Organization of firms across countries” *Quarterly Journal of Economics* 127(4): 1663-1705
- Bloom, Nicholas, Mark Schankerman and John Van Reenen (2013) “Technology Spillovers and Product Market rivalry”, *Econometrica* 81 (4) 1347–1393
- Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Itay Saporta-Eksten and John Van Reenen (2013) “Management in America” Census Bureau Working Paper 13-1
- Bresnahan, Timothy, Erik Brynjolfsson, and Lorin Hitt (2002) “Information Technology, Workplace Organization and the Demand for Skilled Labor: Firm-level Evidence”, *Quarterly Journal of Economics*, 117(1), 339-376.

- Caballero, Ricardo and Mohamad Hammour (1994) "The Cleansing Effect of Recessions," *American Economic Review* 84, 1350-1368.
- Card, David, Jörg Heining and Patrick Kline (2012) "Workplace Heterogeneity and the Rise of. West German Wage Inequality" *Quarterly Journal of Economics*
- Corrado, Carol and Hulten, Charles (2010) "How do you measure a technological revolution?" *American Economic Review* 100, 99-104
- Feenstra, Robert and John Romalis (2012). "International Prices and Endogenous Quality" NBER Working Papers 18314
- Foster, Lucia, John Haltiwanger and Chad Syverson (2008) "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98(1): 394-425
- Garicano, Luis, Claire Lelarge and John Van Reenen (2013) "Firm Size Distortions and the Productivity Distribution: Evidence from France" NBER Working Paper No. 18841
- Gibbons, Robert and John Roberts (2013) *The Handbook of Organizational Economics*, Princeton: Princeton University Press
- Gibbons, Robert and Rebecca Henderson (2012) "Relational Contracts and Organizational Capabilities" *Organizational Science*, 23 (5), 1350-1364
- Griliches, Zvi (1998) *R&D and Productivity: The Econometric Evidence* Chicago: Chicago University Press
- Hall, Bronwyn (2006) "Innovation and Diffusion" in Jan Fagerberg, David Mowery and Richard Nelson (eds), *Oxford Handbook of Innovation*, Oxford: Oxford University Press:
- Hall, Robert and Jones, Charles (1999) "Why do some countries produce so much more output per worker than others?" *Quarterly Journal of Economics*, 114, 83-116
- Helpman, Elhanan, Marc Melitz, and Stephen Yeaple (2004) "Export versus FDI with Heterogeneous Firms", *American Economic Review*, 94(1), 300-316.
- Hopenhayn, Hugo (1992) "Entry, Exit and Firm Dynamics in Long-Run Equilibrium" *Econometrica*, 60(5), 1127-50
- Hsieh, Chiang-Tai and Pete Klenow (2009), "Misallocation and Manufacturing TFP in China and India", *Quarterly Journal of Economics*, 124(4), 1403-1448
- Ichniowski, Casey, Kathryn Shaw, and Giovanna Prennushi (1997) "The Effects of Human Resource Management Practices on Productivity: A Study of Steel Finishing Lines", *American Economic Review*, 87(3), 291-313.

Johnson, Norman, Adrienne Kemp and Samuel Kotz (1993) *Continuous Univariate Distributions* New York, N.Y., John Wiley & Sons.

Jones, Chad and Romer, Paul (2010) “The New Kaldor Facts: Ideas, Institutions, Population, and Human Capital”, *American Economic Journal: Macroeconomics*, 2 (1), 224-245.

Keane, Michael and Susan Feinberg (2007) “Advances in logistics and the growth of intra-firm trade” *Journal of Industrial Economics*, 55(4), 571-632

Lucas, Robert. (1978) “On the Size Distribution of Business Firms”, *Bell Journal of Economics*, 9: 508-523.

Melitz, Marc (2003) “The impact of trade on intra-industry reallocations and aggregate productivity growth” *Econometrica*, 71, 1695-1725

Milgrom, Paul (1988) “Employment Contracts, Influence Activities, and Efficient Organization Design” *Journal of Political Economy* 96 (1): 42–60

Mundlak, Yair (1961), “Empirical Production Function Free of Management Bias”, *Journal of Farm Economics* 43(1): 44-56

Prescott, Edward and Visscher, Michael (1980) “Organization Capital.” *Journal of Political Economy*, 88 446-61.

Syverson, Chad (2011) “What determines productivity?” *Journal of Economic Literature*, 49(2) 326–365

Woodward Joan, (1958) *Management and Technology*, Cambridge: Cambridge University Press.

TABLE 1: DECOMPOSITION OF SHARE WEIGHTED AVERAGE MANAGEMENT SCORE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country	Share- Weighted Average Management ($M = (2)+(3)$)	Reallocation effect (OP , Olley-Pakes)	Unweighted Average Management Score (\bar{M}_i)	“Deficit” in Share-weighted Management rel. to US, (1)-0.67	“Deficit” in Reallocation relative to US, (2)-0.36	% deficit in management due to worse reallocation (6)=(5)/(4)	TFP GAP with US	Proportion of TFP Gap due to Management
US	0.67	0.36	0.31	0	0			
Sweden	0.42	0.22	0.20	-0.25	-0.14	56%	32.2	7.8
Japan	0.32	0.18	0.14	-0.35	-0.18	51%	33.6	10.4
Germany	0.23	0.26	-0.02	-0.44	-0.10	22%		
Canada	0.19	0.26	-0.06	-0.48	-0.10	21%	22.3	22.4
Great Britain	-0.05	0.17	-0.23	-0.72	-0.19	26%	20.3	36.5
Poland	-0.13	0.18	-0.32	-0.80	-0.18	22%		
Italy	-0.14	0.07	-0.22	-0.81	-0.29	36%	17.2	47.7
France	-0.33	0.08	-0.41	-1.00	-0.28	28%	25.3	38.7
Brazil	-0.34	0.24	-0.59	-1.01	-0.12	12%	59.6	16.9
China	-0.50	0.10	-0.61	-1.17	-0.26	22%	78.3	14.9
Argentina	-0.51	0.14	-0.66	-1.18	-0.22	19%	57.3	20.6
Portugal	-0.53	0.09	-0.62	-1.20	-0.27	22%	24.9	48.2
Greece	-0.98	-0.13	-0.85	-1.65	-0.49	30%	51	32.4
Average						23%		25%

Notes: Colum (1) is the employment share weighted management score in the country. Management scores have standard deviation 1, so Greece is 1.65 (0.67 + 0.98) standard deviations lower than the US. 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. TFP gap in column (7) is from Jones and Romer (2010). Column (8) = $\alpha_M * (4) / (7)$ where $\alpha_M = 0.10$ the effect of a one standard deviation increase in the management score on TFP (based on Bloom et al, 2013 and Table 3). 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).

TABLE 2: PERFORMANCE REGRESSIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent variable	Ln (Sales)	Ln (Sales)	Ln (Sales)	Ln (Sales)	Ln (Employees)	Profitability (ROCE, %)	5 year Sales growth (%)	Ln (Tobin Q)	Death (%)	Death (%)	Death (%)
Management (z-score)	0.330*** (0.018)	0.150*** (0.016)	0.142*** (0.019)	0.033** (0.013)	0.338*** (0.015)	1.202*** (0.264)	0.039*** (0.013)	0.082** (0.031)	-0.006*** (0.002)	-0.007*** (0.002)	-0.002 (0.003)
Ln(Employees)	0.905*** (0.018)	0.645*** (0.024)	0.632*** (0.030)	0.374*** (0.096)							
Ln(Capital)		0.307*** (0.019)	0.305*** (0.024)	0.237*** (0.078)							
Competition										0.101** (0.046)	0.094** (0.045)
Management × Competition											-0.096** (0.046)
General controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Firm fixed effects	No	No	No	Yes	No	No	No	No	No	No	No
Firms	4,265	3,493	1,543	1,543	7,519	3,917	3,606	657	7,532	7,532	7,532
Observations	9,352	8,314	6,364	6,364	15,608	9,163	8,365	1,743	7,532	7,532	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 3: THE EFFECTS OF THE GREAT RECESSION ON FIRM GROWTH

Dependent variable: Growth in firm sales	(1)	(2)	(3)	(4)	(5)	(6)
Shock (Comtrade)	-0.051*** (0.014)	-0.052*** (0.014)				
Management*Shock (Comtrade)		0.018* (0.010)				
Shock (ORBIS)			-0.033** (0.014)	-0.035** (0.014)		
Management*Shock (ORBIS)				0.027** (0.011)		
Shock (NBER)					-0.062*** (0.017)	-0.063*** (0.017)
Management*Shock (NBER)						0.011 (0.013)
Management	0.001 (0.006)	-0.008 (0.009)	0.002 (0.006)	-0.014 (0.010)	0.001 (0.006)	-0.007 (0.012)
Firms	1,599	1,599	1,567	1,567	1,629	1,629
Observations	1,685	1,685	1,653	1,653	1,716	1,716

Notes: Estimation by OLS with standard errors clustered by firm. The dependent variable is the percentage change in firm sales before and during the Great Recession, defined as mean sales in 2006 and 2007 pooled as pre-crisis and mean sales in 2008 and 2009 pooled as during crisis. All columns include a full set of country and two digit industry dummies; firm controls (log share of employees with a college degree, log employment, share of plant employment, multinational status, listed status, CEO onsite dummy); noise controls (analyst dummies, interview reliability, interview duration, manager tenure in position, manager seniority, years used to compute the change in firm sales, and dummies to flag companies that appear to have changed ownership or sector, or to be out of business in 2010). SHOCK is a dummy variable equal to unity if a negative shock was experienced in the firm three-digit industry and country cell, and zero otherwise. “SHOCK(ORBIS)” is defined using information on aggregate sales growth before and during the Great Recession, excluding the firm itself. SHOCK=1 if the change in sales in the three digit industry and country cell before and during the Great Recession is negative (defined as mean sales in 2006 and 2007 pooled as pre-crisis and mean sales in 2008 and 2009 pooled as during crisis). “SHOCK(COMTRADE)” is defined in an analogous way, but using data on exports to the world at the three digit industry-country level, derived from the COMTRADE dataset. “SHOCK(NBER)” is defined in an analogous way but using value added at the three digit industry level in the US from the NBER dataset. All firm and industry data used to compute the changes are expressed in constant 2005 US dollars. Standard errors are clustered at the three digit by country cell level.

TABLE 4: PERFORMANCE REGRESSIONS: MANAGEMENT AROUND THE INDUSTRY BY COUNTRY MEAN

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Ln (Sales)	Ln (Sales)	Ln (Sales)	ROCE	Sales growth	Death	Ln (Tobin Q)
Cell	SIC3 ×Country	Country	SIC3	SIC3 ×Country	SIC3 ×Country	SIC3 ×Country	SIC3 ×Country
Management*(Management≤Cell average)	0.236*** (0.032)	0.219*** (0.034)	0.226*** (0.039)	1.681*** (0.528)	0.038 (0.028)	-0.018*** (0.005)	0.133** (0.060)
Management*(Management >Cell average)	0.226*** (0.027)	0.219*** (0.030)	0.223*** (0.030)	1.679*** (0.436)	0.044* (0.024)	-0.014*** (0.004)	0.130*** (0.048)
Ln(Employment)	0.642*** (0.028)	0.645*** (0.046)	0.644*** (0.026)				
Ln(Capital)	0.305*** (0.022)	0.307*** (0.041)	0.309*** (0.021)				
P-value on F-tests:							
Joint: Man.*(Man.≤Cell ave.)=0 & Man. *(Man. ≤Cell ave.)=0	0.000	0.000	0.000	0.00	0.036	0.001	0.003
Equal: Man.*(Man.≤Cell average) = Man.*(Man.≤Cell ave.)	0.230	0.984	0.785	0.990	0.388	0.006	0.861
Cell Clusters	796	18	177	900	921	1,137	309
Observations	8,003	8,314	8,292	8,793	8,007	6,607	1,698

Note: All columns estimated by OLS with standard errors in parentheses clustered by cell. Only cells with 3+ observations are used. *** denotes 1% significant, ** denotes 5% significance and * denotes 10% significance. For sample comparability columns (1) to (5) are run on the same sample of firms with sales, employment, capital, ROCE and 5 years of sales data. “**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). “**ROCE**” 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. **Death**” is the probability of exit by 2010 (sample mean is 1.6%). “**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. All columns include a full set of general controls comprised 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 country, three digit industry and time dummies.

