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Management and firm dynamism

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Abstract

We show better-managed firms are more dynamic in plant acquisitions, disposals, openings and closings in U.S. Census and international data. Better-managed firms also birth better-managed plants and improve the performance of the plants they acquire. To explain these findings. We build a model with two key elements. First, management is a combination of firm-level management ability (e.g. CEO quality), which can be transferred to all plants, and plant-level management practices, which can be changed through in tangible investment (e.g. consulting or training). Second, management both raises productivity and also reduces the operational costs of dynamism: buying, selling, opening and closing plants. We structurally estimate the model on Census microdata, fitting our key dynamic moments, and then use it to establish three additional results. First, mergers and acquisitions raise economy-wide management and productivity by reallocating plants to firms with higher management ability. Banning M&A would depress GDP and management by about 15%. Second, greater product market competition improves both management and productivity by reallocating away from badly managed plants. Finally, management practices account for about a fifth of the cross-country productivity differences with the US.

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

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1 Introduction

The existing literature has shown the important role that management plays in driving productivity in firms, using both cross-sectional and panel data.[1] Relatively little is known, however, about the mechanism through which management affects within-firm changes in productivity. In this paper, we focus on a specific aspect of this question, i.e., whether and how management affects firm dynamism around entry, exit, acquisitions, and divestitures. Exploring this mechanism is important because such reallocation has been identified as a key margin of productivity growth.[2]

To investigate whether and how management influences within-firm reallocation we draw on two databases. First, we examine the U.S. Census Bureau Management and Organizational Practices Survey (MOPS), which has management data for approximately 60,000 US plants in 2010, 2015, and 2021. Importantly, this plant-level management data can be matched to firm ownership information in the Longitudinal Business Database (LBD), which allows us to examine plant-level acquisitions and disposals alongside plant-level openings and closings. Second, we examine the World Management Survey (WMS), providing original survey data on management practices for over 11,000 firms in 34 countries. Besides its rich cross-sectional nature, both in terms of countries and industries covered, this dataset also features a significant panel component built through six different survey waves from 2004 to 2021.

We start by analyzing the U.S. Census micro-data to examine the relationship between management and different margins of firm expansion and contraction. We document four key facts. First, better-managed firms more frequently purchase and open new plants. Second, better-managed firms also more frequently sell and close existing plants. Since the relationship of management with expansion is stronger than the relationship of management with contraction, well-managed firms on net expand more than poorly-managed firms through plant purchases and openings. Third, better-managed firms set up plants with better management practices at birth. Finally, better-managed firms improve the performance of plants they acquire, significantly increasing their management, productivity, and sales.[3]

We use these stylized facts to build a model in which some forms of management act like a "technology," in the sense that they raise productivity and can be shared across plants within a firm. The model has two key features. First, management practices are a combination of a firm-level component, which we label *central management ability*, plus a plant-level component, which we label local *management practices*. Firm-level central management ability is common to all plants within the same firm, much like a good or bad CEO, and follows an exogenous random process that slowly evolves over time as, for example, senior executives come and go. In contrast, plant-level management practices are endogenous and, like physical capital, can be improved by plant-level investment

[1] Examples include Bertrand and Schoar (2003), Bloom and Van Reenen (2007), Bruhn et al. (2018), Friebel et al. (2017), Gosnell et al. (2020), Cai and Wang (2022), Iacovone et al. (2022), McKenzie and Anderson (2021), and Adhvaryu et al. (2022).

[2] Foster et al. (2008), Hsieh and Klenow (2009), and Bartelsman et al. (2013).

[3] The evidence for this fourth fact is corroborated by similar findings in the WMS data.

in activities like training and consulting. Second, firms can buy, sell, open, and close plants. However, these dynamic activities are subject to transaction costs. Importantly, these transaction costs are lower for firms with better central management ability. This is a reduced form way of reflecting that good top managers are more effective at dealing with these organizational changes.

We estimate the key parameters of the model by Simulated Method of Moments using the Census microdata, and find evidence consistent with all the results we see in the empirical data. First, well-managed firms have a lower cost of plant entry and acquisition, so they are more active on the expansion margin. Second, well-managed firms have a lower cost of plant exit and disposal, so they are more active on the contraction margin. Since well-managed firms are overall more profitable, the expansion margin response to management is stronger, so they are also on net expansionary. Third, better-managed firms birth better-managed plants because of the common central management effect. Finally, when a well-managed firm takes over a new plant, its management practices, productivity, and sales all rise due to its higher central management quality.[4] Overall, these results suggest that reallocation of management across and within firms is a key channel through which management affects productivity.

We then use this model to run two counterfactuals on key policies that influence economy-wide management and productivity. First, we investigate the impact of banning M&A activity. This reduces the reallocation of plants towards firms with high central management ability, reducing both management and GDP by abut 15%, highlighting the costs of constraining M&A. Second, we reduce product market competition by making consumers less sensitive to prices. This reduces overall output by 10% through slowing the closure of poorly-managed units and the expansion of well-managed units, highlighting the importance of competition for driving reallocation.

In the final part of our analysis, we leverage firm-level international data on management practices to evaluate the extent to which differences in the strength of reallocation towards better-managed firms may help account for differences in management and productivity between the US and other countries.[5] To do so, we compute size-weighted, country-level management gaps, which we then decompose into a reallocation gap (differences in size-management covariance, a proxy for the strength of reallocation towards better-managed firms) and an absolute gap (differences in unweighted management scores across firms). We find that differences in the strength of reallocation account for 25% of differences in management between the US and other countries, and that this gap is especially relevant in the comparison with other high-income countries. This, combined with the estimate that variations in management practices account for about 19% of cross-country TFP differences, highlights the critical role management and reallocation play in accounting for international differences in productivity and, ultimately, the wealth of nations.

In summary, this paper makes four major contributions over the existing literature. First, we show new facts on the relationship between management and the extensive margins of firm growth

[4]This channel provides a potential explanation for improvements in efficiency when ownership changes, demonstrated by, e.g., Demirer and Karaduman (2024).

[5]We are unfortunately unable to access similar plant-level data outside of the US.

through entry, exit, acquisitions, and disposals. Management practices appear to play a crucial role in the dynamism of firms. Second, we develop and structurally estimate a model in which management ability and management practices both feature in the production function, at both the firm and plant level. This tries to combine the often disparate leadership and management literature into one overall framework. Third, we use this model to run quantitative policy evaluations on mergers and acquisitions and competition policy. Finally, we determine the extent to which reallocation to better-managed firms can account for variations in productivity across firms and countries.

Our paper relates to several literatures. First, there is a large body of empirical literature on the importance of management for variations in firm and national productivity, from Walker (1887) to more recent papers including Bertrand and Schoar (2003), Bloom and Van Reenen (2007), Friebel et al. (2017), Bruhn et al. (2018), Gosnell et al. (2020), Hoffman and Tadelis (2021), Sandvik et al. (2020), McKenzie and Anderson (2021), Iacovone et al. (2021), Bai et al. (2022), and Adhvaryu et al. (2022).[6] From a theoretical perspective, the paper is related to Dessein and Prat (2022), who present a model in which CEOs' ability to build organizational capital maps into persistent performance differentials across firms. Similar to our setting, they model CEOs as key inputs for the accumulation of organizational capital, an intangible, slow-moving variable that encompasses management practices, differs across firms, and determines firm productivity. While extremely appealing, the Dessein and Prat (2022) model would not be compatible with the plant level optimization approach we leverage in our estimations to study the relationship between management and M&A activity.

Second, there is a growing macro literature on aggregate implications of firm management and organizational structure, ranging from Lucas (1978), to Gennaioli et al. (2013), Garicano and Rossi-Hansberg (2015), Guner et al. (2018), Akcigit et al. (2021), and Pastorino (2024). Third, there is a long literature on the causes of the slow diffusion of new technologies (of which one might be management practices) and the implications for productivity differences (Griliches, 1957; Gancia et al., 2013). Finally, there is another growing literature focusing on explaining cross-country TFP in terms of the degree of reallocation of inputs to more productive firms, most notably Hsieh and Klenow (2009) and Restuccia and Rogerson (2008).

The structure of the paper is as follows. In Section 2 we introduce the data, and in Section 3, we describe our key stylized facts from the Census data on entry, exit, and M&A. In Section 4, we set up a model of management to explain these results, and in Section 5 estimate the model against the data. Section 6 performs some counterfactual calculations and policy simulations, with Section 7 offering some concluding comments. Online Appendices include more information on data (A) and on methods (B).

[6] In more recent work, **?** leverage rich Glassdoor data and machine learning techniques to build empirical estimates of organizational capital at the firm-year level and study its evolution over time and relationship with performance.

2 Data

This section sketches the two main datasets we use, with more information in Appendix A.

U.S. Census Data: For the analysis of the relationship between management and firm expansion, we leverage the U.S. Census Bureau Management and Organizational Practice Survey (MOPS). The MOPS evaluates structured management practices using 16 questions. The first eight questions score plants on their use of monitoring and operations. Plants with high scores report detailed, frequent, and ongoing monitoring of their production process. The second eight questions evaluate plants on HR practices. Plants with high scores report strong performance-related rewards, including monetary rewards and promotions for high performers and retraining and corrective measures for low performers. The MOPS was run in 2010, 2015 and 2021, with each wave collecting management data on approximately 32,000 U.S. manufacturing plants.

We merge the MOPS database with the Census Longitudinal Business Database (LBD) and the Annual Survey of Manufacturers (ASM). The LBD linkage enables us to identify plant entry and exit as well as changes in plant ownership. Entry and exit are relatively simple to identify: we define the entry year as the first year a plant appears in the LBD (which occurs in the first year the plant has at least one paid employee). The exit year is the first year a plant disappears from the LBD.[7] Changes in plant ownership are defined by changes in the LBD firm identifier for a plant. We identify an acquisition year as a year in which an existing plant has a new firm identifier recorded.

International Data: We use the World Management Survey (WMS) to establish basic stylized facts on the relevance of management for firm and country-level productivity and the transferability of management practices with ownership change. The WMS uses an interview-based evaluation tool that defines 18 basic management practices and scores them from one ("worst practice") to five ("best practice") on a scoring grid.[8] This evaluation tool was first developed by an international consulting firm and scores these practices in three broad areas.[9] The first practice area is *Monitoring*: how well do companies track what goes on inside their firms, and use this for continuous improvement? The second practice area is *Target setting*: do companies set the right targets, track outcomes, and take appropriate action if the findings are inconsistent? The third practice area is *People management*:[10] are companies promoting and rewarding employees based on performance, and systematically trying to hire and retain their best employees? The data are obtained from firms

[7] At the firm level, we define a plant entry as an event in which a new plant appears in the LBD under the firm identifier of the focal firm in the focal year. Similarly, we define a plant exit as an event in which an existing plant under the firm identifier of the focal firm disappears from the LBD in the focal year.

[8] More details can be found at http://worldmanagementsurvey.org/.

[9] Bertrand and Schoar (2003) focus on the characteristics and style of the CEO and CFO, and more specifically on differences in strategic management (e.g. decision making applied to mergers and acquisitions), while Lazear et al. (2015) focus on individual supervisors. The type of practices we analyze in this paper are closer to operational and human resource practices, which have a long precedent in the management and strategy literature–for example, Osterman (1994), Huselid (1995) and Capelli and Neumark (2001).

[10] These practices are similar to those emphasized in earlier work on management practices, by for example Ichniowski et al. (1997) and Hoffman and Tadelis (2021).

using telephone interviews of plant managers with a double-blind technique. The WMS has been collected in six major survey waves from 2004 to 2021 across 38 countries, with wide cross- and within-country variation in management scores, aligning with the similar results on productivity spreads (e.g. Hsieh and Klenow (2009) and Syverson (2011)). These management scores also show a very high correlation with firm performance, including growth, productivity, and survival.

3 Management, Productivity and Dynamism: Stylized Facts

3.1 Management and Plant Entry and Exit

Figure 1, Panel A plots the rate of plant entry per firm over a five-year period against the average firm management score in the baseline year. This includes only new entrant plants at the parent firm and excludes plants that are acquired from other firms (we look at this margin in Figure 2).[11] We calculate the management score of a MOPS firm in year t by averaging the management score of all the plants it owns for which we have a management score. We then follow the plants that are born from this parent firm in the subsequent five years through $t + 5$. Because we need only the LBD to detect new entrants, we can examine entry over two waves of MOPS: entry between 2010 and 2015 as a function of 2010 firm management, and entry between 2015 and 2019 as a function of 2015 firm management.[12] We express entry rates as a proportion of the number of plants owned by the firm in the base period. The y-axis shows that unsurprisingly, there are relatively few new plants born (this is manufacturing, which is a declining sector): most entry rates are between 1% and 4%. Notably, however, there is a significant positive correlation between the average baseline firm management score and the plant entry rate.

Panel B of Figure 1 is symmetric to Panel A, but examines plant exit. This includes only total exits from the economy and excludes plants that are acquired by other firms (see below for this). In addition to creating more plants, well-managed firms also *exit* a disproportionately larger share of their plants.[13]

Taken together, Panels A and B of Figure 1 show that firms with higher management scores have a higher rate of plant churn. This parallels the findings regarding Private Equity (PE) takeovers in Davis et al. (2014), showing that PE owners tend to be involved in higher rates of plant churn. For both entry and exit, results look similar when we weight plants by their employment.

[11] Obviously, this only includes firms that are alive in the baseline period, so excludes de novo entrant firms as we cannot construct an initial management score for these firms. From the U.S. Census Business Dynamics Statistics data, which is publicly available, we calculate that in the manufacturing sector from 2010 to 2019 (matching our sample), 67.5% of new entrant plants are part of new entrant (age 0) firms, but these new-firm entrant plants represent only 45.5% of job creation at new entrant plants and 9.29% of overall job creation.

[12] At the time of analysis the 2020 LBD and 2021 MOPS were not yet available.

[13] This might seem surprising, as prior work shows that well-managed plants are less likely to exit (Bloom et al., 2019, e.g.). However, all panels in Figure 1 condition on surviving firms over the five-year period. If instead we include in Panel B firms that fully exited (exit rate = 1 for such firms–all their plants leave the economy), then we see that plants in well-managed firms are less likely to exit.

In Panel C of Figure 1, we examine net entry. We find that the gross entry effect (Panel A) outweighs the gross exit effect (Panel B). That is, net entry (the number of entering plants minus exiting plants from the same firm) is higher for firms with a higher management score.

In Panels A and B of Figure 2 we perform the same analysis, but on the rates of plant acquisition and disposal. Overall, we see surprisingly consistent patterns. Panel A shows that firms with higher management scores acquire proportionately more plants. Panel B shows that they also dispose of a greater proportion of plants. Even though well-managed firms are more active on both sides of the M&A market, the acquisition effect outweighs the disposal effect: Panel C shows that the net acquisition rate (the number of acquired plants minus the number of disposed plants as a fraction of the initial number of plants) is greater for well-managed firms. These results also look similar when we weight by employment.

In summary, Figures 1 and 2 establish a novel stylized fact: firms with more structured management have greater dynamism. They both birth and destroy more plants and acquire and dispose of more plants on the secondary M&A market.[14]

3.2 Transferring management practices across plants within firms

Earlier analysis of MOPS has shown that, although there is a wide dispersion of management practices within firms across plants, there is still a strong "firm effect." Case study work typically ascribes this to the (partially) non-rival nature of management within a firm, for example the impact of firm-level CEOs on management practices. To examine this idea in MOPS, we explore two margins of management non-rivalry. First, do well-managed firms birth new plants with higher management scores? Second, when a well-managed firm takes over a plant from a poorly managed firm, does the plant's management proportionately improve?

Well-managed firms give birth to better-managed plants Figure 3 examines the management scores of plants "born" to firms of different management scores in MOPS. We follow plants that are born between 2010 and 2015 to a parent firm that had at least one plant in the MOPS in 2010. We then examine the 2015 management scores of these newborn plants. We see that plants born to firms with higher management scores are more likely to have better management practices themselves. For Census disclosure reasons we are only allowed to display five points, but in a finer detail bin-scatter (available in the Census), the results are similar. We show in Table 1 that these results are significant and that the relationship between parent firm and new entrant plant management changes little when controlling for the plant's state and industry, as well as the parent firm's employment.