TABLE 5: COMPETITION AND MANAGEMENT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. variable:		Management			Management			Management			ΔManagement	
(1 – Lerner)	5.035** (2.146)	17.534*** (3.846)	4.915* (2.747)									
Δ(1-Lerner)										20.677*** (6.467)		
Ln(Import Pen.)				0.081* (0.044)	0.805*** (0.236)	0.095** (0.042)						
ΔLn(Import Pen.)											0.608** (0.230)	
Number of Rivals							0.115*** (0.023)	0.121*** (0.023)	0.141*** (0.041)			
ΔNumber of rivals												0.120** (0.052)
Observations	2,819	2,819	858	2,657	2,657	810	2,789	2,789	864	429	412	432
Number of clusters	76	76	64	65	65	55	2,352	2,352	432	64	55	432
Fixed effects	No	Industry by Country		No	Industry by Country		No	Industry by Country		No (Long Differences)		
Clustering		Industry by Country					Firm	Firm	Firm	Industry by country		Firm

Notes: ** indicates significance at 5% level and * at the 10%. OLS estimates with clustered standard errors in parentheses below coefficients. All columns include a full set of linear country dummies. Countries are US, UK, France and Germany. “**Number of rivals**” is the perceived number of competitors on a 0 to 10 scale (where 10 is 10+ competitors and 0 is no competitors); **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; **Lerner** is the (lagged) median gross margin across all firms in the plant’s two-digit industry by country cell. Columns (1) to (9) are on the full cross section of all firms (and include controls for the proportion of employees with a college degree, ln(size) and whether the first is publicly listed). Columns (10) to (12) are restricted to the balanced panel (up to 432 firms in 2004 and 2006). Apart from the differenced specifications all columns include noise controls.

TABLE 6: MANAGEMENT, FIRM SIZE AND GROWTH ACROSS COUNTRIES

Dep. Variable:	(1)	(2)	(3)	(4)
	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 7: FIRM SIZE AND MANAGEMENT ACROSS COUNTRIES – IMPACT OF POLICY VARIABLES

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Employment	Employment	Employment	Management	Employment
Management	231.46*** (37.12)	356.73*** (55.89)	381.84*** (62.88)		110.970* (66.302)
Management*Employment Protection	-1.43** (0.69)		-1.16 (0.75)		
Management *Trade costs		-0.18*** (0.05)	-0.18*** (0.05)		
Tariff Levels				-0.007*** (0.002)	-4.961 (4.122)
Management *Tariff Levels					-8.249** (3.349)
Management *country interactions	No	No	No	No	Yes
Observations	5,760	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 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*** (0.020)	0.128*** (0.026)	-0.097*** (0.022)				0.027 (0.018)	0.108*** (0.023)	-0.106*** (0.022)
R&D Intensity				0.174** (0.077)	-0.040 (0.140)	0.261** (0.115)	-0.002 (0.057)	-0.247** (0.097)	0.312*** (0.091)
ln(%degree)							0.197*** (0.010)	0.174*** (0.011)	0.016 (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 (0.046)	0.044 (0.033)	-0.060 (0.043)				-0.020 (0.044)	0.044 (0.034)	-0.080* (0.042)
R&D Intensity				0.461 (0.340)	0.017 (0.344)	0.535** (0.221)	0.372 (0.356)	-0.142 (0.340)	0.630*** (0.218)
ln(%degree)							0.206*** (0.017)	0.136*** (0.019)	0.076*** (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: COMPETITION IS ASSOCIATED WITH MORE REALISTIC SELF-PERCEPTIONS OF MANAGEMENT

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	Management	Management	Management	Self-score Management	Self-score Management	Self-score Management
Mean	2.98	3.05	3.05	7.13	7.01	7.01
Fixed Effect	SIC3	SIC3	Firm	SIC3	SIC3	Firm
Sample	All	2+ obs per plant	2+ obs per plant	All	2+ obs per plant	2+ obs per plant
Competition	0.069*** (0.018)	0.081*** (0.029)	0.093** (0.047)	-0.044** (0.022)	-0.051 (0.037)	-0.068 (0.070)
%College degree	0.110*** (0.008)	0.101*** (0.013)	0.043* (0.023)	0.040*** (0.011)	0.065*** (0.018)	-0.001 (0.033)
Ln(Employment)	0.177*** (0.009)	0.169*** (0.016)	0.050 (0.035)	0.065*** (0.011)	0.052** (0.021)	0.020 (0.048)
Foreign MNE	0.428*** (0.024)	0.302*** (0.038)		0.105*** (0.029)	0.059 (0.051)	
Ln(Firm age)	0.198*** (0.026)	0.101** (0.042)		0.078** (0.033)	0.066 (0.054)	
Observations	8,182	3,732	3,732	8,182	3,251	3,251

Notes: ** indicates significance at 5% level and * at the 10%. OLS estimates with clustered standard errors by firm in parentheses below coefficients. All columns include a full set of linear country dummies, time dummies, four digit industry dummies, average hours and noise controls. **Competition** is measured in terms of the number of rivals the firm reports facing, with a sample mean and standard deviation of 7 and 3 respectively. Management is scored on a 1 to 5 scale. **Self-score management** is evaluated on a 1 to 10 scale, with respondents asked “*Excluding yourself, how well managed would you say your firm is on a scale of 1 to 10, where 1 is worst practice, 5 is average and 10 is best practice*”.

Appendix A1: Modelling management and production

We consider a model that encompasses both Design and Technology perspectives. Firm output¹ Y is determined by productivity A , capital K , labor L and management M . These are all 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, but will later discuss GE issues as well.

$$Y_i = \widetilde{A}_i K_i^\alpha L_i^\beta \Gamma(M_i) \quad (0.1)$$

where $\Gamma(M)$ is a yet to be determined management function (common to all firms in the industry). Industry output is a CES aggregator of individual firms:

$$Y = N^{\frac{1}{1-\rho}} \left(\sum_{i=1}^N Y_i^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \quad (0.2)$$

where $\rho > 1$ is the elasticity of substitution and $N^{\frac{1}{1-\rho}}$ is the standard adjustment factor to make the degree of substitution scale free (see Bartelsman et al, 2013). Our main index of competition will be ρ , consumer sensitivity to price. Applying the first order conditions gives each firm an individual inverse demand curve with elasticity ρ where we have normalized the industry price $P = 1$

$$\begin{aligned} P_i &= \left(\frac{Y}{N} \right)^{\frac{1}{\rho}} Y_i^{\frac{-1}{\rho}} \\ &= B Y_i^{\frac{-1}{\rho}} \end{aligned}$$

where the demand shifter is $B = \left(\frac{Y}{N} \right)^{\frac{1}{\rho}}$.

These production and demand curves generate the firm's revenue function $P_i Y_i = A_i K_i^a L_i^b G(M_i)$ where for analytical tractability we defined $A_i = \widetilde{A}_i^{1-1/\rho} \left(\frac{Y}{N} \right)^{\frac{1}{\rho}}$, $a = \alpha(1-1/\rho)$, $b = \beta(1-1/\rho)$, $G(M_i) = \Gamma(M_i)^{(1-1/\rho)}$. Profits are defined as revenues less capital, labor and management costs ($c(K)$, $c(L)$ and $c(M)$) and a fixed overhead cost F

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

In terms of the management function $G(M_i)$ we consider two broad classes of models.

0.1. 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

¹This is actually value added as we are abstracting away from intermediate inputs.

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 be improved - for example, by hiring in management consultants 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 treats management as an intangible capital stock with depreciation, analogously to other forms of capital:²

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

where I_{it}^M reflects (say) “consulting investment” in management practices.³ The capital accumulation equation is

$$K_{it} = (1 - \delta_K)K_{it-1} + I_{it}^K$$

0.2. Factor 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. We assume changing management practices involves a quadratic adjustment cost

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

Likewise, we also assume that costs involve a quadratic adjustment costs for capital

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

Finally, 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 , so that $c(L) = wL$. Given this assumption

²See Corrado and Hulten (2010) for this general approach to intangible capital which is becoming standard for US GDP accounting.

³We use the word “consulting” as a stand in for all expenditures aimed at improving management practices, including consulting but also extending activities like training and investment in IT systems like ERP (electronic resource planning).

on labor we can define the optimal choice of labor by $\frac{\partial PY(A,K,L^*,M)}{\partial L} = w$, and imposing this optimality define the labor optimized revenue function

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

where $A^* = \left(\frac{b}{w}\right)^{\frac{b}{1-b}} A^{\frac{1}{1-b}}$. The cost of capital is R and the cost of management is

0.3. Distortions and Frictions

We can also allow for frictions in the model, τ_{it} , reflecting the lost output from corruption, taxes and regulation. We assumed these are a stochastic firm-level random variable which can fluctuate over time, and is known to the firm but are unobservable in our data.⁴ We also want to allow the distribution of these to vary across industries and countries - for example, the dispersion of frictions may be much larger in India than in the US, reflecting the greater potential for corruption and distortive regulations.

0.4. Optimization and equilibrium

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

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

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. Of course 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, friction and management values from a distribution of $G(A, \tau, M)$ and start with $K_0 = 0$. Hence, entry occurs until the point that

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

⁴This is the standard approach and follows inter alia Restuccia and Rogerson (2008) and Bartelsman et al (2013). It reflects the uncertainty entrants face over how even known regulations will be implemented. An alternative approach is to assume that some of the distortions are know ex ante and this will affect entry behavior (e.g. Garicano et al, 2013).

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 characterized in terms of their state values A, K, M and τ , plus their optimized choice of labor L .

0.5. Numerical Simulation

We choose a set of calibration values to simulate the model as below.⁵

Table A1: Values of parameters used for calibration

Parameter	Mnemonic	value	Rationale
TFP AR(1) process	ρ_A	0.95	Cooper and Haltiwanger (2006)
Capital Share	α	1/3	NIPA
Labor share	β	1/2	
Management share	$\gamma = \frac{c}{(1-1/\rho)}$	1/6	
sunk cost of entry	κ	100	Assumed 100 times unit price
Fixed cost of production	F	25	Assumed 25 times unit price
Demand elasticity	e	4	Mark-up of 25% (Bloom, 2009)
Adjustment costs for capital	Q_K	100	Costs 5% revenue (Bloom, 2009)
Adjustment costs for management	Q_M	100	Costs 5% revenue (Bloom, 2009)
Upper Bound of distortions	D_T	10%	Hsieh and Klenow (2009)
Discount Factor	ϕ	0.91	Based on real interest rates
Capital depreciation rates	δ_K	10%	
Management depreciation rates	δ_M	10%	
Costs deviating from M (MAD)	b	2	

Notes: These are the baseline values of parameters used in the numerical simulations across all model runs

Firms draw stochastically and independently from a triple of idiosyncratic shock for TFP, management and distortions $\{A, M, \tau\}$ when they enter from a known distribution. The distributions of distortions are assumed uniform over $[0, D_T]$, and the distributions of A and M are assumed bivariate normal. Each period firms are subject to i.i.d. shocks in A . We discretize the state space for M, K, A and distortions, τ into bins for purposes of the numerical

⁵Some of these we take from the existing literature as noted. We chose to keep management values the same as capital to avoid obtaining results that are dependent on deviations between adjustment costs and depreciation rates based on these (unknown) differences.

simulation. This means that there is a transition matrix between discrete points of the grid with fixed transition probabilities.

We then generate the value functions for entrants and incumbents. Using the contraction mapping (e.g. Stokey and Lucas, 1986) we iterate until we obtain a fixed point of the value functions. The policy correspondences for M and K are formed from the optimal choices given these value functions. Labor is simply the static period by period level based on the first order condition.

We simulate data for 2,500 firms over a 50 year period. This time span was sufficient for the data to settle down to a steady state. From these “steady state” distributions we can look at different moments of the data in the different models. And we can also see how these change when we alter key model parameters.

Figure 1 through 4 show predictions arising from the simulation. Using the data from the last 5 years of the simulation we simply plot the local linear regression (lowess) of firm $\ln(\text{sales})$ against management. Figure 1 shows the first result, the correlation between performance and management. We use size (sales) as our performance measure, but we obtain similar results for TFPQ, TFPR and profits. There is a positive and monotonic relationship as we expect. The second prediction relates to competition as indexed by changes in the elasticity of demand (ρ , consumers sensitivity to price). We run all the simulations 5 times for increasingly high levels of the absolute price elasticity of demand between 2 and 10 (recall that our baseline is elasticity=6). Figure 2 shows that average management scores are higher as the poorly managed (low productivity) firms have a much lower (often zero) market share. This is because under higher competition less efficient firms will be smaller (with lower M) and also less able to cover the fixed cost of production (increasing exit probabilities).

Figure 3 examines management and distortions . We implement this by increasing the upper support of the distribution of distortion from 2 to 20 (recall that the baseline uses an upper support of 10 and lower support of 0). To do this we plot out the sales weighted management for different levels of distortions in Figure 3. We see clearly that size-weighted management declines as the variance of distortions increases. Just as in our simpler analytic model, highly distorted economies reward well managed firms with lower market shares than less distorted economies. Finally in Figure 4 we confirm the obvious, namely that management falls as it’s own price increases.

0.6. An alternative model: Management by Design (MAD)

0.6.1. Theoretical set-up

Alternatively we can assume that management practices are contingent on a firm's environment. Increases in M do not always increase output as they do in the MAT perspective. In some sectors high values of M will increase output and in others they will reduce output depending on the contingent features of the industry. The motivation for this is the contingency literature building on Woodward (1956) but it is also consistent with much of the conventional organizational economics literature (e.g. Gibbons and Roberts, 2013). 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.⁶ For example, firms may provide too little or too much incentive pay for maximizing production. Note that in the general way we set up MAT, firms do choose M and this will vary depending on the environment (so this is more general than say Melitz, 2003).

We implement the Design model by assuming $G(M_i) = 1/(1 + \theta|M_i - \bar{M}|)$. Note that $G(M_i) \in (0, 1]$ and is decreasing in the absolute deviation of M from its optimal level \bar{M} . Our baseline case assumes that M is a choice variable that does not have to be paid for on an ongoing basis so that $\delta_M = 0$.⁷

0.6.2. Simulation Results

Panels A, B and C in Figures A1 are the analogs to the Figures 1, 2 and 3 in the main results. In Figure A1, performance is an inverse U - maximized for a management score of around 2.8 and declining as firms are above and below this level. This is again as 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 Figures A2 (and A3) we show the relationship between management and competition (and distortions). There is no correlation in either case in contrast to the findings under the original MAT model, that management, especially size-weighted management, rises

⁶For example, industries employing large numbers of highly-skilled employees, like pharmaceuticals, may require more academic styles of promotion (long-run tenure systems) while low-tech industries like textiles may want piece-rate pay incentives. 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)

⁷Although this assumption is flexible and is not qualitatively material.

with competition and decreases with distortions.

0.6.3. Contrast of models

The Table below summarizes the empirical findings from the numerical simulations which is intuitive and consistent with the intuition from the simpler analytical model.

Table A2: Moments in the simulated data from the two models

Moments in the data	MAT	MAD	Empirics
Covariance of firm size with management	+	(0)	+
Deviation of firm management from industry/country mode	0	-	0
Covariance of average management and competition	+	0	+
Impact of distortions on management-size covariance	-	0	-

APPENDIX A2: SPECIAL CASE OF THE MANAGEMENT AS TECHNOLOGY MODEL

We consider a special case of the general model where can derive some analytical results. The set-up is the same as Appendix A1 except we abstract away from endogenous management and assume the initial draw is fixed and does not depreciate over time. Hence the initial draw of TFP (A) and management are one and the same. We further assume that capital cannot be adjusted for one period, but then after this is completely flexible (a la Olley and Pakes, 1996) rather than being subject to quadratic adjustment costs. There remain iid productivity shocks, ε_{it} . Given the simpler production function we put fixed costs in terms of overhead labor. Value added for firm i in period t is:

$$Y_{it} = A_i \varepsilon_{it} (L_{it} - F)^{\gamma - \alpha} K_{it}^\alpha$$

With these assumptions we can write the free entry condition in terms of a threshold that is a function of the initial draw of management quality and distortions, S_i . Firms drawing below this will immediately exit. This threshold is:

$$S_i = \frac{\bar{Y}^{\rho-1} R^{\rho\alpha} w^{1-\rho\alpha} F^{1-\rho\gamma}}{\alpha^{\rho\alpha} (\gamma - \alpha)^{\rho(\gamma-\alpha)} \rho^{\rho\gamma} (1 - \rho\gamma)^{1-\rho\gamma}}$$

The threshold is increasing in the level of fixed costs (F) and the degree of product market competition (ρ). The optimal capital stock is:

$$K_i^* = S_i^{1/(1-\rho\gamma)} \Omega$$

Where $S_i = \left[(1 - \tau_i) A_i^\rho \right]$ and $\Omega(w, \bar{Y}) = \left[\bar{Y}^{1-\rho} \rho R^{(\gamma-\alpha)\rho-1} \alpha^{1-(\gamma-\alpha)\rho} w^{-(\gamma-\alpha)\rho} (\gamma - \alpha)^{(\gamma-\alpha)\rho} \right]^{1/(1-\rho\gamma)}$ is a function of factors that do not vary across firms (i.e. average firm size, factor prices, and parameters). Optimal variable labor is:

$$(L_{it}^* - F) = S_i^{1/(1-\rho\gamma)} \frac{R(\gamma - \alpha)}{w\alpha} \Omega$$

General Equilibrium

The simplicity of this model means that we can also allow for general equilibrium considerations. We assume a fixed number of households supply labor inelastically so aggregate labor supply is L^S . A representative household chooses consumption (C_t) to maximize

$$\sum_{t=0}^{\infty} \beta^t U(C_t)$$

Subject to

$$\sum_{t=0}^{\infty} P_t (C_t + K_{t+1} + (1 - \delta)K_t) = \sum_{t=0}^{\infty} P_t (w_t N_t + R_t K_t + \pi_t)$$

Where K_t is the aggregate capital stock. The standard result from this set up is that the real interest rate is $r_t = R_t - \delta = (1/\beta) - 1$ the cost of capital is constant. Aggregate labor demand is from aggregation the FOC across all firms. Wages are determined by equating aggregate labor demand and supply. There is an aggregate resource constraint that ensures that aggregate

consumption plus resources spent on entry (E_t = mass of entrants) and capital depreciation will equal output in the stochastic steady state: $C_t + E_t \kappa + \delta K_t = Y_t$

Given this set up we can show three main propositions that are the basis of the predictions that we take to the data.

Proposition 1: Firm performance is an increasing function of management quality

Proof. From the optimal factor demand equations above both capital and variable labor are increasing in management quality A_t . Hence output will also be increasing in management quality.

For all operating firms, revenue over variable labor is (the Hsieh and Klenow, 2009, insight):

$$\frac{P_i Y_i}{N_i^* - F} = \frac{1}{1 - \tau_i} \left\{ \bar{Y}^{1-\rho} \left(\frac{R(\gamma - \alpha)}{w\alpha} \right)^{\rho(\gamma - \alpha) - 1} \Omega^{\rho\gamma - 1} \right\}$$

The term in curly brackets is constant across firms so there is no variation in term except for distortions. However, labor productivity, LPR , is:

$$LPR_i = \frac{P_i Y_i}{N_i^*} = \left(\frac{1}{1 - \tau_i} - \frac{F}{(1 - \tau_i) N_i^*} \right) \left\{ \bar{Y}^{1-\rho} \left(\frac{R(\gamma - \alpha)}{w\alpha} \right)^{\rho(\gamma - \alpha) - 1} \Omega^{\rho\gamma - 1} \right\}$$

Hence, larger firms (higher n_i^*) will have higher labor productivity (unlike Hsieh-Klenow who do not have overhead labor/fixed costs). Since better managed firms will be larger they will also have higher labor productivity. Further, there will be variation in labor productivity across firms even in the absence of distortions ($\tau_i = 0$).

Corollary A of Proposition 1

Higher management quality will be positively correlated with higher labor productivity (and higher TFPR).

Proof. See the equation for LPR (labor productivity) above

Corollary B of Proposition 1

Firms with higher management quality will grow more quickly and be less likely to exit.

Proof. This follows from the stochastic nature of management quality. If a firm gets a positive draw in period t from ε_{it} it will be larger and less likely to exit

Proposition 2. Average Management Quality is increasing in competition

This follows from the definition of the threshold level of the profit shock, S_t . As competition increases indexed by ρ , the threshold increases. Hence, all else equal a firm needs to have a better management quality in order to make positive profits. Therefore, economies with greater competition will have higher average management quality.

Corollary A of Proposition 2

The variance of management across firms is lower when there are fewer distortions. Less distortions will mean that fewer of the badly managed firms who get a lower distortion draw will survive (and vice versa). This follows from the cut-off rule again.

Proposition 3. The Covariance between size and management is higher the lower are distortions

Proof

The claim here is that the covariance between output and management (the Olley-Pakes reallocation term) is greater the smaller is the variance of distortions. For example, $\text{cov}(n_{it}, A_i \varepsilon_{it})$ is an increasing and monotone function of $\text{Var}(1 - \tau_i - \kappa_{it})$. Bartelsman et al (2013) do not try to give an analytic proof of this but show that it is robust through numerical simulations. They show that this seems to be true for parameter values calibrated to US economy. We have shown that this insight is robust in a much more general model.

APPENDIX B: 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/>.

B1. 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.

B2. 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.²² In Japan and China we used all manufacturing firms with 150 to 5000 employees since Oriana only samples firms with over 150 employees.²³ We checked the results by conditioning on common size bands (above 150 in all countries) to ensure that the results were robust.

²² 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 $\ln(\text{employees})$ on $\log(\text{assets})$ for public firms.

²³ 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.

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 least²⁴ 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 than 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 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.²⁵ 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

²⁴ 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.

²⁵ 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.

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 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.²⁶

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.

²⁶ 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.

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 through 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.²⁷ 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 interviewed²⁸. 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, 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 is 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.

²⁷ 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.

²⁸ 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.

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 abroad and the country where the parent company is headquartered) to be able to distinguish domestic multinationals from foreign multinationals.

We collected many variables through our survey including information on plant 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 $(1 - \text{profit}/\text{sales})$ 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.