Well-managed firms increase the management score in plants they acquire To test the hypothesis of transfer of management practices from acquirer to target, we analyze how management

[14] The latter evidence on management and acquisitions is consistent with Bai et al. (2022).

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

$$M_{e,j,t} - M_{e,j,t-5} = \beta(M_{j,t-5} - M_{i,t-5}) + \upsilon_{it}. \tag{1}$$

The dependent variable in equation (1) is the change in an acquired plant e's management score over the five-year period 2010-15. The independent variable is the average management score in the acquiring firm j compared to the target firm i. Note that we use the lagged value of firm i's management to avoid conflating the current plant's score with that of the acquiring firm. Our hypothesis is that $\beta > 0$ if the acquiring firms management practices are transferred to the target plant.

Table 2 presents these regression results from the MOPS data. In column (1), we find that, consistent with our hypothesis, $\hat{\beta} > 0$. The coefficients imply that moving from a firm with a management score of zero to a firm with a management score of one is associated with a 0.31 increase in the plant's management score. This effect is statistically significant. Because the firm management score ($M_{i,t-5}$) is constructed partially from the management score of the target plant itself, column (2) constructs the seller firm management scores excluding the target plant's management score, showing that the results are robust. Including four-digit NAICS dummies (Column 3), state dummies (column 4), and both state and industry dummies (column 5) has little effect on the coefficient. In the final column, we break up the two components of the right-hand side of equation (1), showing that both components take the expected signs.

Well-managed firms increase the performance of the plants that they acquire The MOPS data also show that performance improves faster in plants that move to a relatively better managed firm, that is, when $(M_{j,t-5} - M_{i,t-5})$ is greater. We show this in Table 3 where we regress the change in productivity, measured as log revenue per worker, of acquired plants on the management scores of the adoptive and birth parent firm and the difference between these management scores. In other words, we estimate versions of:

$$PROD_{e,j,t} - PROD_{e,j,t-5} = \alpha(M_{j,t-5} - M_{i,t-5}) + \epsilon_{it}. \tag{2}$$

We find that productivity improves more at plants that are acquired by better-managed firms, especially if the birth parent firm was poorly managed. In columns (1) to (3) we find that the change in revenue per worker is higher when a plant is taken over by a well-managed firm, even after controlling for industry and state fixed effects. In columns (4) to (6), we show a similar result when using the difference between management scores of the acquirer firm and the seller firm as the independent variable. Our most general specifications are in columns (7) to (9) when the two management scores are examined independently and both variables take their expected (opposite) signs.

We also investigate equations analogous to equation (2) in the WMS to see if there are performance improvements after being taken over by better-managed parent firms in international data. We use a sample of subsidiary firms moving between parent groups ("global ultimate owners") for which we have an estimate of the management score of the parent (the average of the management of the subsidiaries). The nature of the WMS means it has a limited panel element for the management score, so we do not observe the change in management for many firms. However, it does have a long time series for accounting data so we can estimate:[15]

$$y_{e,t} = \gamma_1 POST_{e,t} + \gamma_2 (POST_{e,t} * M_j) + \gamma_3 x_{j,t} + \eta_e + \tau_t + u_{e,t} \tag{3}$$

where $y_{e,t}$ is an outcome (such as log revenues), $POST_{e,t}$ is a dummy variable for the years after the target is acquired, $x_{j,t}$ are controls such as the size, country, and industry of the acquiring parent firm, η_e are target fixed effects, τ_t are time dummies, and $u_{e,t}$ is an error term.

We estimate equation (3) in Table 4. In column (1), we use log revenues as the outcome. The positive and significant coefficient on the post-merger dummy indicates that there is an increase in size of the target post-merger. Column (2) interacts the post-merger dummy with the (lagged) management of the acquiring firm, $M_{j,0}$. We find a positive significant interaction, indicating that firms taken over by groups with a one-standard-deviation higher management score have about 14% higher revenue than the average target. Column (3) conditions on log employment so that the outcome can be considered to be labor productivity, with little change to the coefficient of interest on the interaction. Column (4) also includes log capital on the right-hand side of the equation, so the coefficient now reflects associations with TFP, again with little effect to the key post-merge dummy coefficient. Column (5) includes an interaction of the post-merger dummy with parent employment, which is insignificant, indicating that parent management reflects more than simply parent size. Column (6) repeats the specification in column (2) but uses log employment as the outcome. Although targets grow in size post-merger, this effect is smaller in well-managed acquirers. Column (7) repeats this specification, but uses log capital as an outcome. This reveals that post-merger, the better-managed acquirers tend to cut investment at the target firms, so the growth effects do not simply reflect increases in inputs by well-managed acquirers. Rather, the opposite occurs, and acquired firms produce more with lower capital inputs. This highlights how takeovers by well-managed firms are followed by increases in productivity of the target firm.

We generalize equation (3) in an event study form in Figure 4 for revenues, employees, labor productivity and capital (all in log terms). Note first that in all cases, there do not appear to be significant pre-trends. The top left panel shows the revenue effects, implying a significant increase

[15] This is with a slight abuse of notation as e is the WMS target firm (which is almost always a WMS plant, as the survey rarely has multiple survey respondents in a single plant).

in revenue a few years after an acquisition by well-managed firms (relative to poorly-managed). The bottom left panel shows large positive effects on productivity. The two right-side panels show how inputs fall post-merger for well-managed firms. The fall in capital (bottom right) comes relatively quickly, whereas the labor fall (top right) takes a few more years to be economically and statistically significant, which is why it was less powerful in the Table 4 regressions. The bottom line is that establishments that are taken over by better-managed firms increase their output and reduce their inputs, generating a non-trivial effect on productivity that grows over time.

4 A Model of Management

The empirical results in the previous section suggest two stylized facts about management. First, better firm management is associated with a greater degree of dynamism: better-managed firms have higher rates of plant entry, exit, acquisition and disposal. Second, management has a strong firm-level component that is shared among plants in the firm, including in new plants the firm births and existing plants the firm acquires. In this section, we develop a multi-plant firm model of management to match these key stylized facts.

Firms are modeled as owning a collection of plants that sell their output into a monopolistically competitive industry. Beyond this standard set-up, the key novelties in our model are: (A) the cost of plant openings, closings, acquisitions, and disposals depends on firms' management ability; and (B) multi-plant firms have both firm-level central management *ability* and plant-level management *practices*. We sketch our modeling approach here with more details in Appendix A.

4.1 Production and Demand

Plant-level value added is produced as follows:

$$Y = F(\widetilde{A}, L, K, M, C), \tag{4}$$

where $\widetilde{A}$ is an efficiency term, L is labor, K is physical capital, M is *plant*-level local management practices (which we alternatively refer to as *management capital*), and C is *firm*-level central management ability (perhaps due to a better CEO). We denote firms by subscript i, establishments (plants) by e, and time by t. The overall model environment can be thought of as within a single industry. Time subscripts are omitted unless necessary for clarity. We parametrize the production technology of plant e owned by firm i as:

$$Y_{i,e} = \widetilde{A}_{i,e} K_{i,e}^{\alpha} L_{i,e}^{\beta} \widetilde{G}(C_i, M_{i,e}), \tag{5}$$

where $\widetilde{G}(M_{i,e}, C_i)$ is a management function combining firm-level central management ability (C_i) and local management practices ($M_{i,e}$).

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

$$Y = N^{\frac{1}{1-\rho}} \left(\sum_{i=1}^{N} Y_{i,e}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \tag{6}$$

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

$$P_{i,e} = (\frac{Y}{N})^{\frac{1}{\rho}} Y_{i,e}^{\frac{-1}{\rho}} = BY_{i,e}^{-\frac{1}{\rho}}, \tag{7}$$

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

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

where for analytical tractability we define $A_{i,e} = \widetilde{A_{i,e}}^{1-1/\rho}(\frac{Y}{N})^{\frac{1}{\rho}}$, $a = \alpha(1 - 1/\rho)$, $b = \beta(1 - 1/\rho)$, and $G(C_i, M_{i,e}) = \widetilde{G}(C_i, M_{i,e})^{(1-1/\rho)}$. Profits are defined as revenues minus capital, labor, and management costs ($c_K(K), c_L(L)$, and $c_M(M)$), and fixed production costs F:[16]

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

4.2 Managerial and Non-managerial Capital

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

$$P_{i,e}Y_{i,e} = A_{i,e}K_{i,e}^{a}L_{i,e}^{b}(C_i \cdot M_{i,e})^c. \tag{8}$$

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

$$M_{i,e,t} = (1 - \delta_M)M_{i,e,t-1} + I_{i,e,t-1}^{M} \qquad I_{i,e,t}^{M} \geq 0, \tag{9}$$

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

where $I^M_{i,e,t}$ reflects investment in management practices, which has a non-negativity constraint reflecting the fact that managerial capital cannot be sold. On the other hand, we assume that the firm-level central management ability C_i is drawn exogenously and evolves according to a Markov process. Apart from analytical tractability, we choose this to reflect the idea that a firm's founder or entrepreneur leaves a strong imprint on the firm that is hard to endogenously change.[17] Tangible capital accumulation is standard, and allows for capital resale (at a cost which we discuss later).

$$K_{i,e,t} = (1-\delta_K)K_{i,e,t-1} + I^K_{i,e,t-1}. \tag{10}$$

4.3 Adjustment Costs and Dynamics

In general, changing the managerial or physical capital stock will involve adjustment costs. This could reflect, for example, the costs of organizational resistance to new management practices (e.g. Cyert and March (1963), or Atkin et al. (2017)). We assume changing plant-level management practices involves a quadratic adjustment cost:[18]

$$S_M(M_t, M_{t-1}) = \gamma_M M_{t-1}(\frac{M_t - M_{t-1}}{M_{t-1}} + \delta_M)^2, \tag{11}$$

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

$$S_K(K_t, K_{t-1}) = \gamma_K K_{t-1}(\frac{K_t - K_{t-1}}{K_{t-1}} + \delta_K)^2 - I^K_t(1 - \phi_K \Im(I^K_t < 0)), \tag{12}$$

where ϕ_K is the resale loss on capital and $\Im(I^K_t < 0)$ is an indicator function for disinvestment.

In addition to adjustment costs in capital and management, we impose that firms pay a cost to enter, exit, acquire, or dispose of a plant, which depends on firm management C. We denote this cost function $D^g(C)$, where $g \in \{\text{enter, acquire, exit, dispose}\}$. In the estimation, we impose a log-linear structure on this cost.

We assume that changes to firm-level central management quality C occur at random following a five-state Markov chain. These processes will generate the firm-specific dynamics in the model which, alongside the shocks to business conditions and random initial draws for management and TFP, generate the stochastic dynamics in our model.

[17]See, for example, Bertrand and Schoar (2003), Dessein and Prat (2022) and Lucas (1978). In a more general model we could also allow firms to invest in their firm management ability, but would still need some exogenous firm variation to generate variations in management practices.

[18]For brevity, in this section we omit the firm and plant subscripts.

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

$$Y^*(A, K, M, C) = A^* K^{\frac{a}{1-b}} (C \cdot M)^{\frac{c}{1-b}}, \tag{13}$$

where $A^* = b^{\frac{b}{1-b}} A^{\frac{1}{1-b}}$.[19] Finally, our plant-specific *ln(A)* is assumed to follow a standard AR(1) process so that $ln(A_t) = lnA_0 + \rho_A ln(A_{t-1}) + \sigma_A \varepsilon_t$ where $\varepsilon_t \sim N(0, 1)$.

4.4 Firm and Plant Entry

There are two types of entry in the model.

At the firm level, new firms enter operating a single plant. These *de novo* firms draw a triple of $C_{i,0}, M_{i,e,0}$, and $A_{i,e,0}$ randomly from a known distribution after paying a sunk entry cost F.[20] Assuming that they decide to produce, after this first period of life, these entrant firms (alongside all other incumbent firms) can give birth to new plants (their "children").

At the plant level, existing firms birth new plants. We model the entry of new plants in a similar size-independent way as Klette and Kortum (2004), which satisfies Gibrat's law that firm growth rates are independent of firm size. In our model, each plant has a fixed probability μ of spawning a new entrant plant and λ of exiting. Thus, the total entry rate of new plants for a firm scales linearly with the number of existing plants.

New plants take a draw of plant-level management practices and productivity, while inheriting the firm-level central management ability from their parent firms. These plants start to operate if their initial value given these entry draws is greater than the entry cost $D^{enter}(C)$. We assume that $D^{enter}(C)$ is log-linear in C, but we do not take a stance on the direction of the function. We impose that the slopes of $D^{enter}(C)$ and $D^{acquire}(C)$ are equal, implying that the effect of firm management on the ease of starting a new plant is equal whether it is a new entrant or an acquisition from another firm. We estimate the slope and intercept to match the relationship between entry and management observed in the data. Given our empirical results, we expect that the cost to enter will be lower for well-managed firms, $D'(C) < 0$, reflecting a superior technology for opening plants.[21]

[19] We define the units for labor, management, and capital so that their prices are unity.

[20] For simplicity, we assume this sunk entry cost is the same as the one-period fixed cost of production.

[21] For example, Hsieh and Rossi-Hansberg (2023) discuss how superior management practices within services facilitate the expansion of firms by reducing costs of opening new locations.

4.5 Plant Sales, Exits, and Acquisitions

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

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

where $\mathbb{E}_A$ makes explicit that we are taking expectations over the future evolution of the plant's A. Again, we are agnostic on the direction of $D^{dispose}(C)$, but we assume that its slope is equal to that of $D^{exit}(C)$.

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

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

Again, we estimate $D^{acquire}(C)$ to match the empirical relationship between management and acquisition activity, but impose that its slope is equal to that of $D^{enter}(C)$. We also introduce a random shock $\varepsilon_{i,j}$ in the cost of purchasing a plant to eliminate ties, and give worse-managed firms some opportunity to buy plants if they have a particularly low draw of the purchasing cost shock.[22] Finally, following this purchase, the acquiring firm draws a new TFP $A_{j,e}$ for the purchased plant. If this new productivity draw is high enough, i.e., if $V(A_{j,e}, K_{i,e}, M_{i,e}, C_j) \geq 0$, the purchased plant e continues operations as part of the new firm j. If the new productivity draw is very low, that is, if $V(A_{j,e}, K_{i,e}, M_{i,e}, C_j) < 0$, the plant exits.

4.6 Optimization and Equilibrium

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

$$\begin{aligned}
V(A_t, K_t, M_t, C_t) &= \max[V^c(A_t, K_t, M_t, C_t), \mathbb{E}_A[V(A, M, K, C)] - D(C)] \\
V^c(A_t, K_t, M_t, C_t) &= \max_{K_{t+1}, M_{t+1}} [Y_t^* - wL_t - S_K(K_{t+1}, K_t) - S_M(M_{t+1}, M_t) \\
&\quad - p_K I_{t+1}^K - p_M I_{t+1}^M - F \\
&\quad + r(1-\mu)E_t V(A_{t+1}, K_{t+1}, M_{t+1}, C_{t+1})] + r(1+\lambda)E_t V(A_0, K_0, M_0, C_{t+1})].
\end{aligned} \tag{14}$$

[22] For example, the "Danaher Corporation" case study (Anand et al. (2008)) discusses their ability to reduce the costs of effective M&A thanks to the adoption of structured practices for the evaluation of possible targets.

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

Our framework means that we can consider the value function at the plant level rather than the firm level, which substantially aids computational tractability. We assume there is a continuum of potential new entrants that would have to pay one period of fixed costs F to enter.[23] Upon entry, they take a stochastic draw of their productivity (A), plant management (M), and firm management (C) from a known joint distribution $H(A,M,C)$ and start with non-managerial capital $K_0 = 0$. Hence, entry occurs until the point that the expected value of entry equals the sunk cost of entry:

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

We solve for the steady-state equilibrium by selecting the demand shifter ($B = (\frac{Y}{N})^{\frac{1}{\rho}}$) that ensures that the expected cost of entry equals the expected value of entry given the optimal capital and management decisions. This equilibrium is characterized by a distribution of firms in terms of their state values A, K, M, and C. Upon entry, A is drawn from its steady-state distribution, M is drawn from a uniform distribution, and C is drawn from a five-point distribution.[24]

5 Structural Estimation and Simulations

5.1 Model Estimation

We choose values to calibrate the model from the literature and from our data, and estimate using Simulated Method of Moments (SMM). In short (with details in Appendix C), solving the model requires finding two nested fixed-points. First, we solve for the value functions for incumbent firms using the contraction mapping (e.g. Stokey et al. (1986)) taking demand as given for each firm. The policy correspondences for M and K are formed from the optimal choices given these value functions, and for L from the static first-order condition. Second, we iterate over the demand curve to satisfy the zero-profit condition.[25] Once both fixed points are satisfied, we simulate data for 150,000 plants over 75 years to get to an ergodic steady state, and then discard the first 25 periods

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

[24] Nothing fundamental hinges on the exact distributional assumptions.

[25] If there is positive expected profit then net entry occurs and the demand shifter $B = (\frac{Y}{N})^{\frac{1}{\rho}}$ falls, and if there is negative expected profit then net exit occurs and the demand curve for the remaining firms shifts out.

to keep the last 50 years of data.[26] In steady state, about 65,000 plants belonging to 28,000 firms are active each year.

To solve and simulate this model we also need to select which parameters will be estimated and which will be calibrated externally. We externally calibrate nine parameters from accounting measurement (e.g. the labor share of GDP, the depreciation rate on capital) or estimates in the prior literature and normalize two parameters (fixed costs to 100 and the mean of ln(TFP) to 1). We estimate the remaining 10 parameters on our management and accounting data panel. The nine predefined parameters are listed in Table 5, and are all based on standard values in the literature (details in Appendix C).

The ten unknown parameters that we choose to estimate are those where less is known from the prior literature. The adjustment cost (γ_M) and depreciation rates (δ_M) for managerial capital have never been estimated before, to our knowledge. We also estimate the adjustment cost for non-managerial capital (γ_K). While prior papers have estimated labor and capital adjustment costs (e.g. Bloom (2009), and the survey therein), they have typically ignored management as an input, so these parameters are not directly transferable to our set-up. We also estimate the parameters of the exit, entry, acquisition, and disposal cost functions $D^g(C)$ which are unique to our model. We impose that the structure of this cost function is log-linear in C. Formally, we estimate

$$D^g(C) = a_g + b_g \cdot [log(C) - log(C_0)] + d_g \varepsilon_{g,i}, \tag{15}$$

for $g \in \{\text{enter, acquire, exit, dispose}\}$ where C_0 is the lowest possible value of firm management C and $\varepsilon_{g,i}$ is a random shock whose distribution depends on the action g. We impose that $b_{enter} = b_{acquire}$ and $b_{exit} = b_{dispose}$, so that the marginal effect of C is the same for the two methods of "adding" or "subtracting" a plant. We also impose that $d_{enter} = d_{exit} = 0$, so there is no noise in the entry and exit process, and $\varepsilon_{acquire}$ and $\varepsilon_{dispose}$ are drawn from uniform distributions.

To estimate the model by SMM we picked three sets of data moments to match. First, we match the variances of management, capital, and revenue to tie down the adjustment cost and depreciation parameters. These data moments were generated on the matched management-accounting panel dataset from the WMS. Second, we match a set of moments on the relationship between management and firm growth measured in the MOPS, described in Section 3.1, to determine the parameters of the firm growth cost function $D(C)$. For each mode of firm growth (entry, exit, acquisition, disposal, and net entry and net acquisition) we match both the constant and the coefficient on firm management from the MOPS regressions. Third, we match the coefficients from the event study regressions measuring the effect of acquirer management on the performance of acquired plants from the WMS. The full set of moments in the data and from the simulation is shown in Table 6.

[26] For computational ease, we run 15 simulations of 10,000 plants each and pool the results.

5.2 Simulation results

Table 7 contains the SMM estimates for the 10 parameters we estimate. These are split into four sections: depreciation rates, quadratic adjustment costs, entry and acquisition costs, and exit and disposal costs. Table 6 contains the data moments from the WMS and MOPS and their simulated counterparts. Although we do not match the data moments exactly, the magnitudes and directions are similar.

The estimates of the adjustment costs for management are one of the novel contributions of this paper. We estimate higher quadratic adjustment costs for management (0.123) compared to capital (0.047). Alongside the irreversibility of management, this helps generate smaller variance in management compared to capital (see Table 6, Panel A).[27] These magnitudes are *prima facie* plausible as prior research in this area (Cyert and March (1963)) and anecdotal evidence from the private equity and management consulting industry suggest that management practices are likely harder to change than physical equipment (e.g. Davis et al. (2014)). Depreciation of management capital is 5.9%, smaller than the level of the depreciation rate of capital (10%, see Table 5).[28]

The estimates for the parameters of the firm growth cost functions, $D(C)$, are somewhat more difficult to benchmark relative to the literature. Thus, we discuss their direction and compare them with the average revenue of a plant in the model. The slope of the entry cost function—b_{enter}—is negative. Functionally, this means that better-managed firms have a lower threshold value for entering a new plant: that is, they are willing to take on less productive or valuable plants. The constant term in the entry cost function, a_{enter}, is about 65% of the average plant revenue, which allows us to match the level of the entry rate in the data.

In estimation, we impose that the slope of the acquisition cost function $D^{acquire}(C)$ is equal to that of the entry cost function $D^{enter}(C)$. Thus, the slope of the acquisition function is also negative, implying better-managed firms have lower costs of acquisition on average. Importantly, however, we estimate a high variance in the cost of acquisition. This means that the acquisition process is highly variable—a plant on the M&A market can be bought by any firm if they draw a low random cost value. Numerically, this is necessary to match the effect of acquirer firm management on acquired plant revenue that we see in the WMS and MOPS. Having a wide range of firm C types making acquisitions allows low C firms to sometimes acquire plants, enabling us to observe a post-acquisition relationship between acquirer management and target performance.

For exit and disposal, the constant in the cost function is large (at 5 to 36 times average plant revenue), but there is also a high degree of noise in the disposal process, which ensures that all types of firms sell plants. Notably, the slope of $D(C)$ for exit and disposal is almost flat. We can

[27] If we allow management to have the same 50% resale loss as capital, its adjustment cost is estimated to be 0.290.

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

still match the upward slope of exit and disposal in firm management because well-managed firms are so much more likely to enter and acquire plants. These well-managed firms end up with many low-value plants through entry and acquisition, so they consequently sell and exit a larger share of plants. We can think of this as better-managed firms being more willing to experiment on new plants, but also willing to cut their losses and get rid of these plants if they do not perform well.

More generally, these results can be seen as a tractable way of incorporating a Lucas (1978)-style span of control into the model while still keeping decision-making at the plant level. Better-managed (and typically bigger) firms are more willing to sell poorly performing plants, consistent with them wanting to use their scarce firm-level central management (e.g. CEO) time on other activities.

5.3 Model Validation

Before conducting counterfactuals with our structural model, we confirm it can generate the six key stylized facts from the empirical management data. To do this, we simulate data using our estimated parameters. We confirm the six key relationships summarized below (figures in Appendix as indicated):

1. Better-managed firms have more entry, exit, and net entry (Figure A1).
2. Better-managed firms have more acquisitions, disposals, and net acquisitions (Figure A2).
3. Plants born to better-managed firms have higher management scores (Figure A3).
4. Plants purchased by better-managed firms increase their management scores (Figure A4).
5. Plants purchased by better-managed firms see performance improvements (Figure A5).
6. Management practices predicts firm size and productivity (Figure A6).

6 Policy and Macro Implications

We use the model to run two experiments on M&A and competition policy, as well as a cross-country productivity decomposition.

6.1 Increasing M&A Costs

There is an ongoing policy discussion about reforming the rules over antitrust. One view is that M&A should be made much more costly due to excessive market power by mega-firms. Another view is that the M&A market helps to reallocate plants more appropriately across firms, improving management and productivity across firms.[29]

We can use our simulation model to investigate the reallocation impact of making mergers more costly. In the left panel of Figure 5, we consider a boundary case where we make M&A so expensive it closes down the M&A market completely. The density labeled "no M&A" is the distribution of plant management practices without M&A. In comparison, "has M&A" is the baseline distribution of management. Here, we measure $M \cdot C$, the composite of plant-level management capital M and firm-level central management C as it enters the production function. We use composite management because this is the closest analog to measured management practices in the data, which include both firm and plant components of management.

Allowing M&A activity increases the average composite management score in the economy from 0.54 to 0.62, an increase of 15%. There are two forces driving this. First, M&A allows firms with high management ability C (e.g. a good CEO) to expand by buying plants from firms with weak management ability. Since management ability C applies to all plants within a firm, this transfer of plant ownership increases composite management $M \cdot C$. Second, because management ability is complementary to other inputs in the Cobb-Douglas production function, firms invest more in management practices M when they have better management ability C.

The right panel of Figure 5 shows the distribution of plant output with and without M&A, where we see a similar result. M&A increases average output from 3.62 to 4.15, an increase of about 15%.

6.2 Management Practices and Competition

Another important question is: how does product market competition affect management in equilibrium? We can adjust the level of competition in the model by increasing consumer price sensitivity in the demand curve (Equation 6). Figure 6 shows economies from our model simulation with varying elasticities from 2 to 8, where a higher elasticity ρ corresponds to a more competitive economy. The blue bar shows the simple average of managerial capital and the red bar shows the employment-weighted value of management.

The average management score increases with the degree of competition, both in weighted and unweighted terms. Our benchmark calibration is $\rho = 5$. The unweighted management score increases with competition because of two forces. First, when competition is stronger, plants invest more in management practices because of the higher returns to greater productivity and lower prices. Second, when competition is stronger, less productive plants are more likely to exit the economy. These forces level out for unweighted management at higher levels of ρ, but continue to increase employment-weighted management. This is because small, unproductive firms are also

[29] For example, Kaplow (2025) suggests that merger guidelines should take into account potential efficiencies generated by acquisitions: "[...] Also absent are fundamental teachings of economic theory regarding entry and exit and, more broadly, how investment, acquisitions, and other dynamic behavior move resources from lower- to higher-value uses in a well-functioning economy."

more likely to sell their plants when competition is stronger, so the covariance between size and management increases at high levels of competition. Notably, the weighted management score is greater than the unweighted management score at all levels of ρ. This is because firms with higher management scores are larger, as more competitive markets allocate more activity to better-managed firms (analogously to the Olley and Pakes (1996) covariance term).

6.3 Management, Reallocation and Cross-Country Productivity

Finally, we consider to what extent management-related reallocation can explain differences in total productivity across countries. To estimate this, we first calculate the size-weighted management score gaps between each country. This is shown in Figure 7, which plots the *employment share-weighted* management gap with the US by country (in management standard deviation units). This gap is decomposed into two parts, an unweighted management score gap (black bars) averaging -0.87% in total, and a reallocation gap (red bars) averaging -0.30% in total.

We see two results from Figure 7. First, while the majority of the management gap with the US is from worse management practices in absolute terms, with this accounting for 74% of the average difference, the remaining 26% is from the reallocation gap, reflecting a lower size-management covariance than in the US. This reallocation gap relative to the US may reflect differences in market competition, which allocates a greater market share to the best managed firms. Second, the overall management gap with the US in high-income countries like Japan, Germany, and Canada is primarily from a reallocation gap, while the gap in middle- and lower-income countries like Zambia, Ghana and Mozambique is primarily from raw differences in management practices. This reflects the fact that in lower-income countries, the gap in absolute management practices is extremely large (e.g. Bloom et al. (2013); Lemos and Scur (2015); Atkin et al. (2017); Bruhn et al. (2018)), so this dominates the total variation.

We then take this management gap and apply the coefficient on management of 0.1 in the production function (Equation 13) to calculate the resulting productivity gap due to management. The estimated productivity gaps shown in Figure 8 range from 3.3% in Japan to 23.6% in Mozambique. On average there is an implied productivity gap of 11.7% with the US from differences in management practices. Given that the unweighted average total productivity gap of these countries with the US is 62%, this implies differences in management practices account for about one-fifth of total cross-country productivity gaps, of which about one-quarter depends on differences in reallocation across countries.

7 Conclusion

Economists, business people and many policymakers have long believed that management practices are an important element in productivity. We collect original cross-sectional and panel data on over

11,000 firms across 34 countries (WMS) and 60,000 US plants (MOPS) to provide robust firm-level measures of management in a comparable way across industries and geographies.

We document several new facts about the relationship between management and the boundaries of the firm. First, we show that firms with more structured management practices not only birth and acquire more new plants, but they also close and dispose of more plants on the M&A market. Thus, it seems that better-managed firms not only grow faster, but also experience more churn in their stock of plants. This suggests that better-managed firms have lower costs of plant opening, closing, acquisition, and disposal, allowing them to be more dynamic. Second, we show that management practices spread across plants within a firm, both to newly birthed plants and to acquired plants.

We then build a formal model where our management measures have technological elements to match the new facts we have shown in the data. This model has two critical elements. First, management enters the plant-level production function as management practices and also at the firm level as management ability. As such, management ability is akin to a firm-level technology that benefits all plants within the firm. Second, our multi-plant firms can open and close plants, as well as acquire and sell plants via the M&A market. Better management practices reduce the costs of this firm-level dynamism. We show how the qualitative predictions of this simulated model are consistent with the data and present structural estimates to recover some key parameters.

Finally, using our model, we draw out three key results. First, M&A enables reallocation of management practices which improves overall management quality. Preventing acquisitions could decrease average management quality and average revenue by about 15%. Second, product market competition improves management practices. As the degree of competition increases, plants both invest more in management capital and are increasingly reallocated to firms with better centralized management ability. Leveraging international data on management practices, we infer that management quality accounts for a significant share of productivity differences across countries. About a fifth of cross-country productivity gaps are explained by differences in management practices, and one-quarter of this depends on differences in management-related reallocation across firms.

There are many directions to take this work. It would be useful to examine the determinants of management practices in greater detail. We have focused on market-based incentives, but informational frictions and coordination may be equally if not more important. Gibbons and Henderson (2012), for example, argue that the need to coordinate a multitude of dispersed agents within a firm is critical. Second, it would be valuable to examine the relationship between management and dynamism outside of the US, highlighting which market and regulatory factors could influence this. Finally, from a policy perspective, it would be valuable to have direct empirical evidence on the impact of M&A regulations, changes in competition, and reallocative frictions on management practices across industries and countries.

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A APPENDIX: DATA

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

A.1 Firm-level Accounting Databases

Manufacturing firm sampling frame

For the WMS we focus on medium-sized manufacturing firms, so to conduct our surveys we would ideally draw a sampling frame from a business registry of firms. Unfortunately, even when business registers with firm names exist in administrative data, they are usually confidential. Three exceptions were Chile, Colombia and Singapore. In Chile, we worked directly with the government, so it was possible to phone firms using the confidential business register data—the Industrial Annual Survey Sample of Firms (Encuesta Nacional Industrial Annual)—which covers all manufacturing firms with more than 10 employees. We used a similar model in Colombia, working with the Business Ministry and World Bank. In Singapore, the Ministry of Trade and Industry ran the survey (with our training) using their population business register.[30]

For other countries, we used publicly available data sources.[31] Our main sampling frame was based on various accounting databases supplied by Bureau van Dijk (BVD), a private-sector organization that seeks to compile accounting information on companies from all over the world. BVD ORBIS has names, industry, addresses, status (e.g. active or bankrupt), and accounting information such as employment and sales. ORBIS is constructed from a range of sources, primarily the national registries of companies (such as Companies House in the U.K.). For example, in Europe, the firm database is called AMADEUS (France, Germany, Greece, Great Britain, Italy, Ireland, Northern Ireland, Poland, Portugal, Spain, Sweden, and Turkey); in North America it is called ICARUS (U.S. and Canada) and in parts of Asia it is called ORIANA (China, Japan). Other countries where we simply used ORBIS include Argentina, Brazil, Mexico, and Vietnam.

In some countries we were concerned about incomplete coverage by ORBIS so we supplemented it with other sources. We also used Dun & Bradstreet for Australia and New Zealand. In India we used CMIE Firstsource 2005.[32] Low-income countries pose a particular challenge, as there is

[30] Unlike in Chile and Colombia, we were not able to obtain the characteristics of the non-responders in the sampling frame from the Singaporean government due to confidentiality reasons.

[31] Although most of these data sources require an access fee, they reveal names and addresses of firms because they are in the public domain, unlike administrative government data.