TABLE B1

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 B2:
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 B3

	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 B4: RESPONSE RATES TO THE SURVEY

	(1)	(2)	(3)	(4)	(5)
Ln(employment)		0.039*** (0.004)	0.023*** (0.007)	0.023*** (0.007)	0.044*** (0.011)
Ln (Sales/employee)			0.005 (0.007)	0.005 (0.007)	
Age of firm (in years) §				-0.003 (0.014)	0.021 (0.020)
Publicly listed				-0.009 (0.024)	-0.031 (0.033)
Multinational subsidiary				0.003 (0.022)	0.023 (0.036)
Return on Capital Employed §					-0.012 (0.047)
Country is Argentina	0.003 (0.023)	0.032 (0.023)	0.085*** (0.030)	0.086*** (0.031)	
Country is Australia	-0.156*** (0.014)	-0.132*** (0.015)			
Country is Brazil	0.007 (0.017)	0.036** (0.018)	0.129*** (0.028)	0.129*** (0.029)	
Country is Canada	-0.087*** (0.017)	-0.042** (0.018)	-0.003 (0.025)	-0.003 (0.026)	
Country is Chile	-0.015 (0.021)	0.594*** (0.008)			
Country is China	0.089*** (0.019)	0.070*** (0.019)	0.074** (0.030)	0.072** (0.031)	
Country is France	0.222*** (0.024)	0.247*** (0.024)	0.277*** (0.026)	0.278*** (0.026)	-0.074 (0.046)
Country is Germany	0.204*** (0.024)	0.220*** (0.024)	0.248*** (0.026)	0.249*** (0.026)	
Country is Greece	0.159*** (0.029)	0.193*** (0.029)	0.234*** (0.031)	0.234*** (0.031)	-0.108** (0.049)
Country is India	0.259*** (0.021)	0.270*** (0.021)	0.309*** (0.032)	0.306*** (0.032)	
Country is Ireland	-0.102*** (0.022)	-0.045* (0.024)	0.119*** (0.040)	0.120*** (0.041)	
Country is Italy	0.314*** (0.028)	0.341*** (0.027)	0.357*** (0.028)	0.356*** (0.028)	0.046 (0.052)
Country is Japan	-0.175*** (0.024)	-0.176*** (0.025)	-0.163*** (0.030)	-0.162*** (0.031)	
Country is Mexico	-0.091*** (0.021)	-0.066*** (0.022)	0.072** (0.035)	0.073** (0.036)	
Country is New Zealand	-0.028 (0.026)	0.023 (0.027)			
Country is Poland	-0.000 (0.023)	0.024 (0.023)	0.069** (0.028)	0.071** (0.028)	-0.273*** (0.039)
Country is Portugal	0.237*** (0.030)	0.279*** (0.029)	0.316*** (0.029)	0.316*** (0.029)	0.006 (0.053)
Country is Sweden	0.286*** (0.026)	0.310*** (0.025)	0.333*** (0.026)	0.334*** (0.026)	0.007 (0.049)
Country is UK	0.019 (0.017)	0.032* (0.018)	0.061*** (0.023)	0.063*** (0.023)	-0.296*** (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.

APPENDIX C: 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 where 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.

C1. 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.

C2. 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 $\exp[0.7*\ln(\text{labor}) + 0.3*\ln(\text{capital})]$. The results are in Figure C3 and again are similar to the baseline.

C3. 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).

C4. 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, Saporta-Eksten and Van Reenen, 2013).²⁹

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.³⁰ 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 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.

²⁹ The coefficient on $\ln(\text{employment size})$ in the management regression is 0.25. We considered imposing a common constant on each country (-1.46) or adjusting this to be consistent with the country-mean management score in the 50 to 5,000 range. Figure C5 does the latter, but both methods lead to similar results.

³⁰ 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.

TABLE C1: TRANSITION MATRIX FOR MANAGEMENT PRACTICES**PANEL A: 2004-2006, France, Germany, UK and US (396 firms)**

	Bottom Quintile in 2006	Second Quintile in 2006	Third Quintile in 2006	Fourth Quintile in 2006	Top Quintile in 2006	Total
Bottom Quintile in 2004	42	20	15	15	8	100
Second Quintile in 2004	23	39	18	16	3	100
Third Quintile in 2004	20	28	11	29	12	100
Fourth Quintile in 2004	9	14	24	21	32	100
Top Quintile in 2004	4	11	16	25	44	100

PANEL B: 2006-2009, France, Germany, UK and US (789 firms)

	Bottom Quintile in 2009	Second Quintile in 2009	Third Quintile in 2009	Fourth Quintile in 2009	Top Quintile in 2009	Total
Bottom Quintile in 2006	47	22	16	13	3	100
Second Quintile in 2006	24	36	16	14	11	100
Third Quintile in 2006	19	24	22	19	17	100
Fourth Quintile in 2006	9	19	20	23	28	100
Top Quintile in 2006	5	8	17	27	43	100

Notes: Panel A (B) is the balanced panel of firms interviewed in 2004 (2006) and 2006 (2009). Firms are ranked by their initial year management z-score and then grouped by quintile. We follow them through to their position in the distribution in the later year.

PANEL C: 2006-2009, All countries (1,600 firms)

Quintile in 2009	Bottom	Second	Third	Fourth	Top	Total
Quintile in 2006						
Bottom	52	22	15	9	3	100
Second	23	25	25	8	10	100
Third	16	24	26	19	15	100
Fourth	7	16	26	26	24	100
Top	6	8	13	28	46	100

Notes: The top figures in each cell are from the balanced panel of firms who we interviewed in 2006 and 2009. Firms are ranked by their management score in 2006 and then grouped by quintile. We follow them through to their position in the distribution in 2009.

PANEL D – COMPARISON WITH US PLANT DATA USING TFP FROM BAILEY, HULTEN AND CAMPBELL (1992)

Quintile in 1977	Bottom	Second	Third	Fourth	Top	Total
Quintile in 1972						
Bottom	36	18	11	18	16	100
Second	20	19	22	22	17	100
Third	16	24	22	24	13	100
Fourth	9	7	17	35	34	100
Top	5	6	7	16	65	100

Notes: These are quintiles for plant level total factor productivity from Bailey, Hulten and Campbell (1992) comparing productivity quintiles between 1972 and 1977. This panel (as with the others in the Table) is only for survivors.

**TABLE C2: 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 C3: 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).

APPENDIX D: 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).

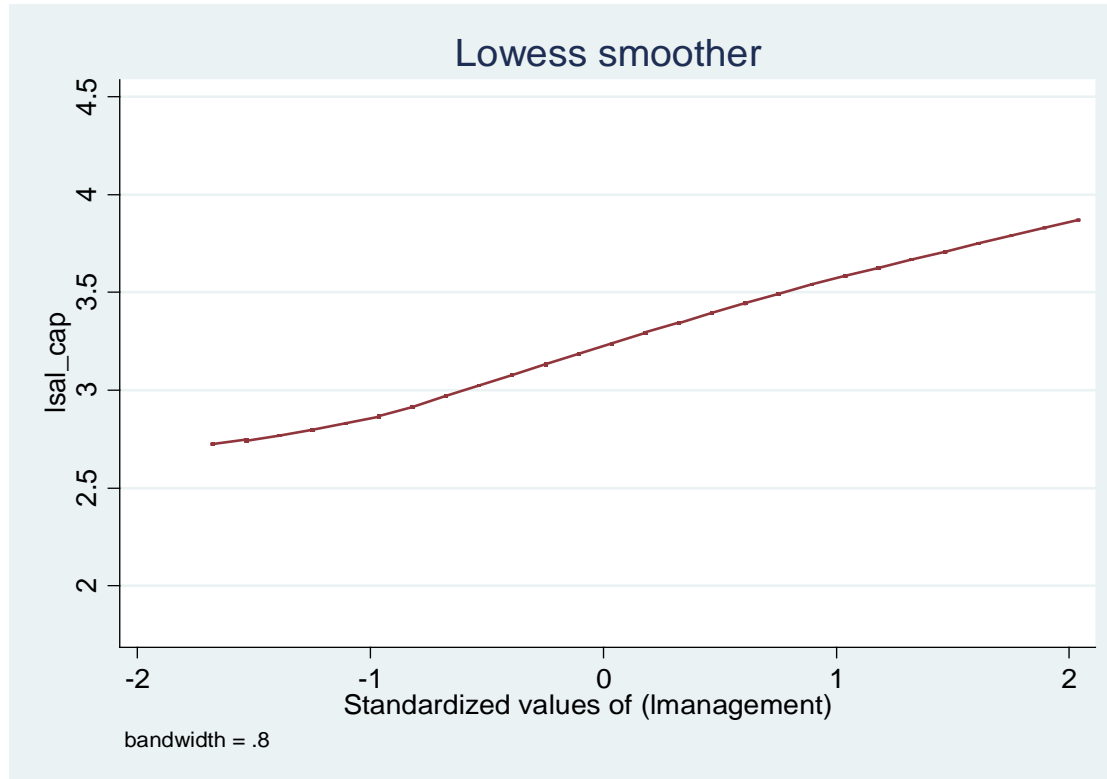
(1) Modern manufacturing, introduction			
Scoring grid:	Score 1 Other than Just-In-Time (JIT) delivery from suppliers few modern manufacturing techniques have been introduced, (or have been introduced in an ad-hoc manner)	Score 3 Some aspects of modern manufacturing techniques have been introduced, through informal/isolated change programs	Score 5 All major aspects of modern manufacturing have been introduced (Just-In-Time, automation, flexible manpower, support systems, attitudes and behaviour) in a formal way
(2) Modern manufacturing, rationale			
Scoring grid:	Score 1 Modern manufacturing techniques were introduced because others were using them.	Score 3 Modern manufacturing techniques were introduced to reduce costs	Score 5 Modern manufacturing techniques were introduced to enable us to meet our business objectives (including costs)
(3) Process problem documentation			
Scoring grid:	Score 1 No, process improvements are made when problems occur.	Score 3 Improvements are made in one week workshops involving all staff, to improve performance in their area of the plant	Score 5 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			
Scoring grid:	Score 1 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)	Score 3 Most key performance indicators are tracked formally. Tracking is overseen by senior management.	Score 5 Performance is continuously tracked and communicated, both formally and informally, to all staff using a range of visual management tools.
(5) Performance review			
Scoring grid:	Score 1 Performance is reviewed infrequently or in an un-meaningful way, e.g. only success or failure is noted.	Score 3 Performance is reviewed periodically with successes and failures identified. Results are communicated to senior management. No clear follow-up plan is adopted.	Score 5 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			
Scoring grid:	Score 1 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	Score 3 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.	Score 5 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			
Scoring grid:	Score 1 Failure to achieve agreed objectives does not carry any consequences	Score 3 Failure to achieve agreed results is tolerated for a period before action is taken.	Score 5 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			
Scoring grid:	Score 1 Goals are exclusively financial or operational	Score 3 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)	Score 5 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			
Scoring grid:	Score 1 Goals are based purely on accounting figures (with no clear connection to shareholder value)	Score 3 Corporate goals are based on shareholder value but are not clearly communicated down to individuals	Score 5 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			
Scoring grid:	Score 1 Top management's main focus is on short term targets	Score 3 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	Score 5 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			
Scoring grid:	Score 1 Goals are either too easy or impossible to achieve; managers provide low estimates to ensure easy goals	Score 3 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	Score 5 Goals are genuinely demanding for all divisions. They are grounded in solid, solid economic rationale

(12) Performance clarity			
Scoring grid:	Score 1 Performance measures are complex and not clearly understood. Individual performance is not made public	Score 3 Performance measures are well defined and communicated; performance is public in all levels but comparisons are discouraged	Score 5 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			
Scoring grid:	Score 1 Senior management do not communicate that attracting, retaining and developing talent throughout the organization is a top priority	Score 3 Senior management believe and communicate that having top talent throughout the organization is a key way to win	Score 5 Senior managers are evaluated and held accountable on the strength of the talent pool they actively build
(14) Rewarding high-performance			
Scoring grid:	Score 1 People within our firm are rewarded equally irrespective of performance level	Score 3 Our company has an evaluation system for the awarding of performance related rewards	Score 5 We strive to outperform the competitors by providing ambitious stretch targets with clear performance related accountability and rewards
(15) Removing poor performers			
Scoring grid:	Score 1 Poor performers are rarely removed from their positions	Score 3 Suspected poor performers stay in a position for a few years before action is taken	Score 5 We move poor performers out of the company or to less critical roles as soon as a weakness is identified
(16) Promoting high performers			
Scoring grid:	Score 1 People are promoted primarily upon the basis of tenure	Score 3 People are promoted upon the basis of performance	Score 5 We actively identify, develop and promote our top performers
(17) Attracting human capital			
Scoring grid:	Score 1 Our competitors offer stronger reasons for talented people to join their companies	Score 3 Our value proposition to those joining our company is comparable to those offered by others in the sector.	Score 5 We provide a unique value proposition to encourage talented people join our company above our competitors
(18) Retaining human capital			
Scoring grid:	Score 1 We do little to try to keep our top talent.	Score 3 We usually work hard to keep our top talent.	Score 5 We do whatever it takes to retain our top talent.