[32] CMIE is constructed from 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

generally no well-maintained business register to draw upon. We used a larger variety of data sources to construct sampling frames for these countries complementing ORBIS with country-specific "enterprise maps" put together by researchers such as John Sutton at the London School of Economics' International Growth Centre (IGC), who worked with local consultants. In Myanmar we supplemented the PEDL Enterprise Map with industry directories and lists of manufacturers provided by the Myanmar Industry Association (see Tanaka (2020)) and in Nicaragua we used business directories and an IADB database.

Representativeness of the sampling frame

How representative are our sampling frames of the underlying population of manufacturing firms? For most of the countries we have evidence that the data is reasonably comprehensive. For example, when comparing aggregate employment in the ORBIS populations to those from census data, we usually find a reasonably close match (e.g. Kalemli-Ozcan et al. (2024); Bloom et al. (2016)).

We analyze this in more detail in Bloom et al. (2012). For example, we compare the number of employees for different size bands from our sampling frame with corresponding national census data when available. There are several reasons for a mismatch between census data and firm-level accounts.[33] Despite these potential differences, our sampling frame appears to cover near to the population of all firms for most countries.[34]

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

It is harder to make such comparisons between our sampling frame and the full population of firms in some of the poorer countries because there are no reliable aggregate employment numbers to

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.

[33]First, even though we only use unconsolidated firm accounts, employment may include some jobs in overseas branches. Second, the timing at which 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 on a regression of sales on employment for firms where we had both variables.

[34]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.

compare to. The enterprise maps by Sutton and others that we draw our sampling frames from are probably the most reliable sources. Given this, we should interpret some of the results from the African countries with more caution than those of the other nations.

Medium-sized manufacturing firms versus all manufacturing firms

A further concern is that even if our sampling frame is fully comprehensive, the proportion of employment covered by medium sized firms differs systematically across countries. Firms employing between 50 and 5,000 workers account for about half of all manufacturing workers in most countries, although the proportion is larger in some countries such as Ireland (72%) and Poland (71%). The proportion employed by very large firms (over 5,000 workers) varies more between nations. The patterns are broadly consistent with our model. In countries where competition is strong and reallocation easier, there is a larger fraction of jobs in very large firms (e.g., 34.7% in the U.S.) and a small fraction in small firms with under 50 employees (e.g., 16.2% in the U.S.). Germany, also a high productivity and high management score country, looks similar to the U.S. (34.9% in large firms versus 16.5% in small firms). By contrast, in countries like Italy and Greece, only 6.4% and 6.2% of employees, respectively, are in these large firms compared to 45.1% and 41.3% in small firms.

A caveat is that total employment in firms with over 5,000 workers is not disclosed in all countries (because of concerns it would reveal individual firms' identities). In the U.S. and Japan we have the exact census numbers from public use tables and in the U.K. we had access to confidential census microdata to estimate coverage ourselves. In the other countries we used accounting data from ORBIS and other sources to estimate employment for the very large firms. Since these firms are so large, data is relatively plentiful as they are almost all publicly listed and so followed closely by market analysts.[35]

A.2 The World Management Survey

In every country the sampling frame for the management survey was all firms with a manufacturing primary industry code and that employed between 50 and 5,000 workers[36] on average over the most recent three years of data prior to the survey.[37] Interviewers were each given a randomly selected

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

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

[37] In the U.S. only the most recent year of employment is provided. In India, employment is not reported for private firms, so for these companies we predicted employment from their total assets (which are reported) using the coefficients from regressing ln(employees) on ln(assets) for public firms.

list of firms from the sampling frame. The size of this sampling frame by country is for the first year that we interviewed a firm. We have conducted the surveys over multiple years as noted in column (6). The five major waves were in 2004, 2006, 2009/10, 2013 and 2014,[38] although we had smaller scale surveys in some of the intervening years (e.g. China in 2007; Brazil, Canada, and Ireland[39] in 2008).

In the first survey in 2004 we covered 732 firms in France, Germany, the U.K., and the U.S.[40] In 2006 we covered eight countries (China, Greece, India, Italy, Japan, Poland, Portugal and Sweden) on top of the four core countries. In addition to the new countries and a refreshment sample of the four 2004 countries, we also re-contacted all firms from 2004 to form a short panel. In 2009/10 we again resurveyed all firms interviewed in 2006 including the original 2004 firms (if they were still alive). For budgetary reasons we did not do a refreshment sample in this wave although we did add New Zealand and Australia. In 2013, we mainly surveyed low-income countries in Africa (Ethiopia, Ghana, Mozambique, Nigeria, Tanzania, and Zambia) and Latin America (Colombia and Nicaragua) for the first time. We also followed Argentina, Mexico, and Brazil in the panel and surveyed Spain and Turkey for the first time. In 2014, we included new countries (Kenya, Myanmar, and Vietnam) and performed refreshment samples of the U.S. and the main EU countries (France, Germany, Greece, Italy, Portugal, and the U.K.). This included attempting to re-survey all the panel firms from the these EU countries and the U.S. that we had from earlier waves.

A.3 Management and Organizational Practices Survey (MOPS)

MOPS was jointly funded by the U.S. Census Bureau and the National Science Foundation as a supplement to the Annual Survey of Manufactures (ASM). The original design was based on the same concepts as the WMS and was adapted to the U.S. through several months of development and cognitive testing by the Census Bureau. It was sent by mail and electronically to the ASM respondent for each establishment, which was typically the accounting, establishment, or human-resource manager. Most respondents (58.4%) completed the survey electronically, with the remainder completing the survey by paper (41.6%). Non-respondents were given up to three follow-up telephone calls if no response had been received within three months. The survey comprised 36 multiple choice questions about the establishment, taking about 20 to 30 minutes to complete. The survey included 16 questions on management practices covering (like the WMS) monitoring, targeting,

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

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

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

and incentives.

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

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

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

B CALIBRATION AND SIMULATION

B.1 Calibration Values

The calibration values in Table 5 are conventional, but the presence of management in the production function generates some additional considerations. Conventional measures of the auto-correlation coefficient on TFPR (ρ_A) assume that we have measured all factor inputs, but since managerial capital is a missing variable, it will implicitly show up in estimated TFPR. For example, consider the value-added production function, $(PY)_i = A_i K_i^a L_i^b M_i^c$. TFPR will be $ln(A_i) = ln(PY)_i - aln(K_i) - bln(L_i) - cln(M_i)$. A standard way to measure TFP is to replace the parameters with cost shares. However, this results in management showing up in the residual so we actually have $ln(A_i) + cln(M_i)$. M and A will co-vary together, implying that we probably overestimate the auto-correlation of "true TFPR" using existing measures. We can assess the extent of this issue by examining how our estimates of TFPR in the data compare with those from conventional measures. We find that the estimated coefficient is, in fact, not much less than the calibrated value from Cooper and Haltiwanger (2006) of 0.885. For example, using the productivity equation of column (2) in Table 3, we can calculate the (net-of-management) TFPR residual and then estimate an AR(1) regression which generates $\hat{\rho_A} = 0.867$ (standard error = 0.009; N=7,463). This is close to the 0.871 we estimate if we do not control for management in our data. The similarity reflects the fact that management capital is a relatively small share of total value added.

An alternative approach is to use the implied values in the dynamic version of the revenue function. Under the assumptions in our model we can write $ln(PY)_{it} = \rho_A ln(PY)_{it} + alnK_{it} - a\rho_A lnK_{it} + blnL_{it} - ba\rho_A lnL_{it} + clnM_{it} - c\rho_A lnM_{it} + e_{it}$ where $e_{it} = lnA_0 + \rho_A \varepsilon_{it}$ is serially uncorrelated. This is the same specification as Cooper and Haltiwanger (2006) and Blundell and Bond (2000); like them, we estimate the equation by system GMM and impose the common factor restrictions (COMFAC) to recover the structural parameters (see Table A5 column (2)). Our estimate of (ρ_A) is 0.854 (standard error = 0.013) which is again very close to the calibrated value used in Table 1.[41]

As noted in the text we use labor's factor share in GDP to guide the calibration of the output elasticities. It seems reasonable to assume that the cost of managerial capital shows up as payments to labor (e.g. executive time and consultancy wages). Recall that our model implies that the labor share of GDP is $\beta = wL\rho/PY(\rho - 1)$. Following Corrado et al. (2005) and Corrado and Hulten (2010), we assume that a fraction ς of total compensation is the investment in building managerial capital. From the U.S. NIPA, the labor share is about 50% (see Autor et al. (2020), Table 1). Using our estimates of the share of management costs in total compensation from subsection 4.4 of $\varsigma = 0.07$ we obtain $\beta = (1 - \varsigma) * 0.5\rho/(\rho - 1) = 0.93 * (0.5 * 5)/(5 - 1) = 0.6$ given the calibrated assumptions on the demand elasticity (Bartelsman et al. (2013); $\rho = 5$). Given our assumption

[41] A similar exercise for the standard deviation of TFPR (σ_A) generates a value of 0.62, higher than the calibrated value of 0.453 in Cooper and Haltiwanger (2006). In our view, these higher order moments are better estimated from near-population Census data, so we prefer to use these external measures over our more specific sample.

on the output elasticity of management (Bloom et al, 2013; $\gamma = 0.1$) we can then derive the output elasticity of capital from our assumption of constant returns to scale in production as $\alpha = 1 - \beta - \gamma = 1 - 0.6 - 0.1 = 0.3$.

B.2 Details of Simulated Method of Moments (SMM) Approach

SMM starts by selecting an arbitrary starting value of the parameter vector to be estimated (θ). The dynamic program is then solved and the policy functions are generated. These policy functions are used to create a simulated data panel of size ($\mu N, T$), where μ is a strictly positive integer, N is the number of firms in the actual data, and T is the time dimension of the actual data. The simulated moments $\Psi^S(\theta)$ are calculated on the simulated data panel, along with an associated criterion function $\Gamma(\theta)$, where $\Gamma(\theta) = [\Psi^A - \Psi^S(\theta)]' W [\Psi^A - \Psi^S(\theta)]$ is a weighted distance[42] between the simulated moments $\Psi^S(\theta)$ and the actual moments Ψ^A.

$$\widehat{\theta} = \arg\min_{\theta \in \Theta} [\Psi^A - \Psi^S(\theta)]' W [\Psi^A - \Psi^S(\theta)] \tag{16}$$

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

B.3 Simulation Results and Model Fit

Figure A1 shows the simulated relationships between firm management and plant entry, exit, and net entry rates. As in the MOPS data, these lines slope upward—better-managed firms not only enter more plants but also exit more plants—but the entry effect outweighs the exit effect. The relationship between the plant entry rate and management is positive in the model for two reasons. First, better management directly increases the revenue of a plant, so potential entrant plants at a firm with a higher central management score are more likely to open and operate (because their present discounted value is higher than the entry cost). Second, we estimate that it is cheaper for firms with better central management to enter plants, so better-managed firms are willing to open a plant even if it has a relatively low value. The positive slope between exit and firm management

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

comes from this same fact: because better-managed firms are willing to enter plants with relatively low value, they have more low-value plants around and thus more plants they will ultimately exit. In practical terms, we can think of this as better-managed firms being more willing to "experiment" on plants that are possibly higher-risk.

Figure A2 shows the simulated relationships between firm management and plant acquisition, disposal, and net acquisition rates. This corresponds to Figure 2 from the MOPS data. These lines also slope upward, as in the MOPS data. The reasons are analagous to those for entry and exit. Better-managed firms are more likely to be able to keep a plant open once they acquire it because they transmit their central management to the plant. This increases the acquisition rate with management. In addition, the cost of acquiring a plant is lower for better-managed firms, so they are more willing to acquire plants that may have lower value. Again, because these firms are more willing to take on these worse-performing plants, they also end up disposing of more plants on the M&A market.

Figure A3 shows the relationship between parent firm management and entrant plant management in the model simulation. As in the MOPS data shown in Figure 3, plants that enter into well-managed firms have better management scores. This is a direct consequence of the central management ability (C) in the model. Plants that enter firms with high C-scores will also have high C-scores, so their overall management ($M \cdot C$) is better.

Figure A4 shows the event study results of plant acquisitions, corresponding to Figure 4 from the WMS. Each plot shows the effect of the management score of the acquirer firm, fixed in year $t-1$, on the outcomes of a plant that is acquired by the firm in year t. The upper left panel shows revenue. As in the WMS data, plant revenue increases more when a plant is acquired by a firm with better management. Notably, in the WMS data this effect is not visible until about 4 years after the acquisition. In contrast, the effect is immediate in the simulation. In the simulation, the central management C of the acquirer transmits to the acquired plant immediately, but in reality it is likely that it takes some time to implement the firm management practices at an acquired plant. The top right panel shows employment. In the simulation, acquirer management increases employment in lockstep with revenue after an acquisition, because labor is perfectly adjustable. In contrast, employment does not increase more at targets purchased by better-managed firms in the WMS. The bottom left panel shows the management score of the acquired plant. Not surprisingly, it sharply increases after the acquisition, because the C immediately increases at the acquired plant. We cannot measure the acquiree management for every plant in the WMS, so we do not have an analogous figure from the data. Finally, the bottom right panel shows assets. In both the WMS data and the simulation, assets decrease more at plants purchased by better-managed firms. In the model, this can occur because plants with higher C can survive despite lower levels of capital.

Figures A6 and A7 illustrate the positive relationship between management and revenue in the WMS data and the model simulation, respectively. In both the WMS and model simulation, log sales increase as management increases.

Tables

Table 1: Plants that enter to well-managed firms have higher management scores

	Management score of entrant plant (year t)			
	(1)	(2)	(3)	(4)
Parent firm management (year t-5)	0.433***	0.391***	0.417***	0.338***
	(0.0471)	(0.0565)	(0.0582)	(0.0583)
Log(parent firm employment) (year t-5)				0.0134***
				(0.00266)
Constant	0.375***	0.404***	0.400***	0.308***
	(0.0330)	(0.0393)	(0.0458)	(0.0498)
N	1100	1100	1100	1100
Industry FE		X	X	X
State FE			X	X

This table shows the regression of the 2015 management score of plants that entered between 2010 and 2015 on the management score of their parent firm in 2010. Standard errors in parentheses. Industry fixed effects are at the 4-digit NAICS level.

Table 2: Plants acquired by well managed firms have higher management scores

	5-year change in plant management: M_t – M_t-5					
	(1)	(2)	(3)	(4)	(5)	(6)
Acquirer – seller management, (t-5)	0.308***					
	(0.095)					
Acquirer – seller management, leave out (t-5)		0.221**	0.185*	0.216**	0.220**	
		(0.096)	(0.117)	(0.094)	(0.122)	
Acquirer management, (t-5)						0.290
						(0.157)
Seller firm management, leave out (t-5)						-0.132
						(0.115)
N	850	850	850	850	850	850
Industry FE			X		X	X
State FE				X	X	X

Notes: Standard errors in second row. Sample includes all plants that were in the MOPS in both 2010 and 2015, were acquired (changed firm identifier) between 2010 and 2015, and whose birth firm (parent firm in 2010) and adoptive firm (parent firm in 2015) had at least one plant other than the focal plant in the MOPS in 2010. Birth and adoptive firm management scores are measured in 2010. Regressions are weighted by the average number of plants in the MOPS in the birth and adoptive firms in 2010. Regressions also include a constant term. Industry fixed effects are at the 4-digit NAICS level.

Table 3: Revenue increases more for plants bought by better-managed firms

	Change in log revenue per worker (t-t-5)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Acquirer management score, t-5	0.210**	0.283**	0.283**				0.399***	0.455***	0.470***
	(0.103)	(0.112)	(0.113)				(0.148)	(0.158)	(0.159)
Acquirer – seller management, t-5				0.315**	0.336**	0.355**			
				(0.135)	(0.142)	(0.143)			
Seller management, t-5							-0.247*	-0.237	-0.258*
							(0.143)	(0.149)	(0.151)
N	4400	4400	4400	4400	4400	4400	4400	4400	4400
Industry FE		X	X		X	X		X	X
State FE			X			X			X

Notes: Standard errors in second row. Sample includes all plants that were in the CMF in 2012 and 2017, were acquired (changed firm identifier) between 2010 and 2015, and whose birth firm (parent firm in 2010) and adoptive firm (parent firm in 2015) had at least one plant other than the focal plant in the MOPS in 2010. Birth and adoptive firm management scores are measured in 2010. Regressions are weighted by the average number of plants in the MOPS in the birth and adoptive firms in 2010. All regressions include a constant term. Industry fixed effects are at the 4-digit NAICS level.

Table 4. Being acquired by a better managed firm leads to better target performance

	Log(target revenue)					Log(emp)	Log(capital)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post merger	0.704***	0.715***	0.680***	0.665***	0.642**	0.350***	-0.0200
	(0.0963)	(0.0974)	(0.0976)	(0.0991)	(0.304)	(0.0538)	(0.0952)
Post merger X		0.143**	0.153**	0.139**	0.145**	-0.0971*	-0.205***
management score		(0.0717)	(0.0722)	(0.0691)	(0.0713)	(0.0566)	(0.0688)
Log(target employment)			0.102***	0.116***	0.115***		
			(0.0378)	(0.0379)	(0.0380)		
Log(target capital)				-0.0688**	-0.0693**		
				(0.0335)	(0.0335)		
Post merger X GUO					-0.000649		
Log(employment)					(0.0270)		
N	6961	6961	6961	6961	6961	6961	6790
Adjusted R-squared	0.681	0.682	0.683	0.685	0.685	0.823	0.627

Notes: (1) A data point is a tuple of WMS acquirer (wave), target, and the year of target financials. (2) 1,253 unique targets. (3) Target-clustered standard errors in parentheses. (4) Controls include: acquirer's sales and employments at the plant and firm levels. Model specification is summarized as equation (3). The base levels are the two years prior to the mergers. “Post merger” captures nine years of data after the merger. Other controlled variables include year of financials, interview length and reliability, and the plant and firm employments of the WMS acquirer. All regressions include fixed effects for year, target and acquirer country and industry, and target company.

Table 5: Calibrated model parameters from literature

Parameter	Symbol	Value	Source
Output-labor elasticity	β	.6	NIPA factor share
Output-management elasticity	λ	.1	Bloom et al (2013)
Output-capital elasticity	α	.3	Implied from Constant Returns
Demand elasticity	ρ	5	Bartelsman et al (2013)
AR(1) parameter on ln(TFP)	ρ_A	.885	Cooper and Haltiwanger (2006)
Standard Deviation of ln(TFP)	σ_A	.453	Cooper and Haltiwanger (2006)*
Discount Factor	r	1/1.1	Standard 10% interest rate
Capital depreciation rate	δ_K	10%	Standard accounting assumption
Capital resale loss	ϕ_K	50%	Ramey and Shapiro (2001)

Notes: The production function in the model is $Y_i = \tilde{A}_i K_i^{1-\beta-\gamma} L_i^{\beta} M_i^{\gamma}$ and the revenue function is $(PY)_i = A_i K_i^{a} L_i^{b} M_i^{c}$. The fixed cost of production is normalized to 100 and the mean of ln(TFP) is normalized to 1. *Assumes measurement error on measured TFP has the same variance as true TFP as estimated in Bloom et al (2013).

Table 6: Model fit for WMS and MOPS moments

Panel A: WMS Moments		
Parameter	**Data**	**Simulation**
Standard deviations of log inputs and revenue		
Management	0.660	0.643
Capital	1.657	1.443
Revenue	1.616	2.283
Acquisition Event Study Coefficients		
post	0.715	1.230
Post x management	0.143	0.048

Panel B: MOPS Moments				
Parameter	**Data**		**Simulation**	
	Constant	*M Coefficient*	*Constant*	*M Coefficient*
Entry	-0.015	0.070	-0.010	0.039
Exit	0.008	0.056	0.010	0.028
Net Entry	-0.024	0.015	-0.020	0.011
Acquisition	-0.041	0.104	-0.035	0.133
Disposal	0.013	0.035	0.016	0.036
Net Acquisition	-0.055	0.071	-0.051	0.096

Notes: The WMS moments come from the entire sample of public and private manufacturing companies for all countries from 2004 to 2014, covering 13,944 firm-year observations. This data is then matched to firm-level panel accounting data since 2004 where available. To fill in holes within the matched management-accounting panel dataset we interpolate missing years, which is important for the management data where we interview firms on a rotating panel rather than every single year. The MOPS moments come from the same sample as Figure 1 and 2: firms that had at least one plant in the MOPS in 2010 (for 2015) or 2015 (for 2019). Only stayer firms are included, i.e., those that had one plant present in 2010 and 2015 or 2015 and 2019. N=32,000 firms. Entry, exit, acquisition, and disposal rates are defined in Figure 1.

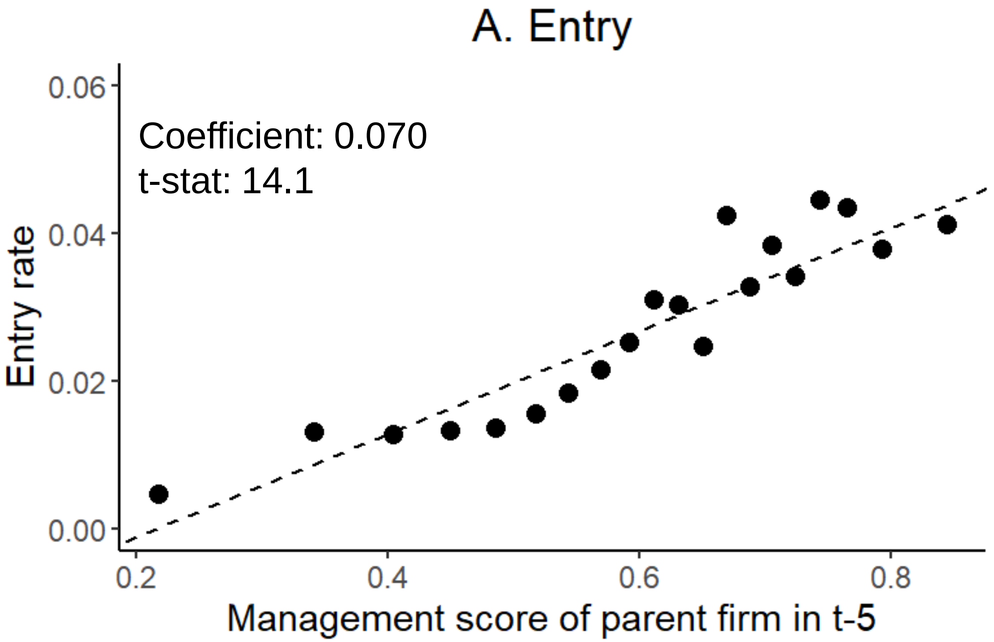
Table 7: Estimated Model Parameters from SMM

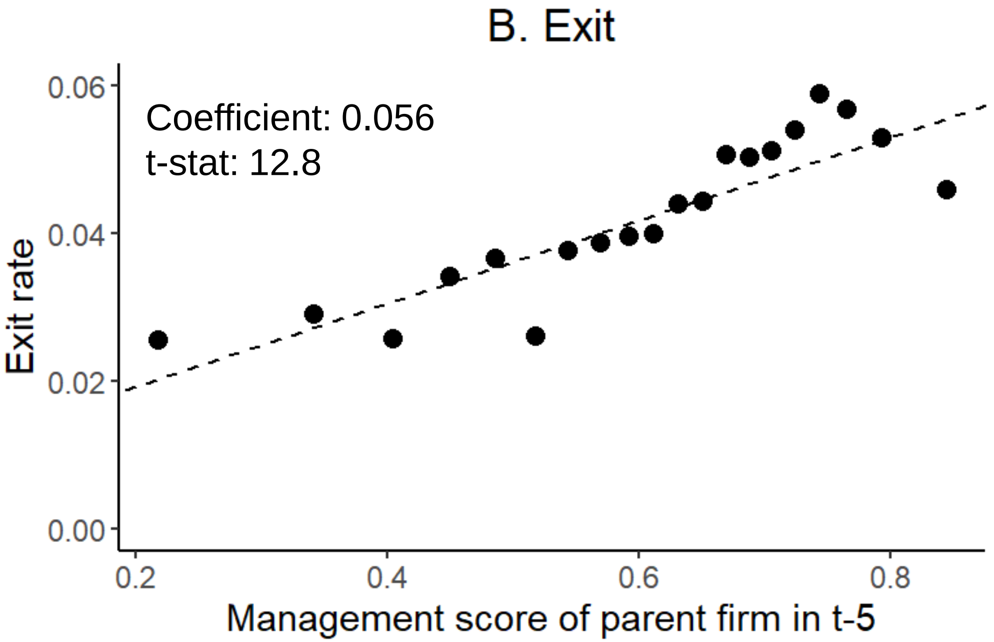
Parameter		Value	Frac. Of Avg. Revenue
Depreciation rates			
Management δ_m		0.059	
Quadratic adjustment costs			
Management γ_m		0.123	
Capital γ_k		0.047	
Entry and Acquisition costs: $Cost_{\{enter,acquire\}} = a_{\{enter,acquire\}} + b_{\{enter/acquire\}}[\log(C) - \log(C_0)] + d_{\{acquire\}}\varepsilon_i$			
Slope in C	$b_{\{enter/acquire\}}$	-88	.18
Constant acquisition cost	$a_{\{acquire\}}$	131	.27
Constant entry cost	$a_{\{enter\}}$	308	.64
SD for acquisition cost	$d_{\{acquire\}}$	149,356	
Exit and Disposal Costs: $Cost_{\{exit,dispose\}} = a_{\{exit,dispose\}} + b_{\{exit/dispose\}}[\log(C) - \log(C_0)] + d_{\{dispose\}}\varepsilon_i$			
Slope in C (b)	$b_{\{exit/dispose\}}$	15	.03
Constant disposal cost	$a_{\{dispose\}}$	17,267	36
Constant exit cost	$a_{\{exit\}}$	2,138	5
SD for disposal cost	$d_{\{dispose\}}$	20,742	

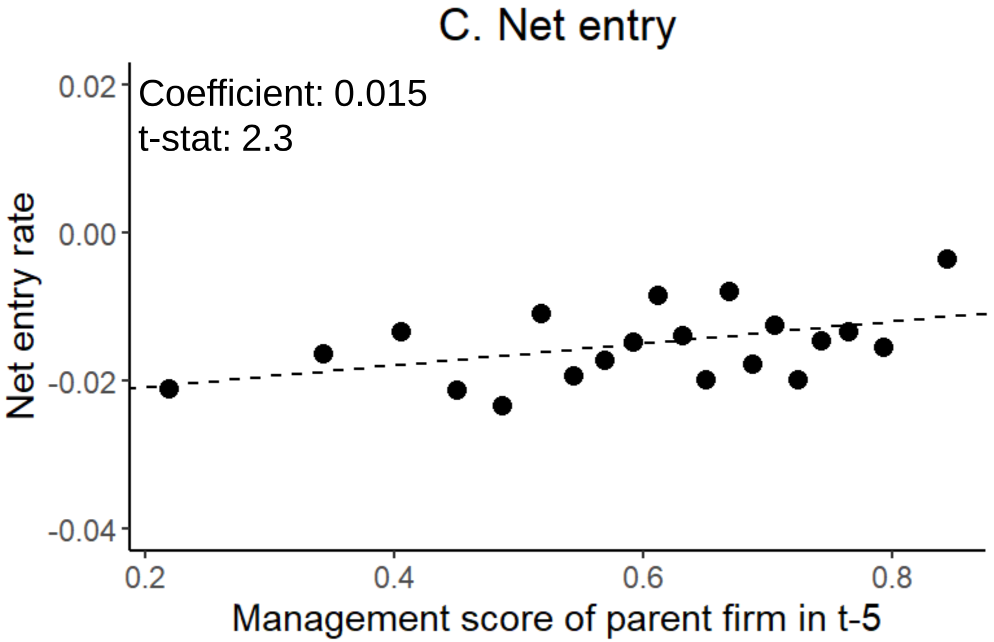
Notes: The adjustment cost functions for M and K, respectively, are $S_{M(M_t,M_{t-1})} = \gamma_M M_{t-1}\left(\frac{M_t - M_{t-1}}{M_{t-1}} + \delta_M\right)^2$ and $S_{K(K_t,K_{t-1})} = \gamma_K K_{t-1}\left(\frac{K_t - K_{t-1}}{K_{t-1}} + \delta_K\right)^2$. We impose a log-linear structure on the cost functions for entry, acquisition, exit, and disposal, where C_0 denotes the lowest possible value of firm management C. We assume that there is no noise in the entry and exit process, and the noise ε for acquisition and disposal follows a uniform distribution for acquisition and disposal. All parameter values in the second column are estimated, and the fraction of average plant revenue in the third column is calculated after the estimation using the simulation results to provide context for the size of the parameter estimates.