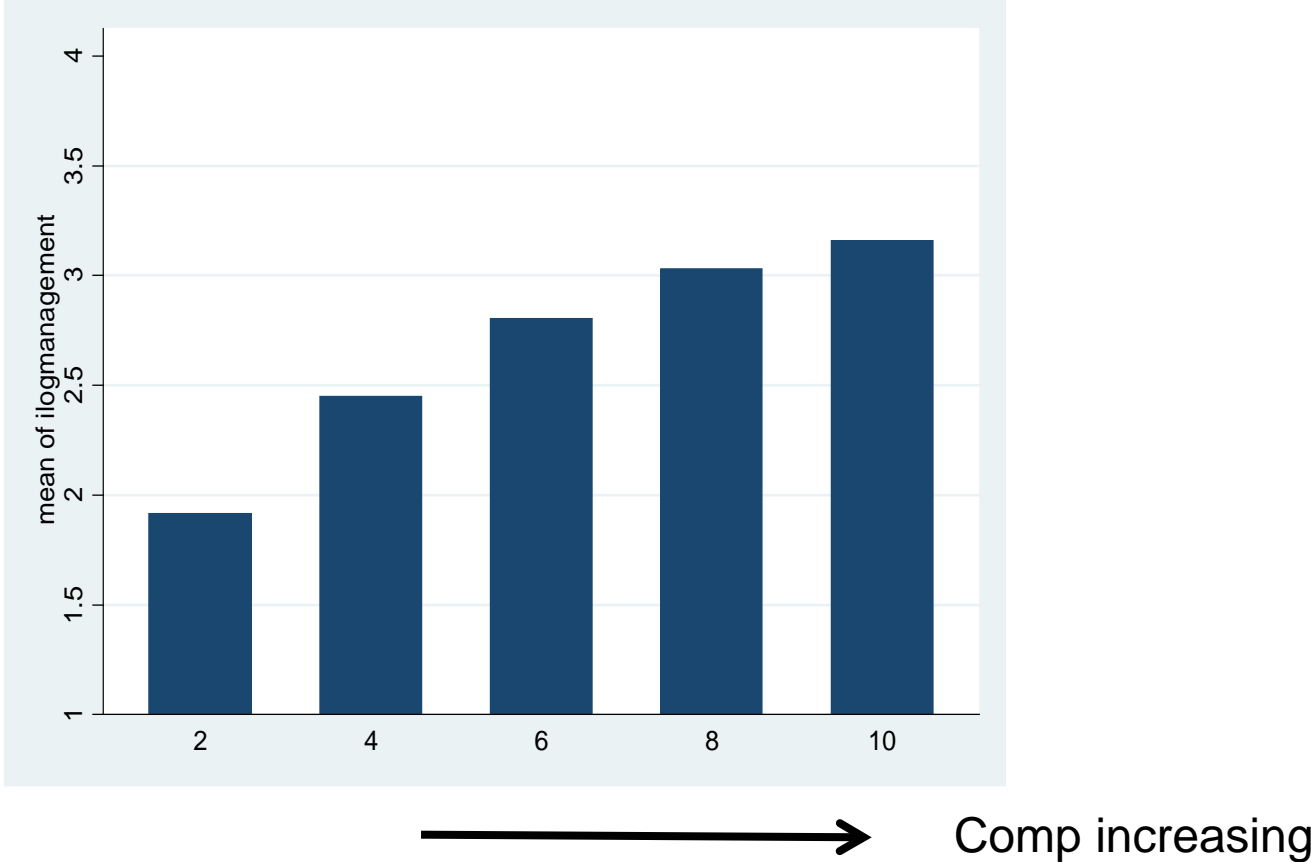
Source: Bloom and Van Reenen (2007)

Figure 1: Performance (Productivity, size, profits) increase in management under MAT



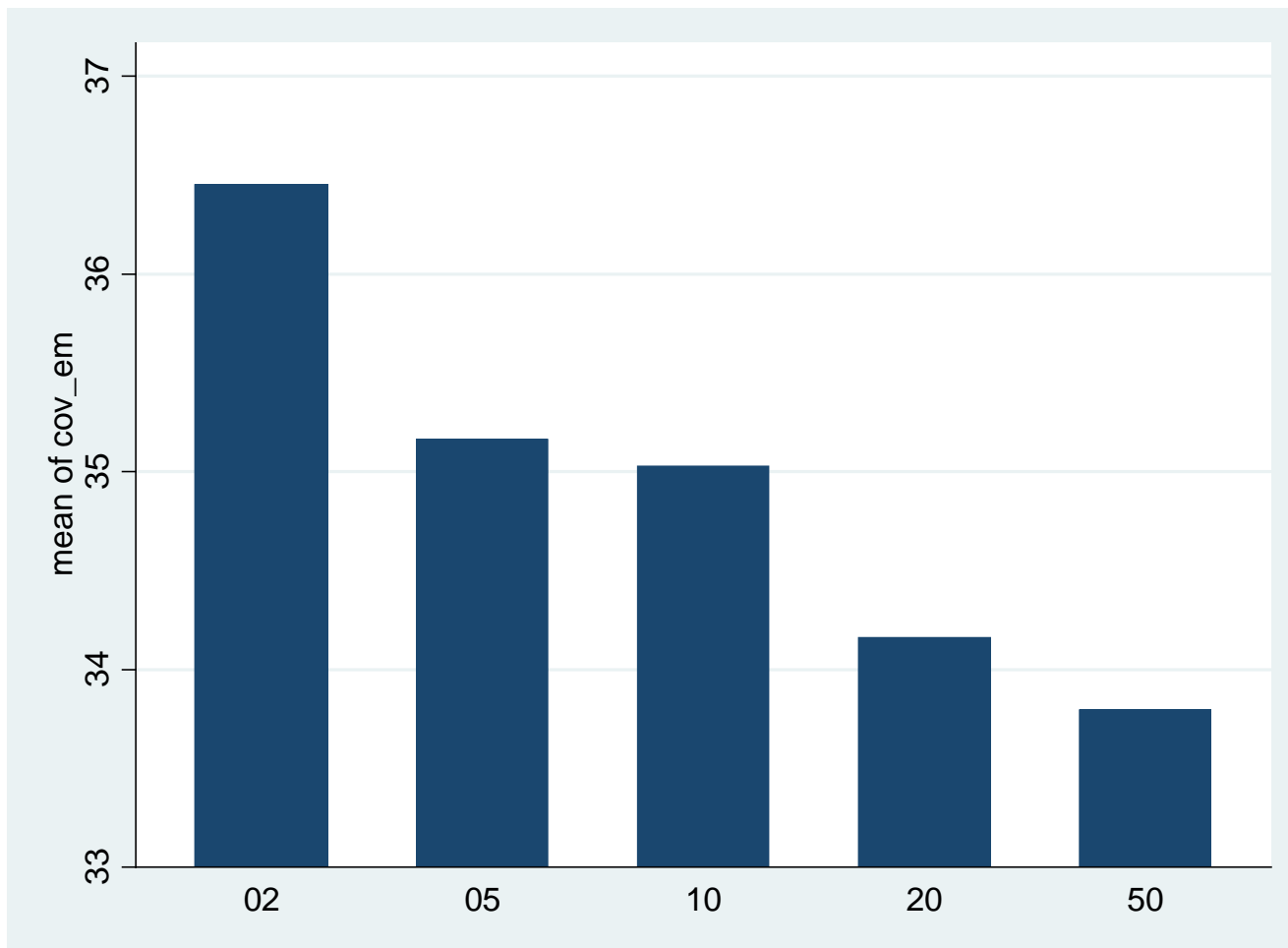
Notes: Results from simulating 2,500 firms per year in the steady state taking the last 5 years of data. Plots log(management) in the simulation data normalized onto a 1 to 5 scale, and log(sales/capital) normalized onto a 0 to 1 scale. Lowess plots shown with Stata defaults (bandwidth of 0.8 and tricube weighting).

Figure 2: Management increases with competition (demand elasticity on x-axis)



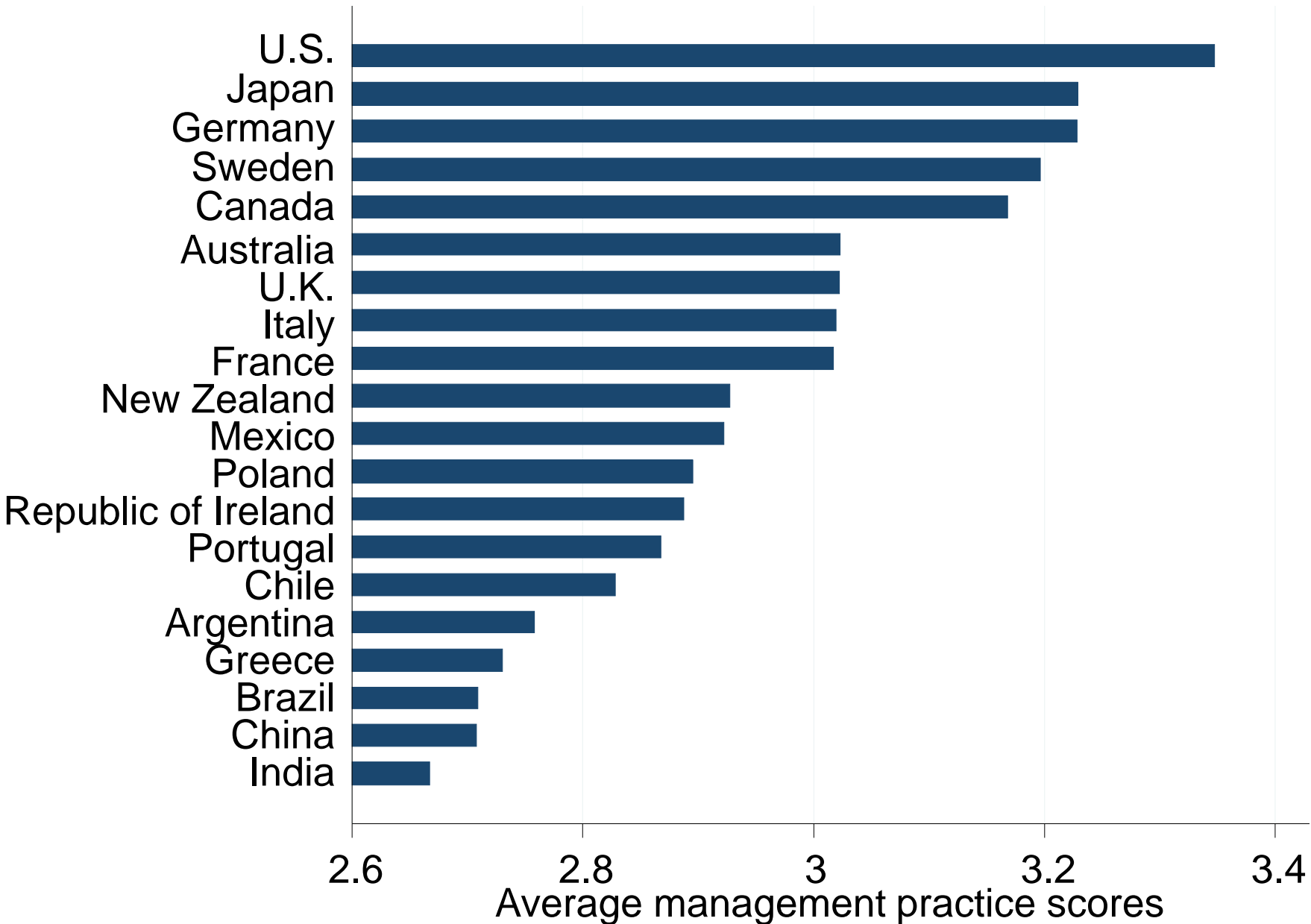
Notes: Results from simulating 2,500 firms per year in the steady state taking the last 5 years of data. Plots log(management) in the simulation data normalized onto a 1 to 5 scale, and log(sales) normalized onto a 0 to 1 scale. Lowess plots shown with Stata defaults (bandwidth of 0.8 and tricube weighting).