Figures

Figure 1: Well managed firms have greater entry, exit, and net entry rates

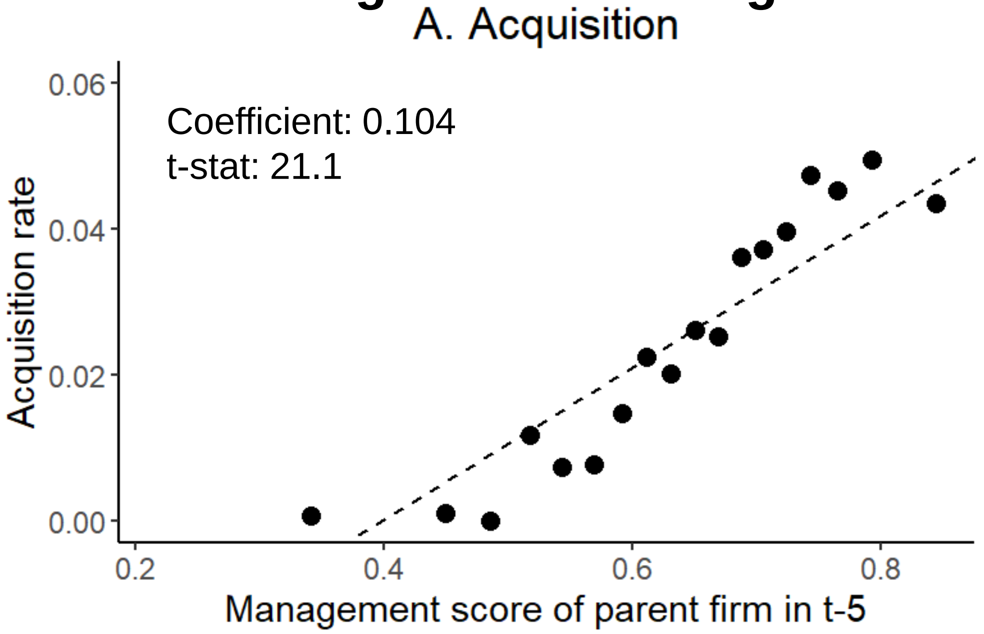


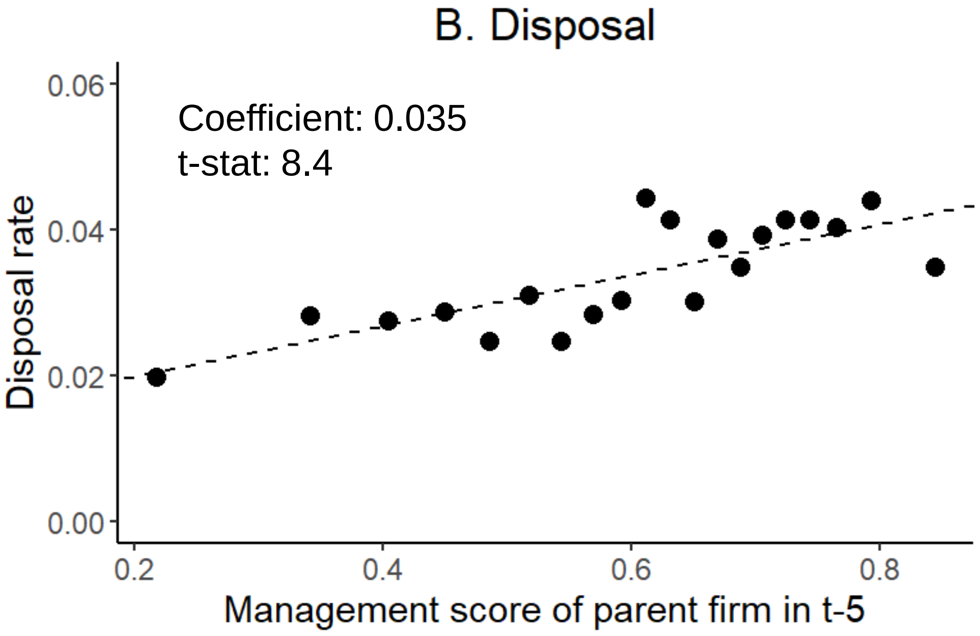


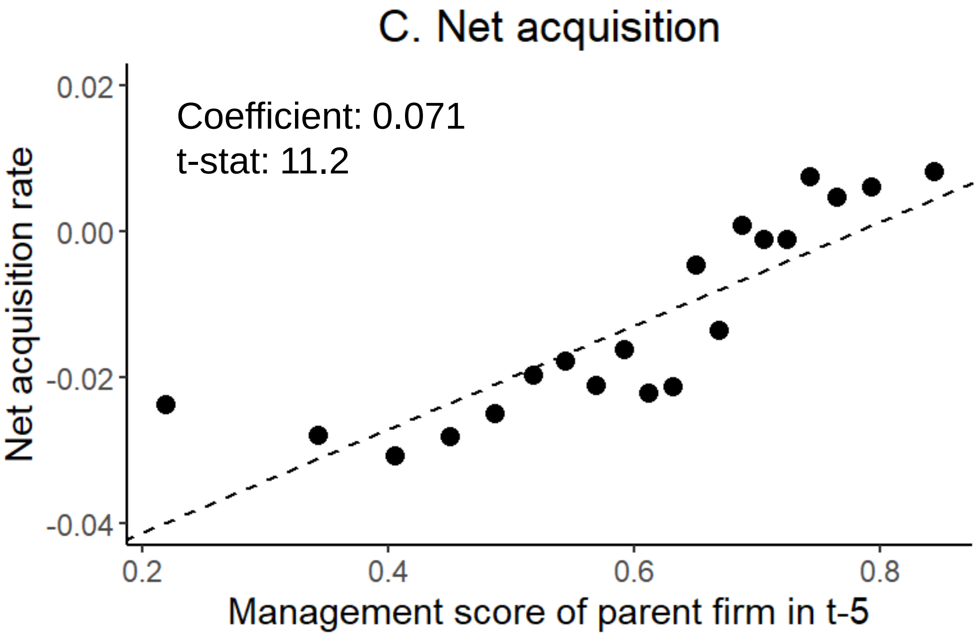


Notes: Data from MOPS of firms that had at least one plant in the MOPS in 2010 (for 2015) or 2015 (for 2019). Only stayer firms are included, i.e. those that had one plant present in 2010 and 2015 or 2015 and 2019. The entry (exit) share is defined as the number of manufacturing plants entering (exiting) between year t-5 and year t divided by the total number of manufacturing plants at the firm in year t-5. Net entry rate is the entry rate minus the exit rate. All shares are winsorized at the 99^{th} percentile. Plot shows means for 20 equally-sized bins of parent firm management scores. Bin scatters include fixed effects for the modal 3-digit NAICS industry and modal state for plants in the firm. Growth rates are defined from 2010-2015 and 2015-2019 (the latest available data at the time of writing). t-statistics are from the regression of entry, exit, and net entry rates on lagged parent firm management. All figures are on the same scale. N=32,000 firms.

Figure 2: Well managed firms have greater acquisition, disposal and net acquisition rates

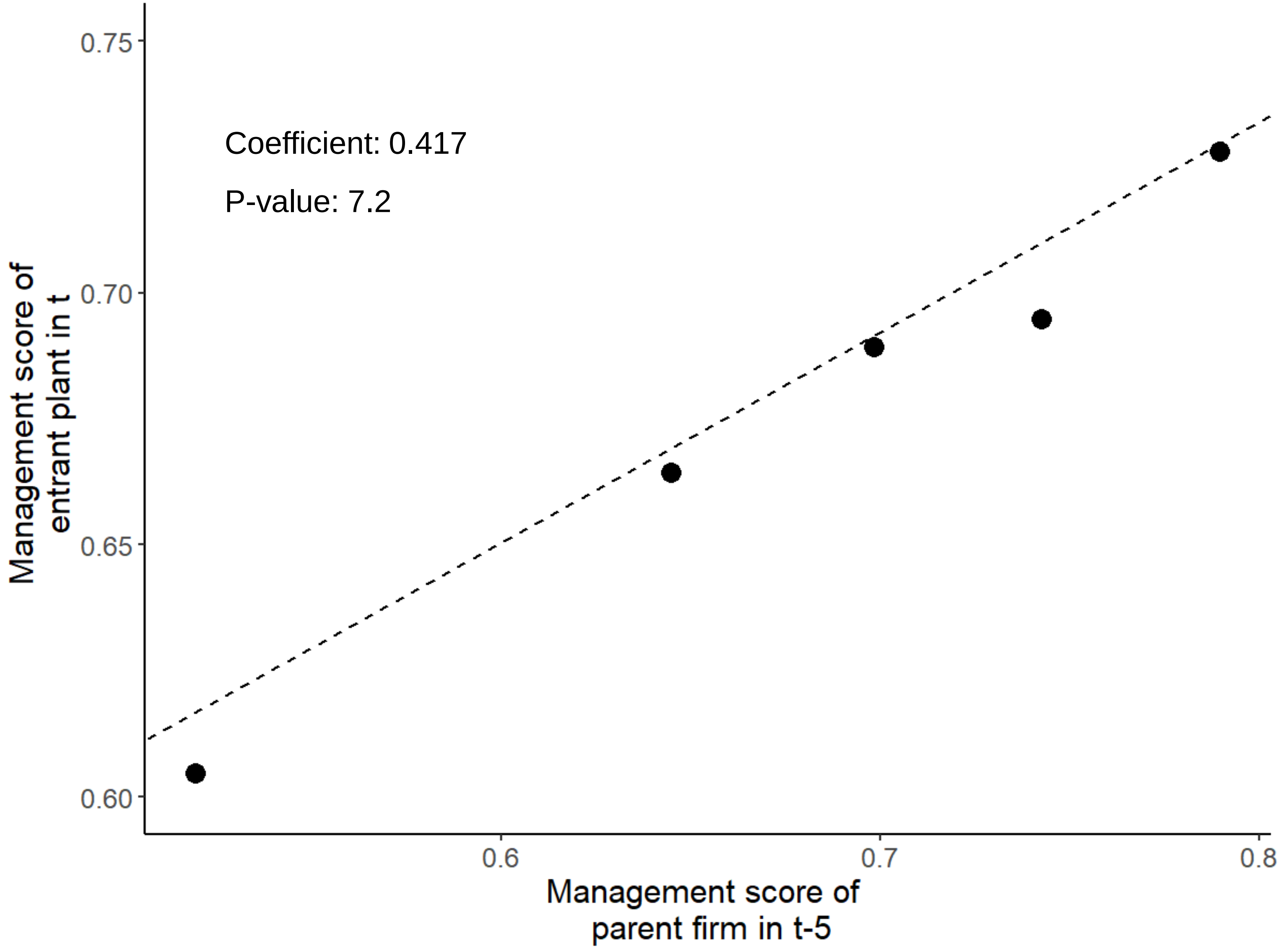






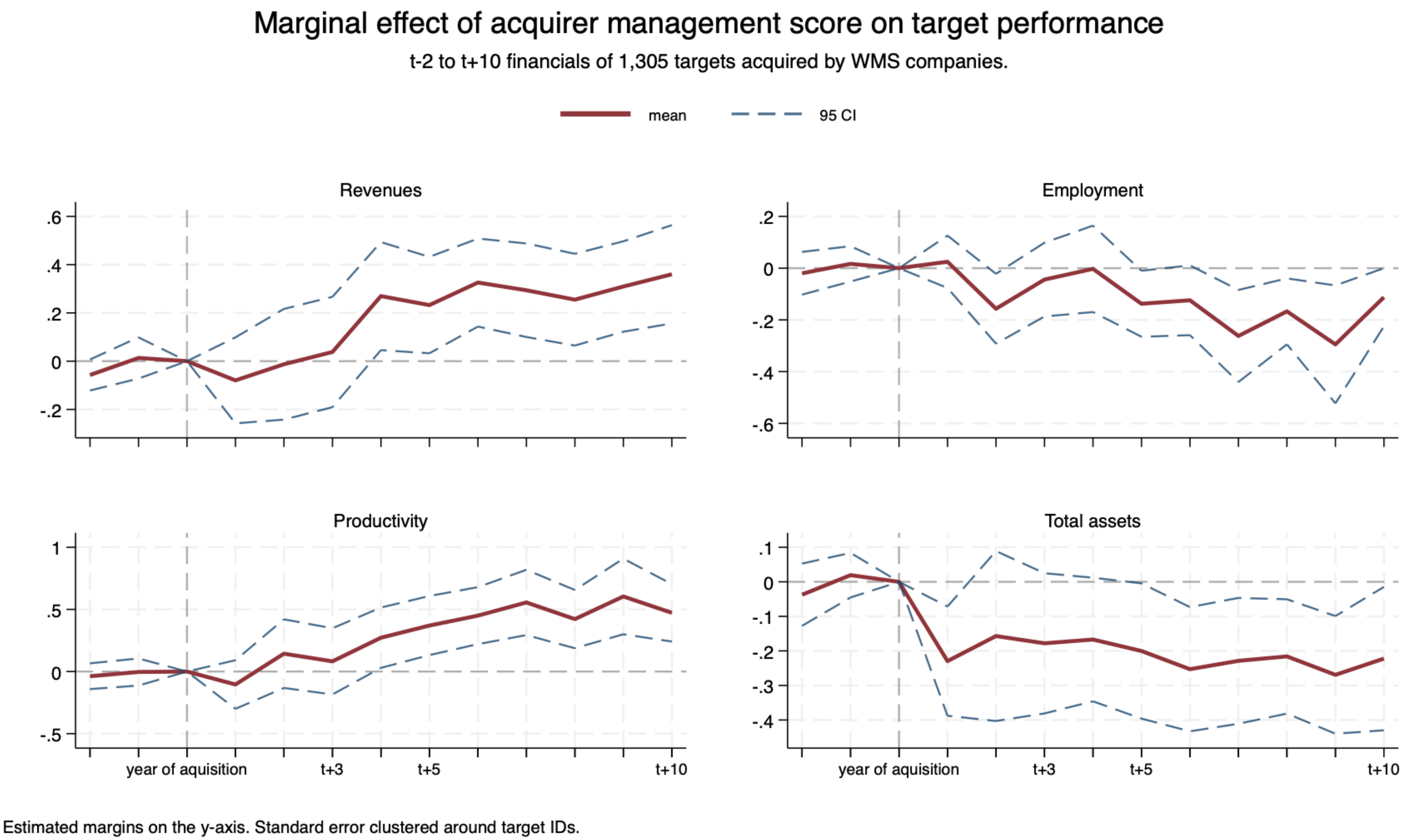
Notes: Data from MOPS of firms that had at least one plant in the MOPS in 2010 (for 2015) or 2015 (for 2019). Only stayer firms are included, i.e. those that had one plant present in 2010 and 2015 or 2015 and 2019. The acquisition (disposal) share is defined as the number of manufacturing plants acquired (disposed of) between year t-5 and year t divided by the total number of manufacturing plants at the firm in year t-5. Net acquisition rate is the acquisition rate minus the disposal rate. All shares are winsorized at the 99th percentile. Plot shows means for 20 equally-sized bins of parent firm management scores. Bin scatters include fixed effects for the modal 3-digit NAICS industry and modal state for plants in the firm. Growth rates are defined from 2010-2015 and 2015-2019 (the latest available data at the time of writing). t-statistics are from the regression of acquisition, disposal, and net disposal rates on lagged parent firm management. All figures are on the same scale. N=32,000 firms.

Figure 3: Plants born to well managed firms have higher management scores



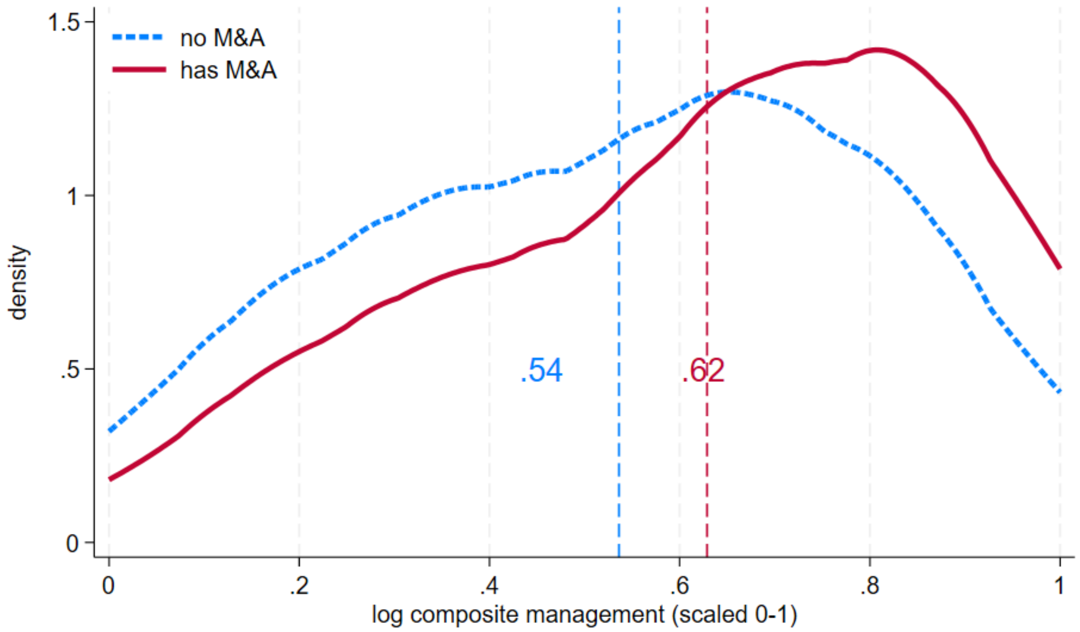
Notes: For Census disclosure reasons, we were limited to five data points in the figure (results within the Census using more points are similarly near monotonically increasing). Data from MOPS plants that entered between 2015 and 2010 whose parent firm had at least one plant in the MOPS in 2010. An entrant plant is defined as a plant that appeared in the LBD between 2015 and 2010 and who had a management score from MOPS 2015.. Binscatter includes fixed effects for 4-digit NAICS industries and states. Coefficients and p-values are from the regression of entrant plant management on lagged parent firm management.

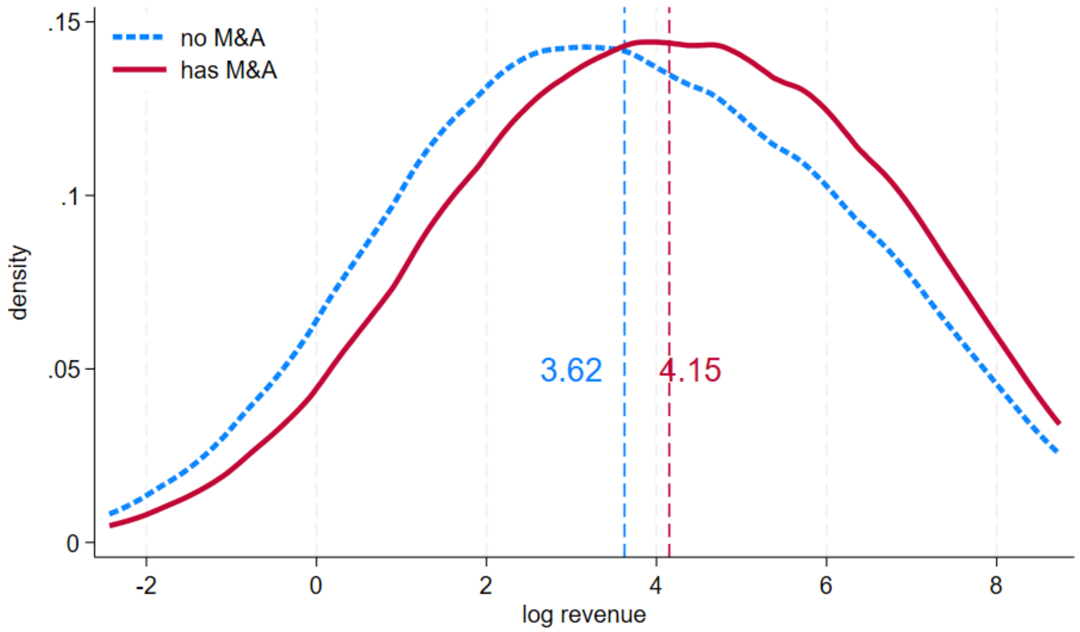
Figure 4: Performance rises after acquisition by well-managed firms



Notes: Data from 1247 targets acquired by 687 firms in the World Management Survey from 1997 to 2018. Estimated margins from event study regression on y-axis with standard errors clustered by target IDs.