Figure 3: Covariance between management & firm size is lower in more distorted economies



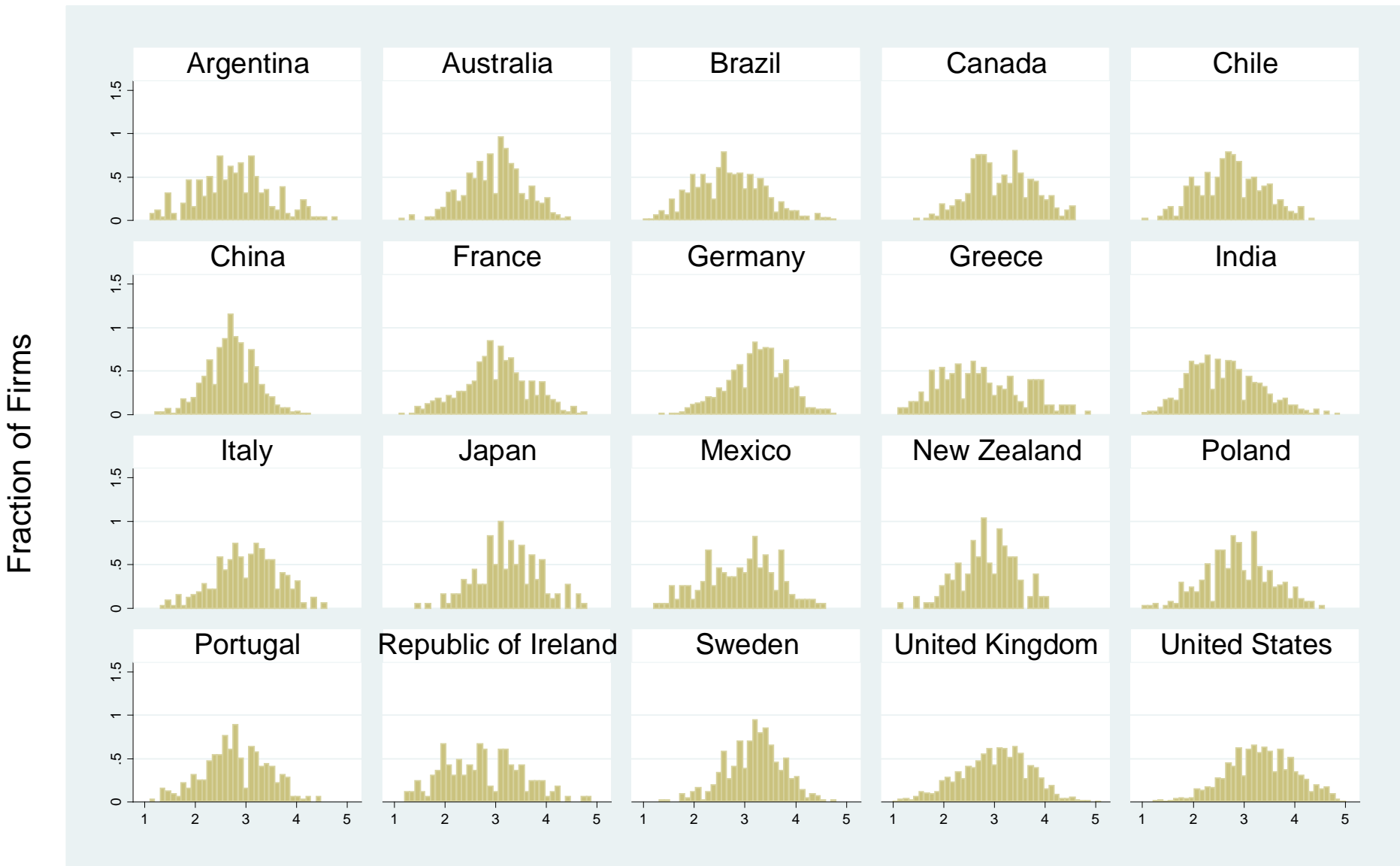
Notes: Plots $\log(\text{management})$ scores weighted by firm sales. Results from simulating 2,500 firms per year in the steady state taking the last 5 years of data for each level of (upper bound) of the distortion distribution (from 2% to 50%, baseline case is 10%). $\ln(\text{management})$ in the simulation data is normalized onto a 1 to 5 scale.

Figure 4. Management Practice Scores by Country



Note: Averages taken across all firms within each country.

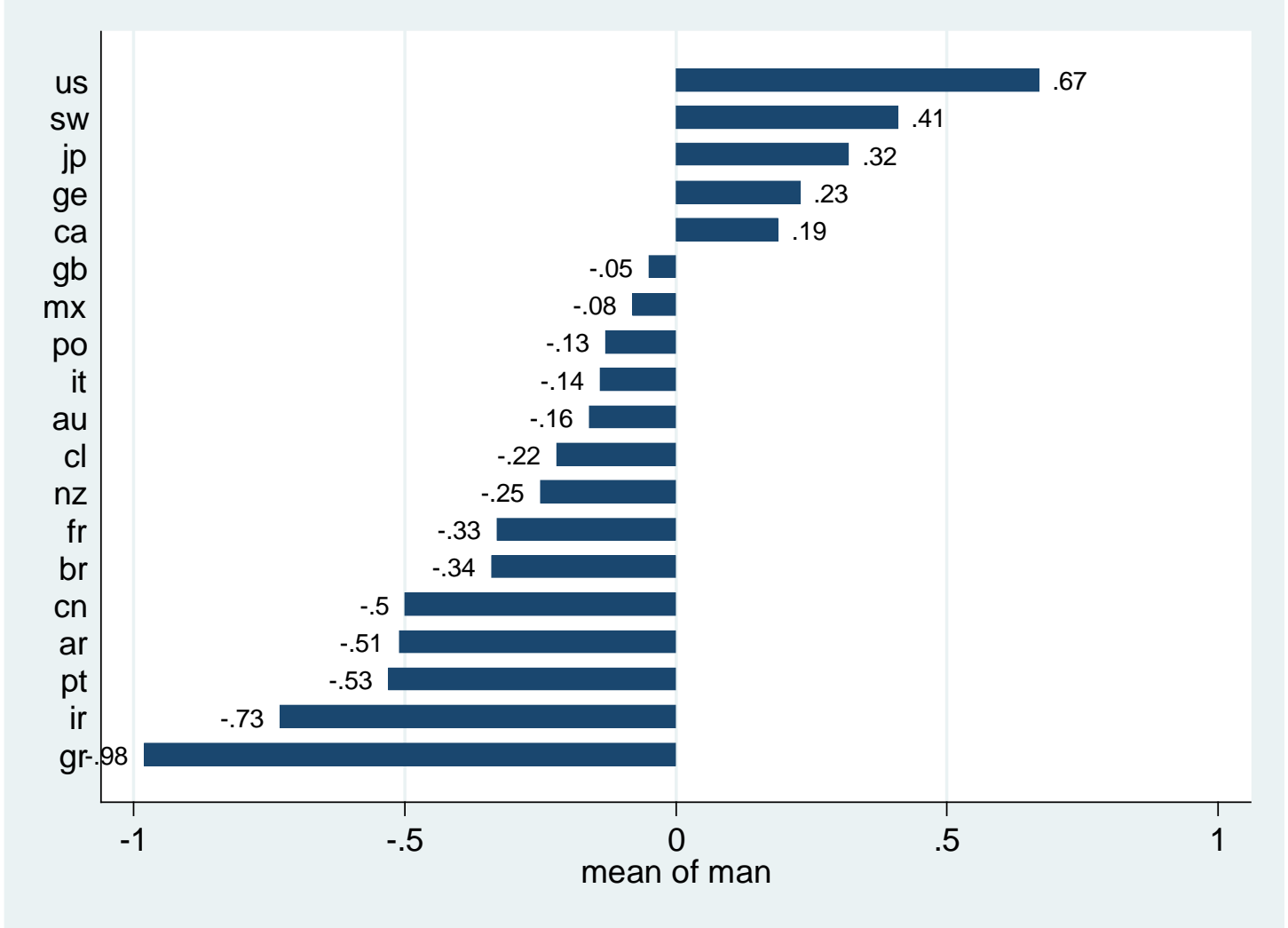
Figure 5: Management Practice Scores Across Firms