Figure 5: Management and revenues decline when M&A is not allowed

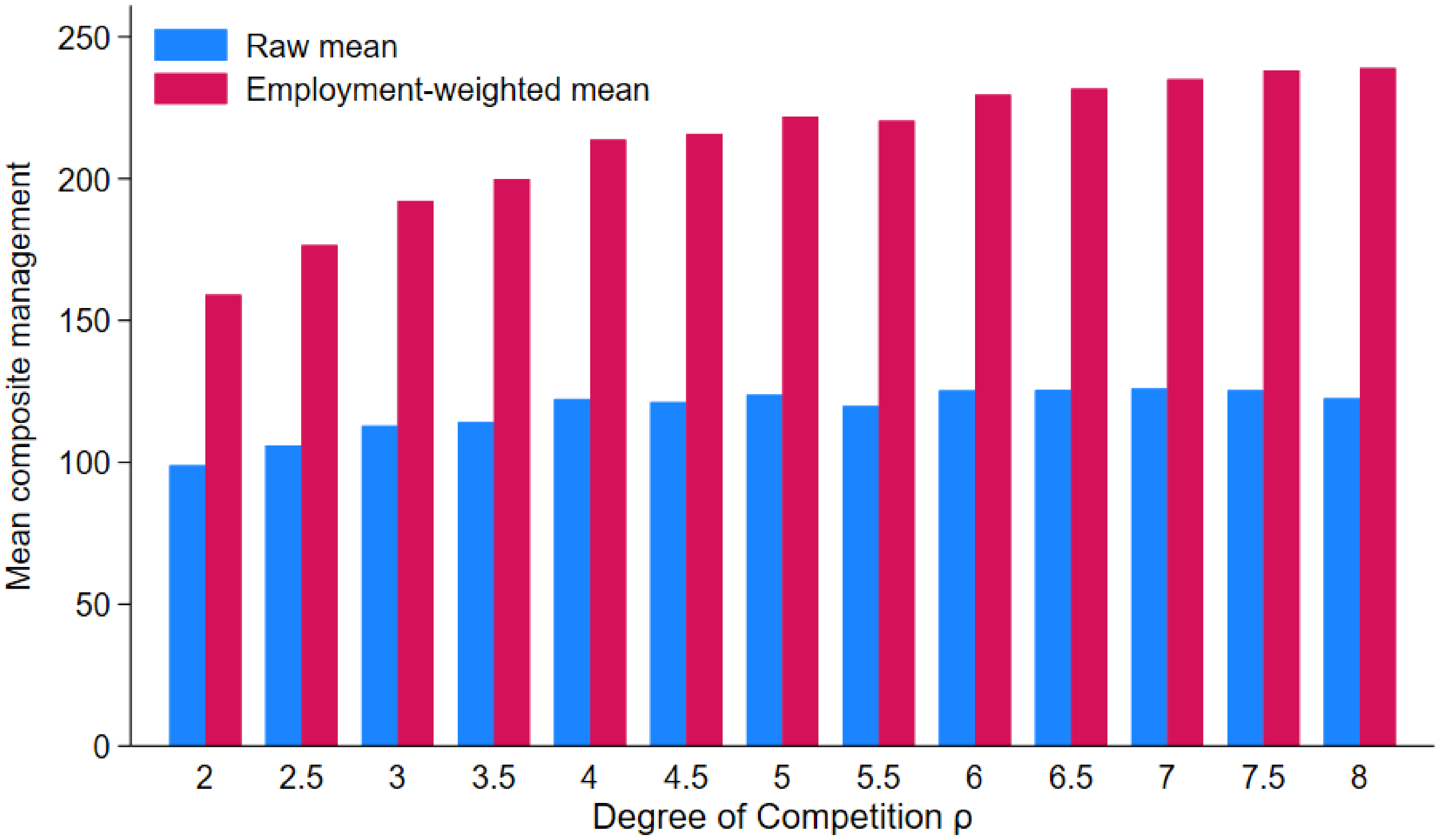




Notes: The kernel density estimate of the distribution of plants by their composite management scores (M*C). Bin width is .05. Composite management scores are logged and rescaled from 0-1 to match MOPS management scores.

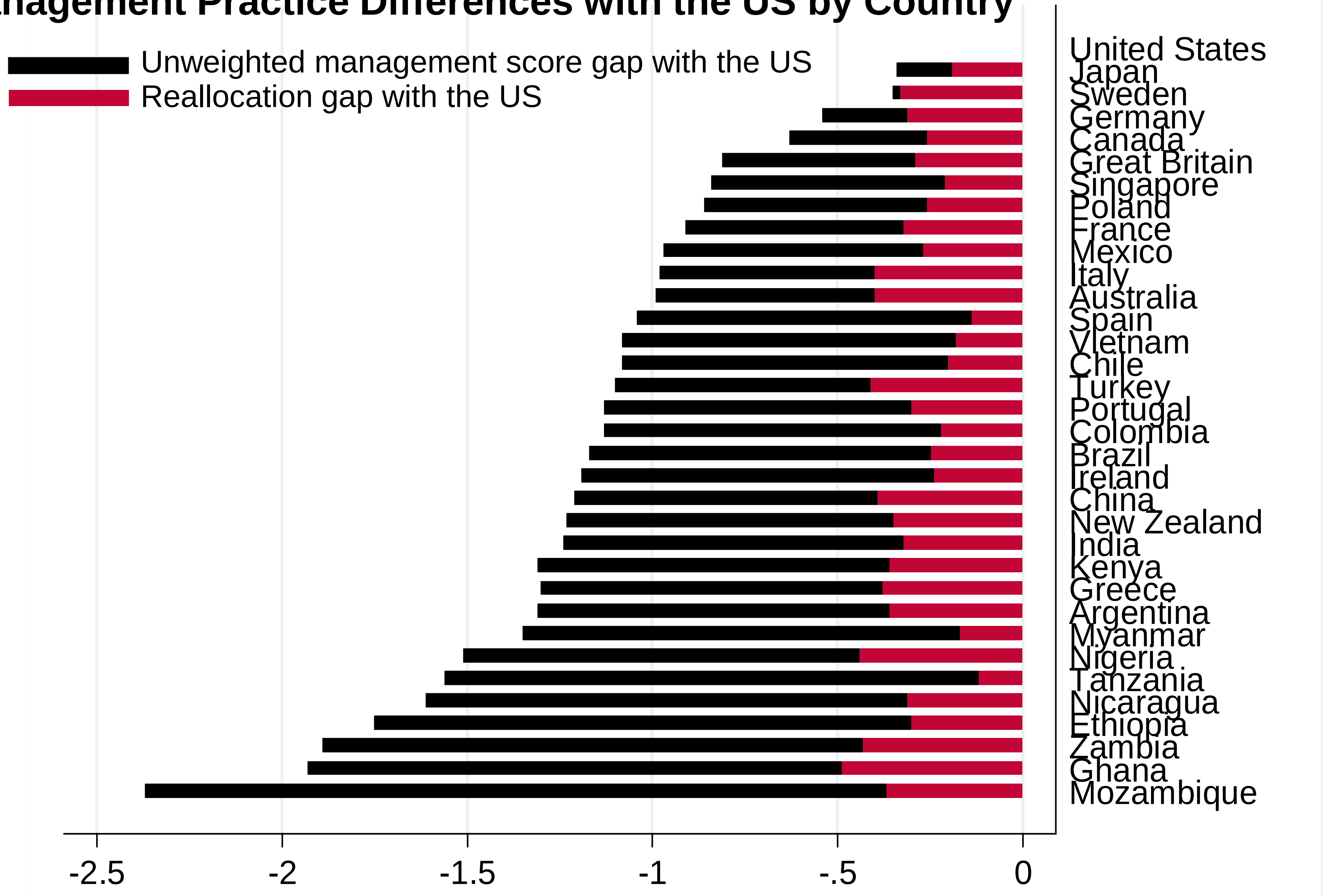
Notes: The kernel density estimate of the distribution of plants by their composite management scores (M*C). Bin width is .05. Composite management scores are logged and rescaled from 0-1 to match MOPS management scores.

Figure 6: Stronger Competition increases average management and improves reallocation



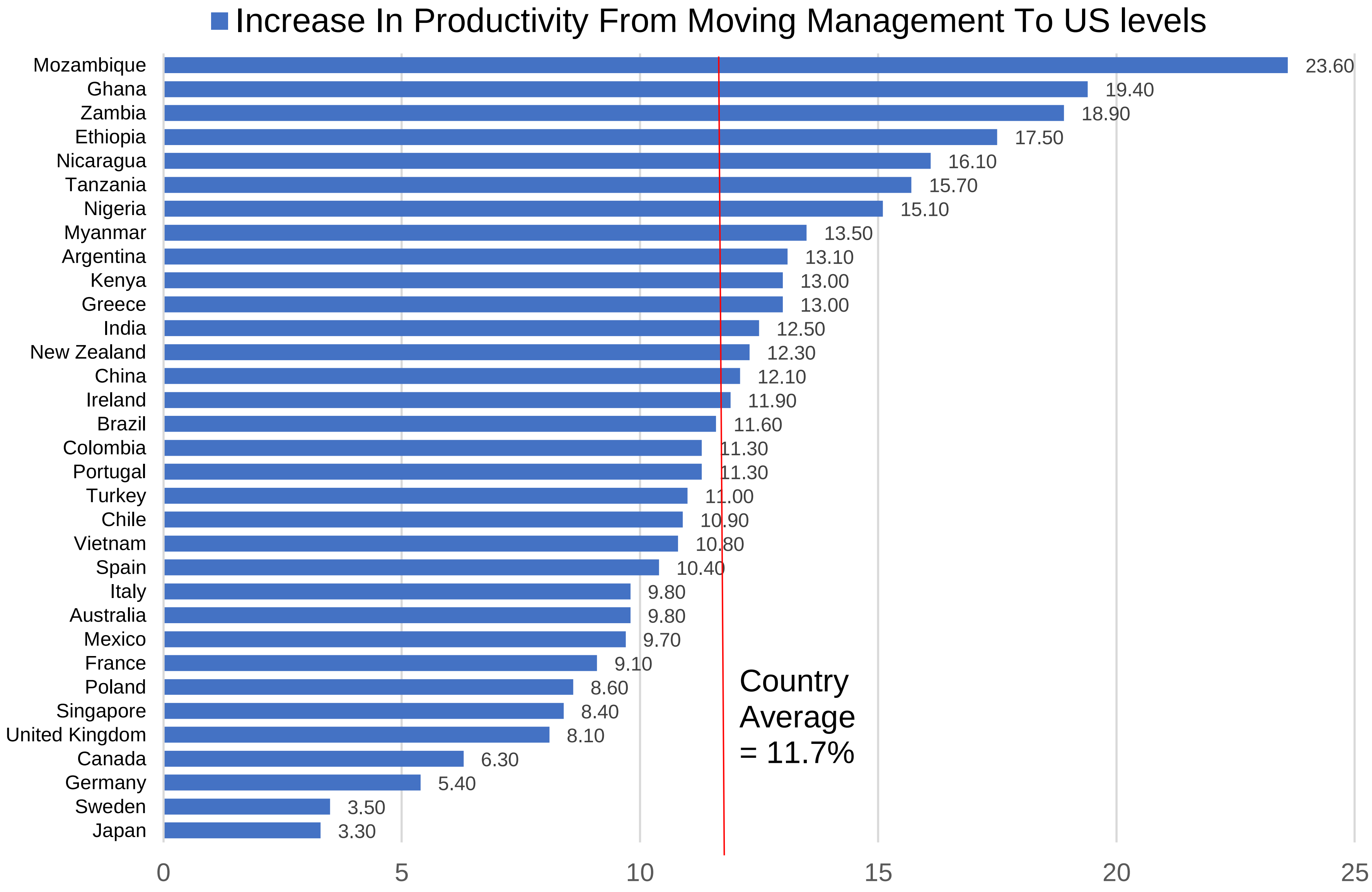
Notes: Results are from using our estimated model to simulate 2,000 firms per year in the steady state. Plots management (M*C) in the simulation data. Competition is indexed by demand elasticity with higher values indicating greater competition (ρ=5 in baseline. Dark Blue bar is unweighted mean across plants, Light Red bar is weighted by plant size (employees). A higher degree of competition is related to higher management.

Figure 7: Management Practice Differences with the US by Country



Notes: Employment share-weighted management score differences vs the US (in management score standard deviation units). Length of bar shows total deficit, composed of the sum of the (i) the unweighted average management scores (black bar) and the Olley-Pakes reallocation effect (red bar). Domestic firms only. Management scores corrected for sampling selection bias.

Figure 8: Productivity Gaps with the US due to Management Differences

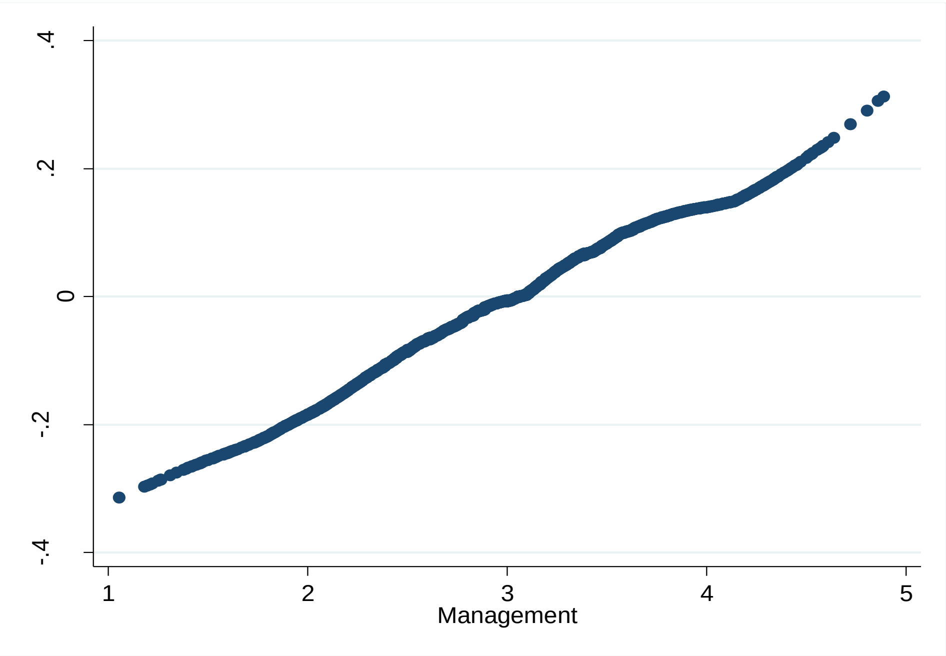


Notes: Length of bar shows increase in productivity from hypothetically moving management capital stock to U.S. levels for a given country using each country's employment share-weighted management score differences vs the US (in management score standard deviation units).