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

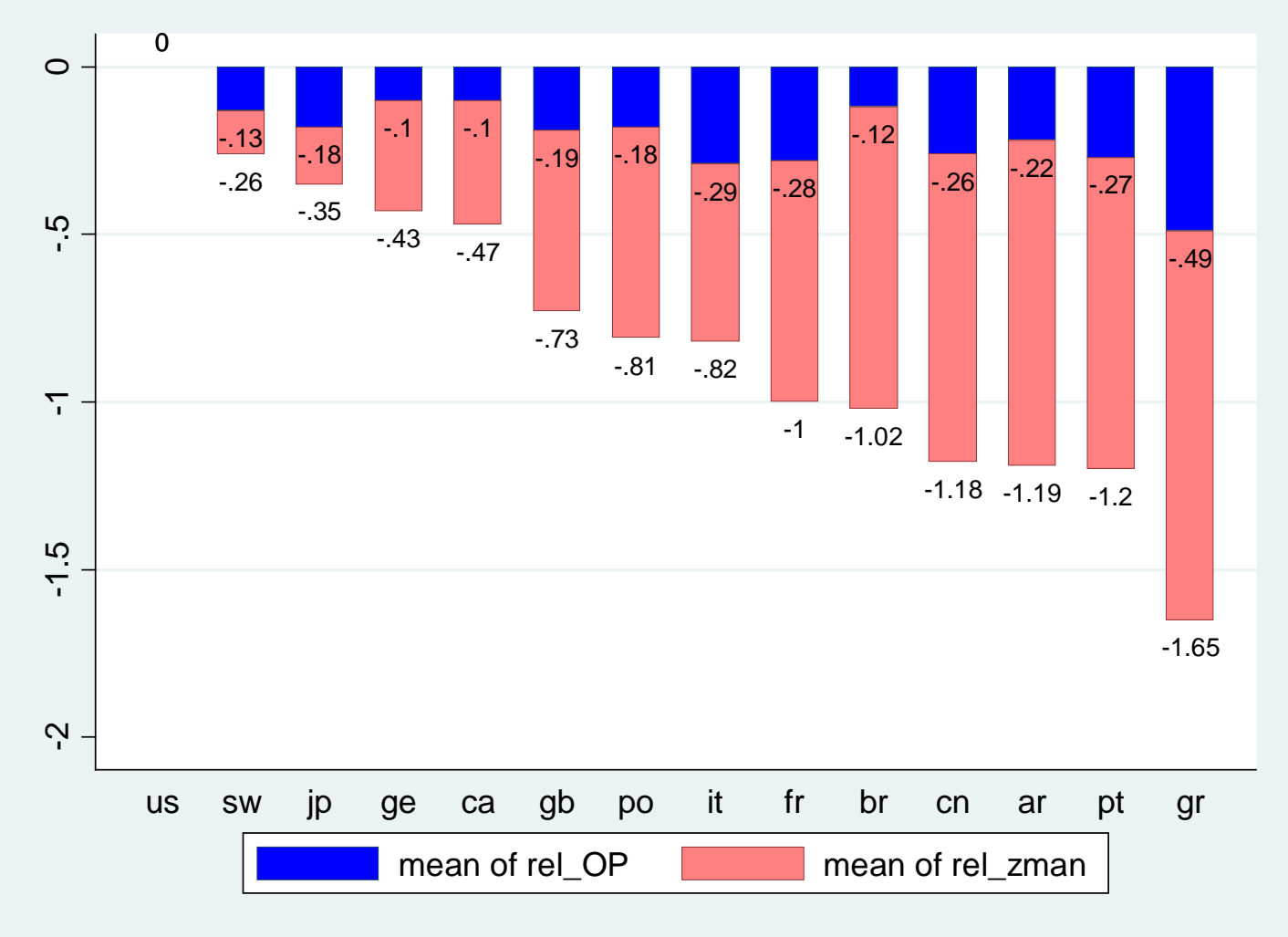
Note: Bars are the histogram of the actual density.

Figure 6: Management Scores Across Countries (weighted by employment shares)



Notes: Firm scores are weighted by share of employment in the country. 2006 wave. Scores are corrected for response biases.

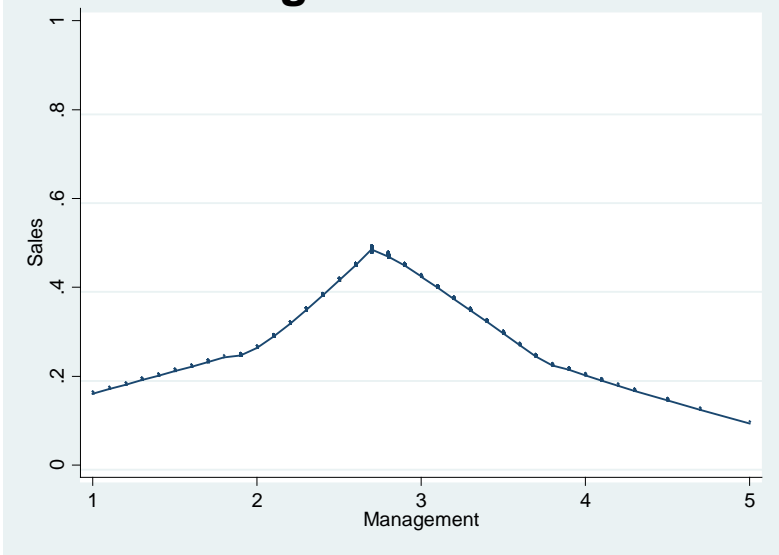
Figure 7: Management Scores and Reallocation across countries relative to the US level



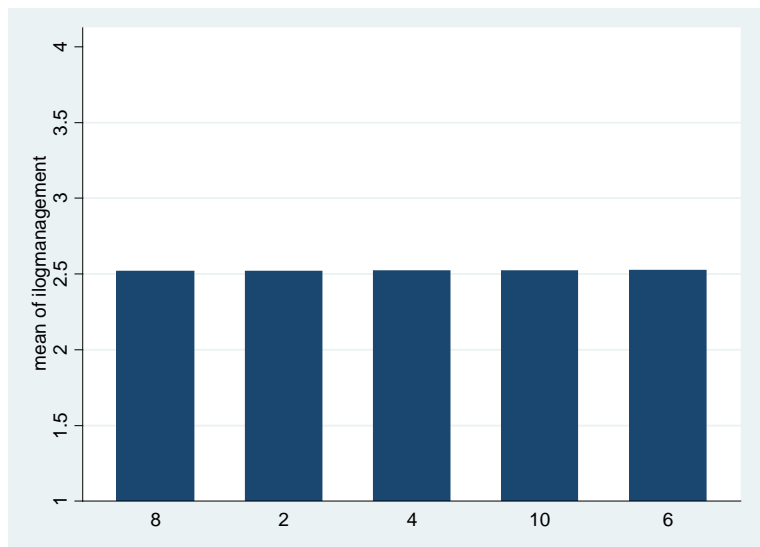
Notes: These are the share-weighted management score differences relative to the US (sd=1). Length of bar shows total deficit which is composed of (i) the unweighted average management scores ("rel_zman", light red bar) and reallocation effect ("rel_OP" blue bar). Domestic firms, scores corrected for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

Figure A1: Management as Design

Panel A: Management & Performance

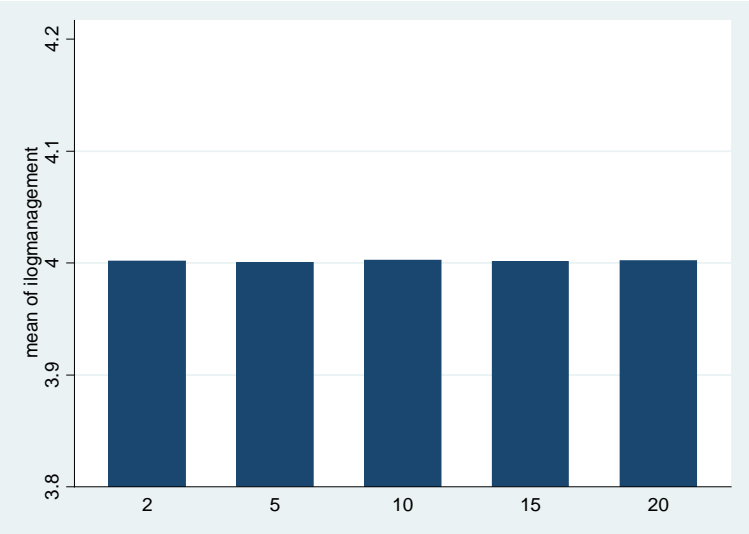


Panel B: Management & Competition



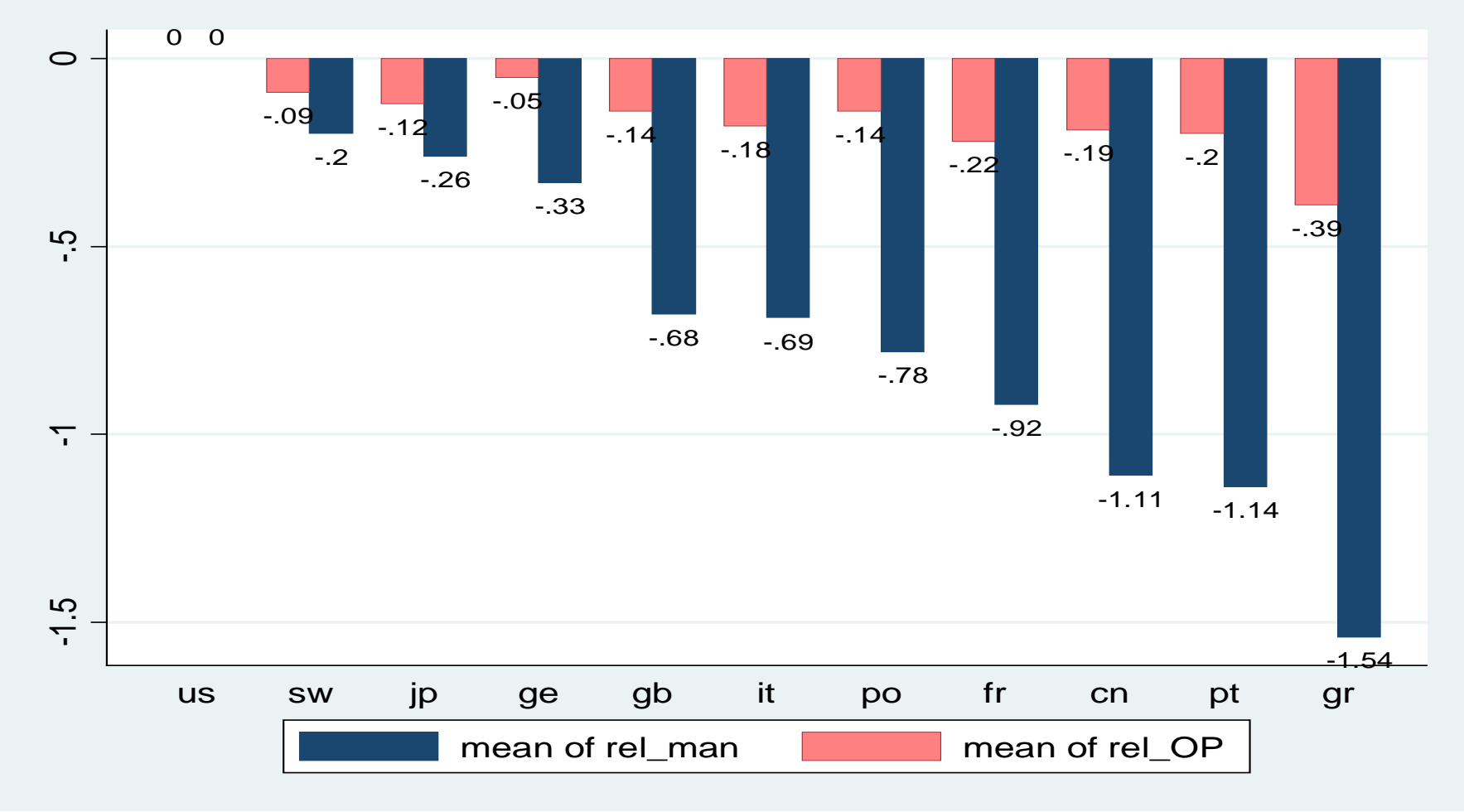
→ Comp increasing

Panel C: Management & Distortions



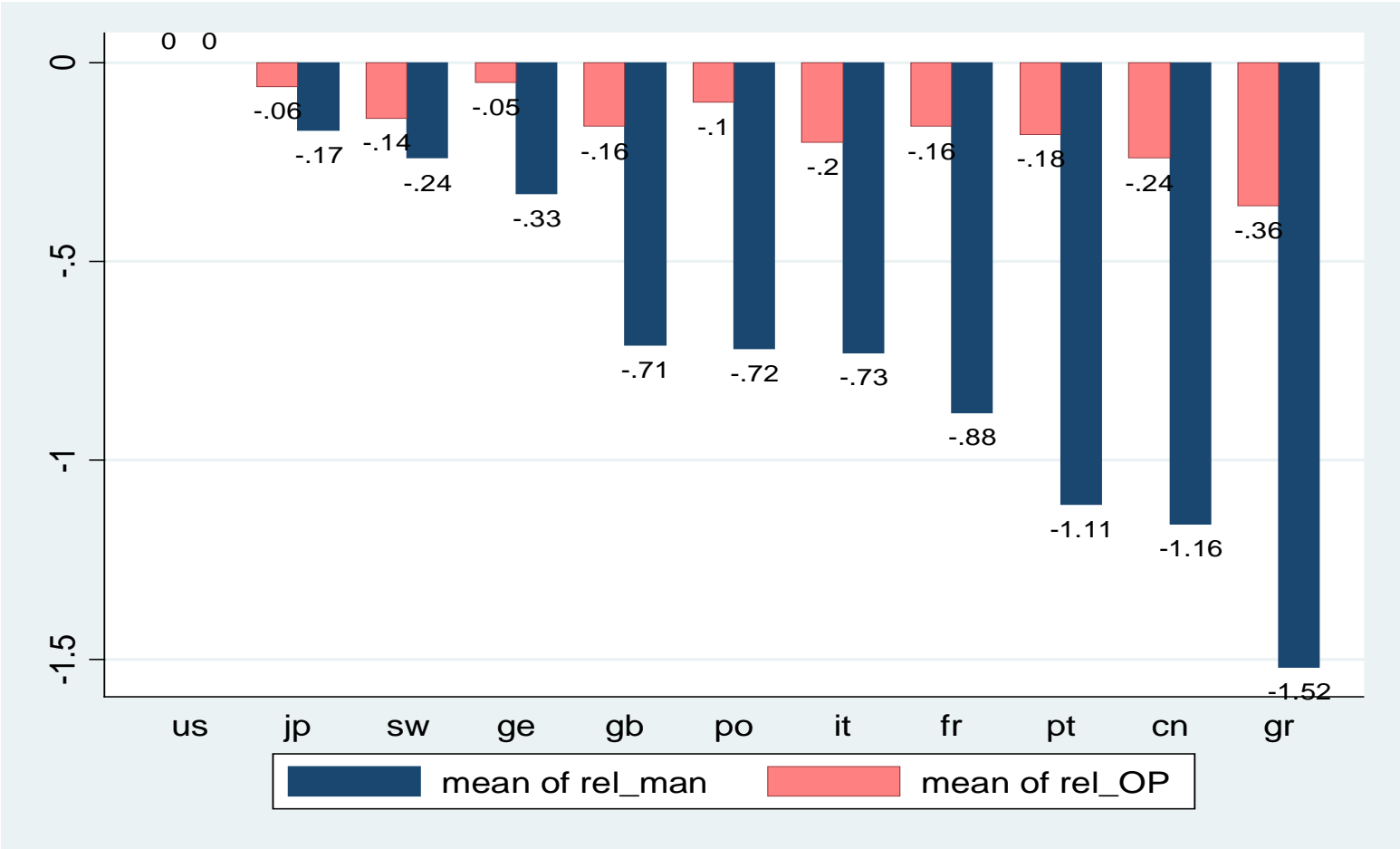
Notes: Results from simulating 2,500 firms per year in the steady state taking the last 5 years of data. Plots $\ln(\text{management})$ in the simulation data normalized onto a 1 to 5 scale, and $\log(\text{sales})$ normalized onto a 0 to 1 scale. Lowess plots shown with Stata defaults (bandwidth of 0.8 & tricube weighting). Production function is $Y=AK^\alpha L^\beta / (1+|M-M^*|)$

Figure B1: Relative Management (weighted by employment shares; only emp in selection equation)



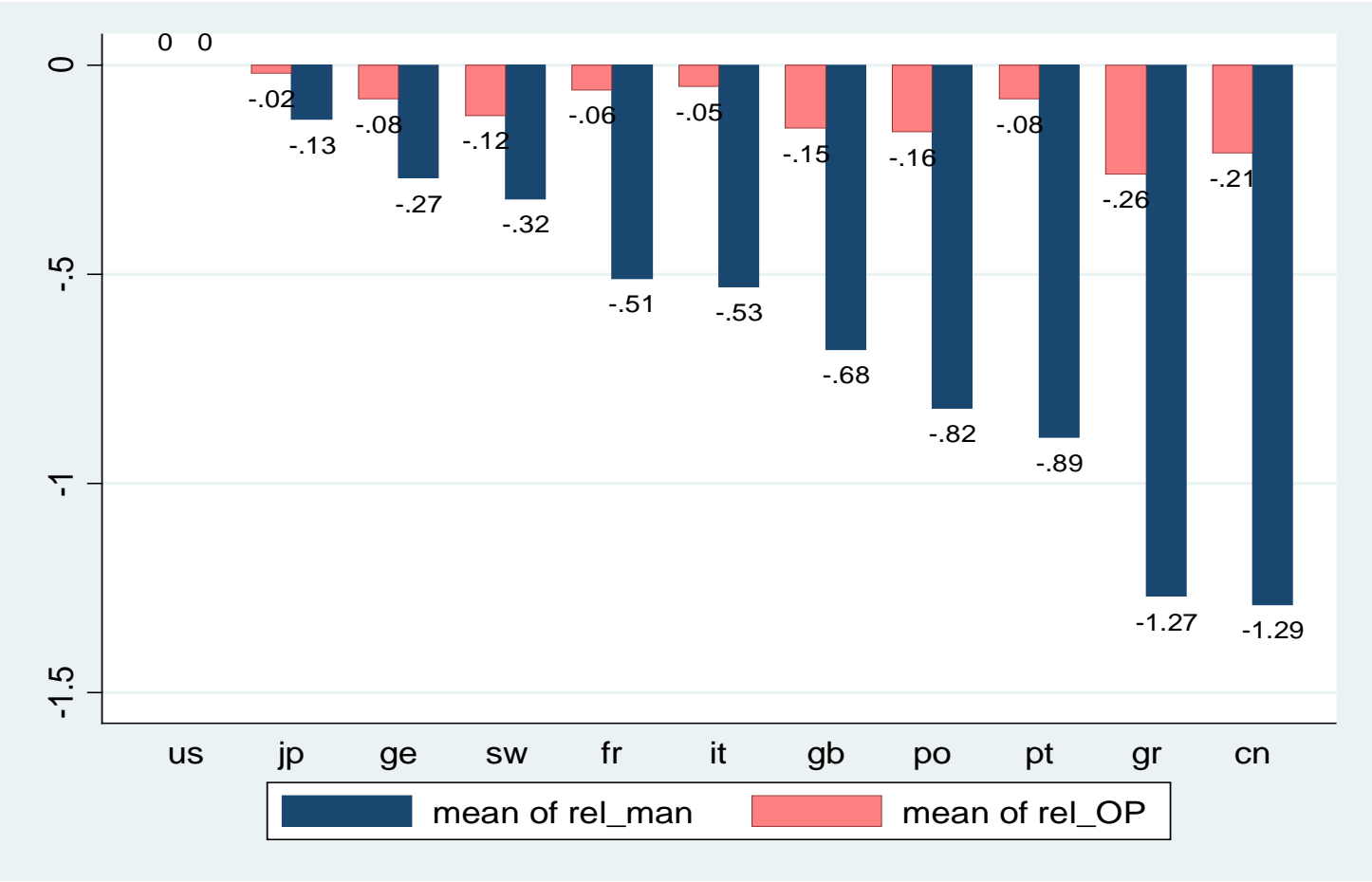
Notes: These are the differences relative to the US of (i) the weighted average management scores (sd=1, blue bar) and (ii) reallocation effect (OP, light red bar). Domestic firms, . 2006 wave. Response bias corrections use country-specific employment only

Figure B2: Relative Management (weighted by labor and capital inputs)



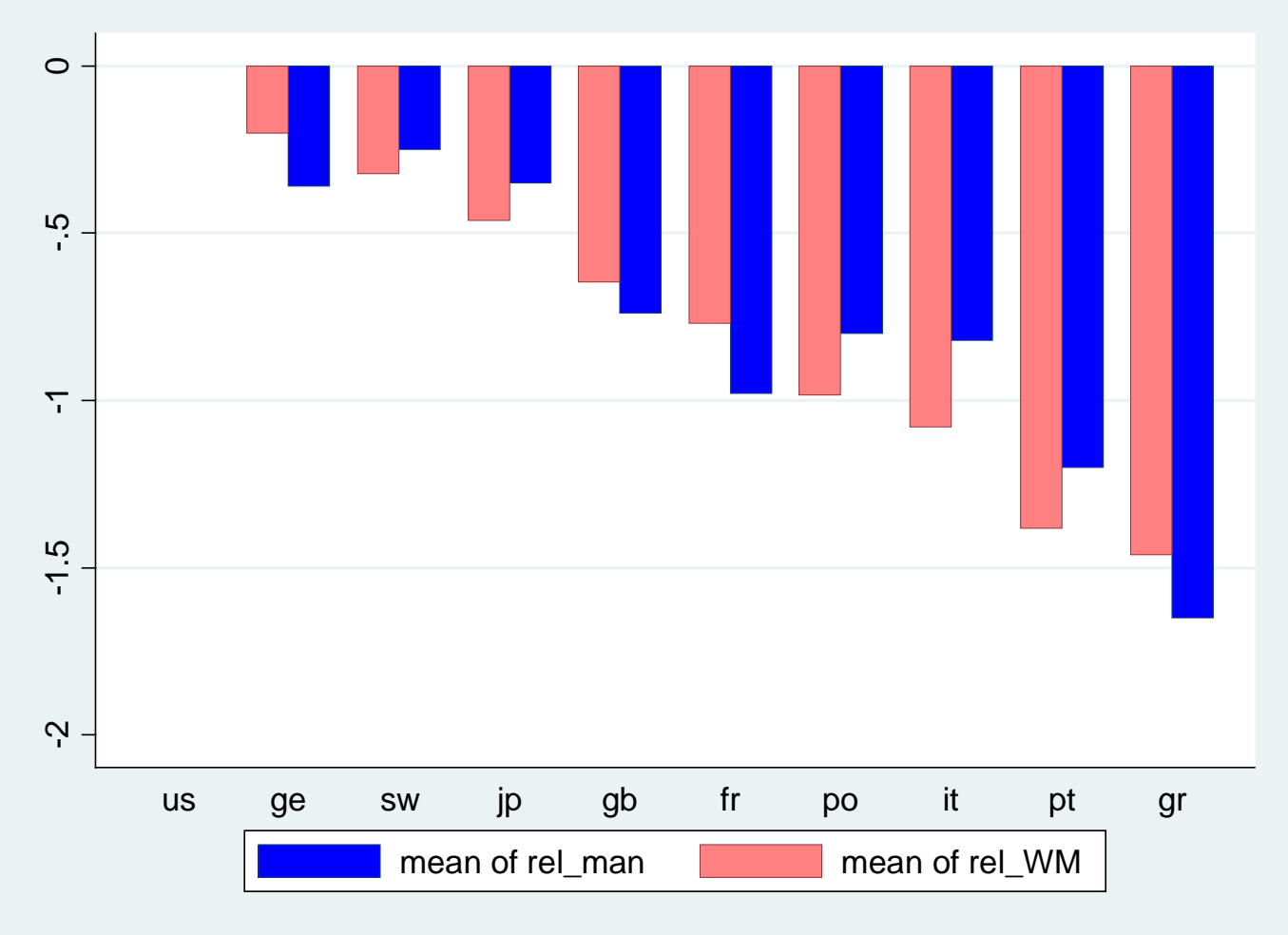
Notes: These are the differences relative to the US of (i) the weighted average management scores (sd=1, blue bar) and (ii) reallocation effect (OP, light red bar). Domestic firms, . 2006 wave. Response bias corrections use country-specific employment only

Figure B3: Relative Management (weighted by employment shares; multinationals included)



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

Figure B4: Relative Management scores. Correcting for missing very small and very large firms.



Notes: These are the differences relative to the US of the weighted average management scores. Response bias corrections. Blue bar is baseline results and red bar corrects for missing firms with under 50 or over 5000 employees. The correlation between the two bars is 0.95.