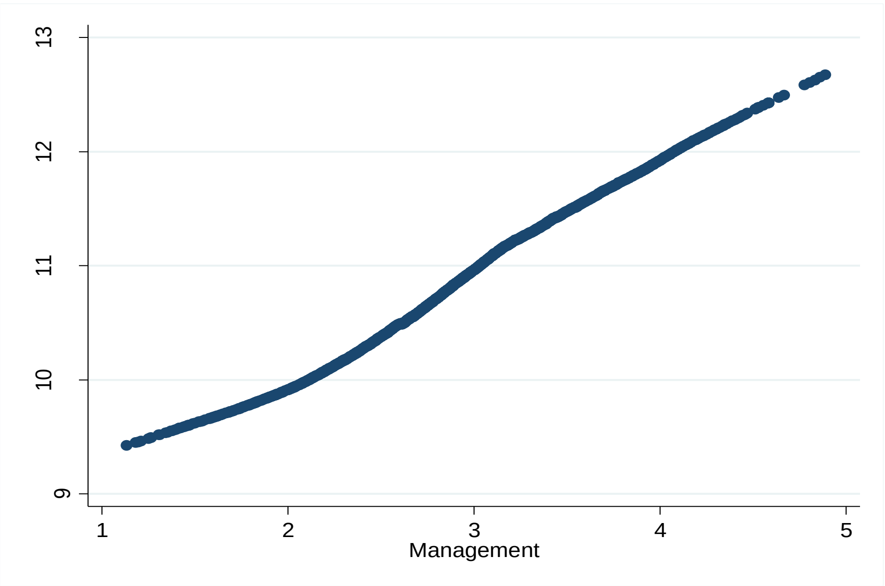
Appendix

Figure A1: Performance is increasing in management

A. TFP

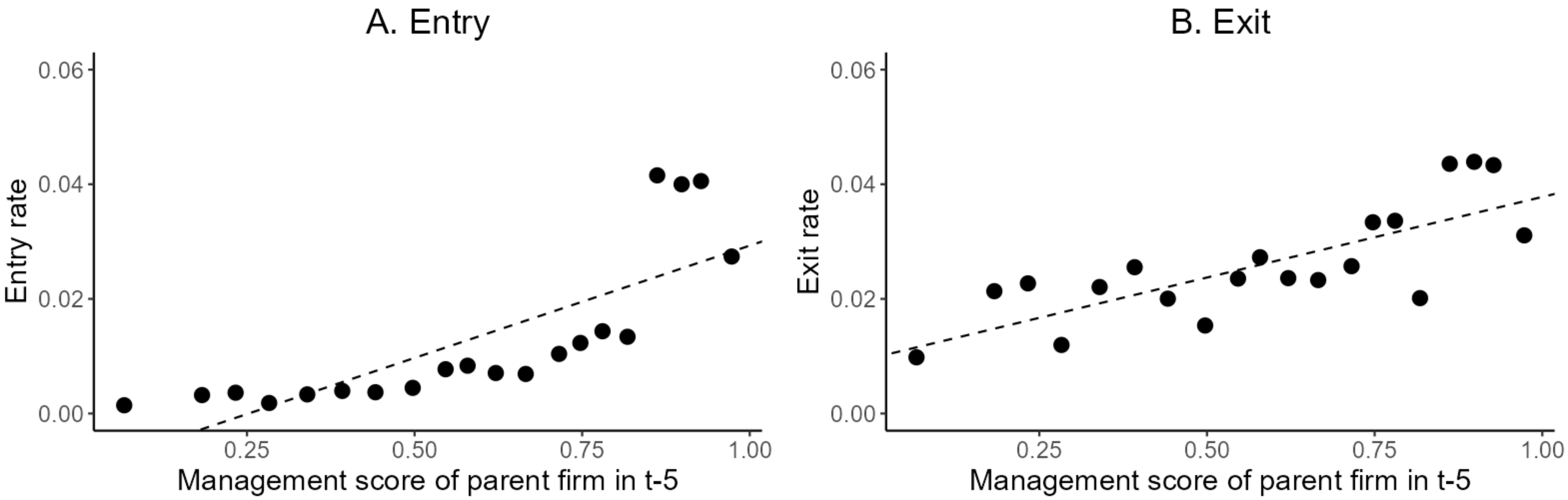


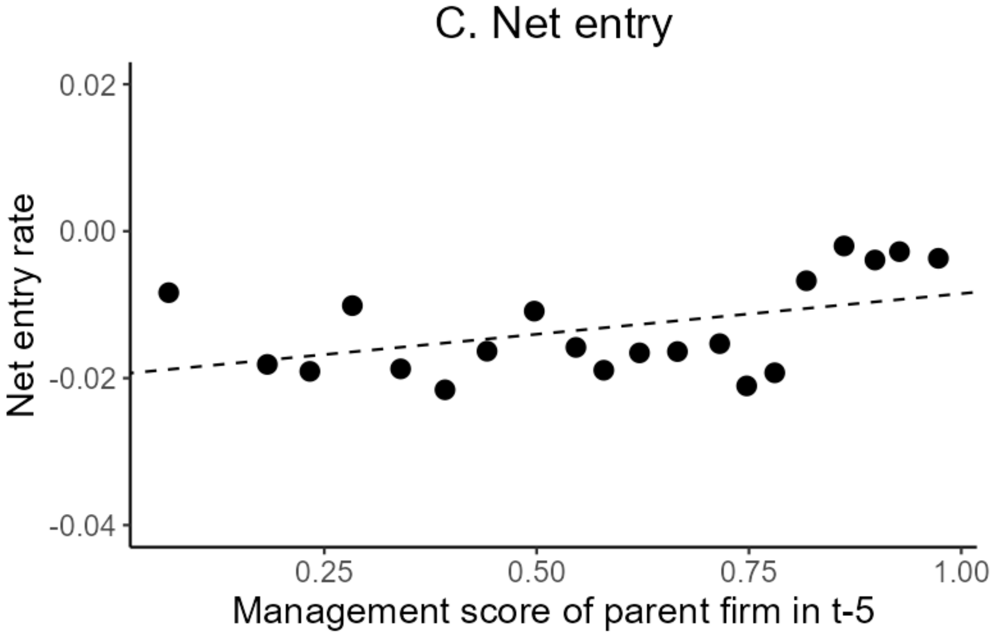
B. Size



Notes: Panel A plots the lowess predicted valued of TFP against management (bandwidth=0.5). TFP calculated as residual of regression of log(sales) on log(capital) and log(labor) plus a full set of 3-digit industry, country, and year dummy controls. N = 10,900. Panel B plots the lowess predicted values of log(sales) against management (bandwidth=0.5). Sales is log(sales) in US$. N=13,854. WMS Data.

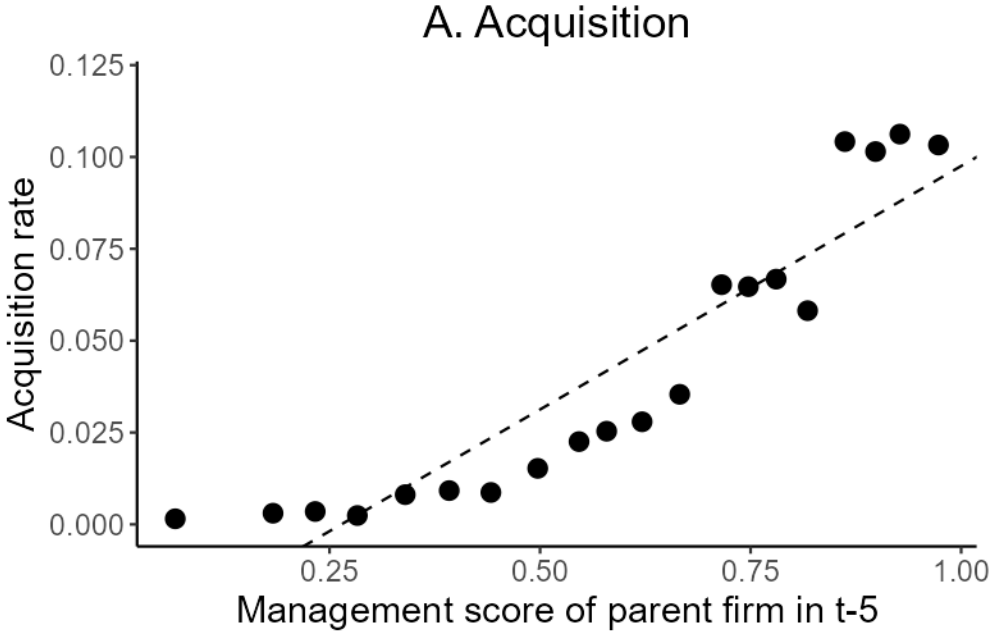
Figure A2: Well-managed firms have greater entry, exit and net entry rates in model simulation

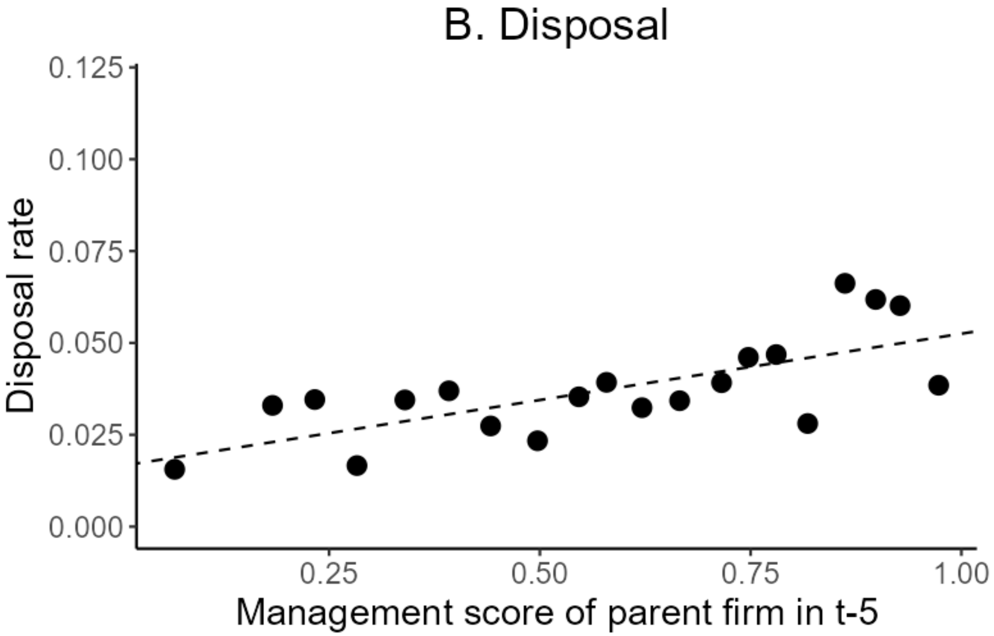


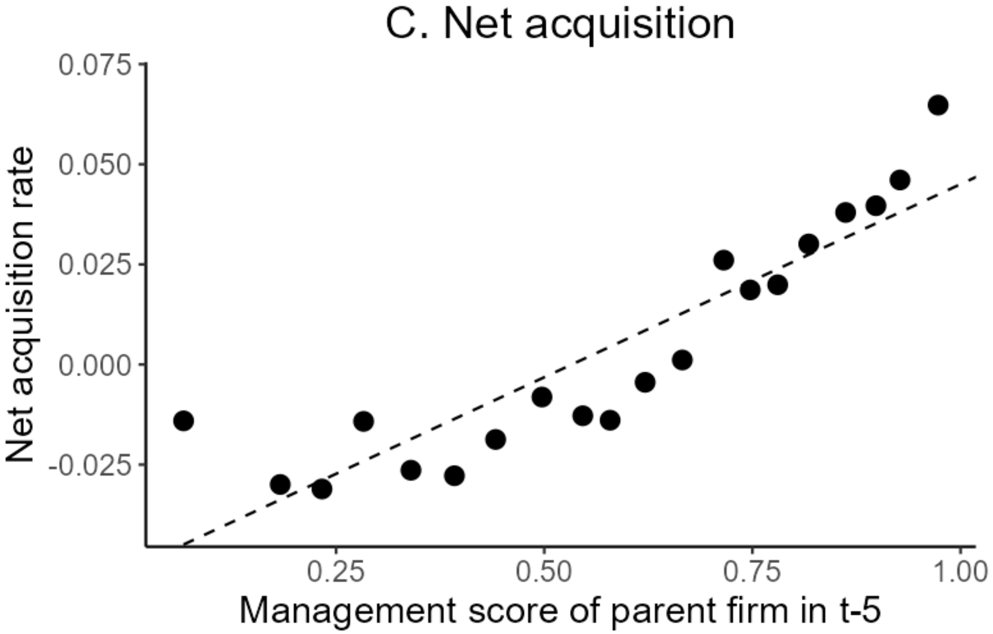


Notes: This Figure shows the relationship between binscattered management and various variables for approximately 65,000 plants at 28,000 firms per year for 50 simulated years. The entry (and exit) rate is calculated as the number of plants that enter between period t+1 and t divided by the total number of plants at a firm in year t. The sample is limited to “stayer” firms, that is, firms that have at least one plant active in years t and t+1. Panel A plots management versus the greenfield entry rate of a firm. Panel B plots management versus the greenfield exit rate of a firm. Panel C plots management versus the net greenfield entry rate of a firm. Management is positively related to entry rates, exit rates, and net entry rates.

Figure A3: Well-managed firms have greater acquisition, disposal and net acquisition rates in model simulation

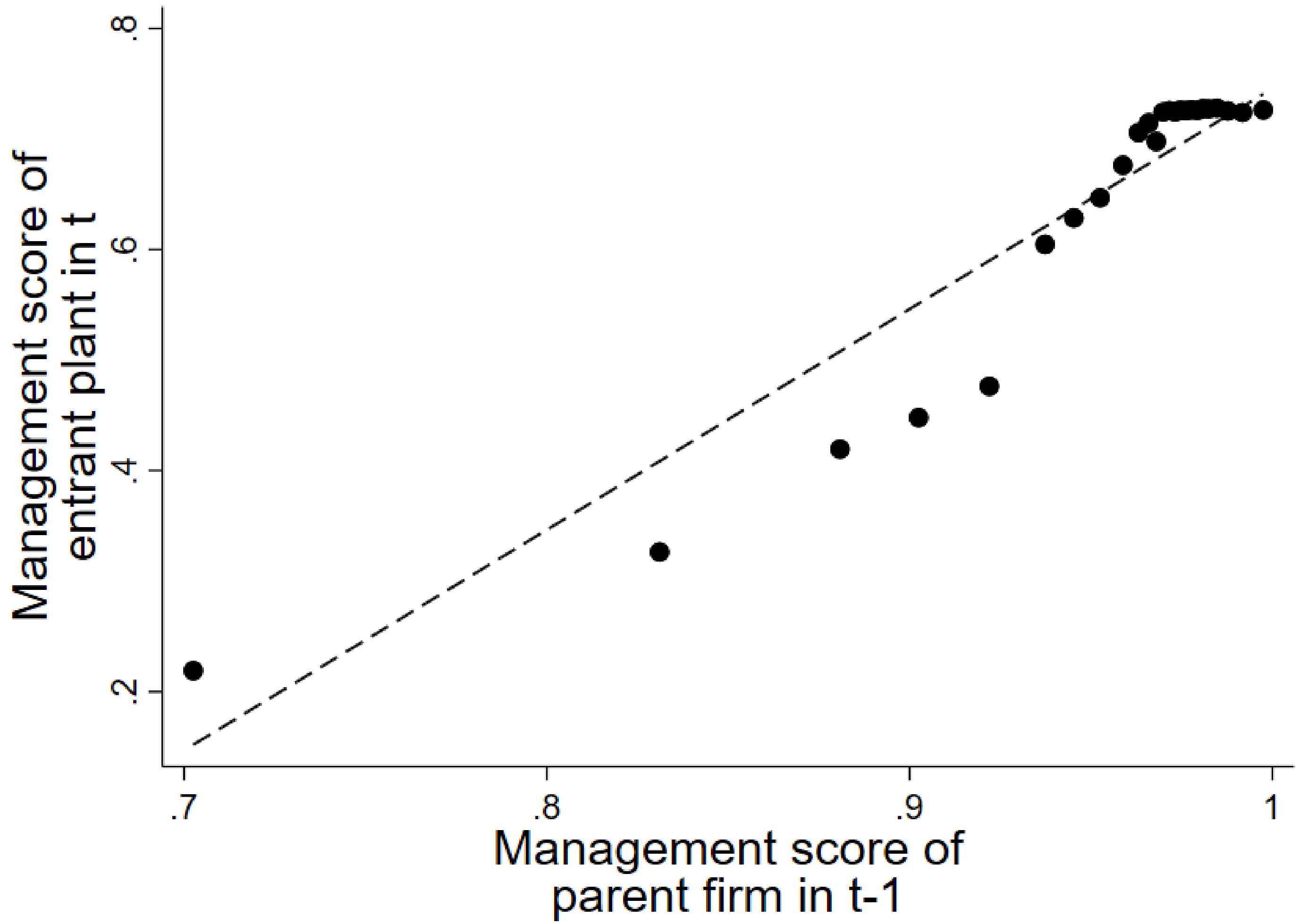






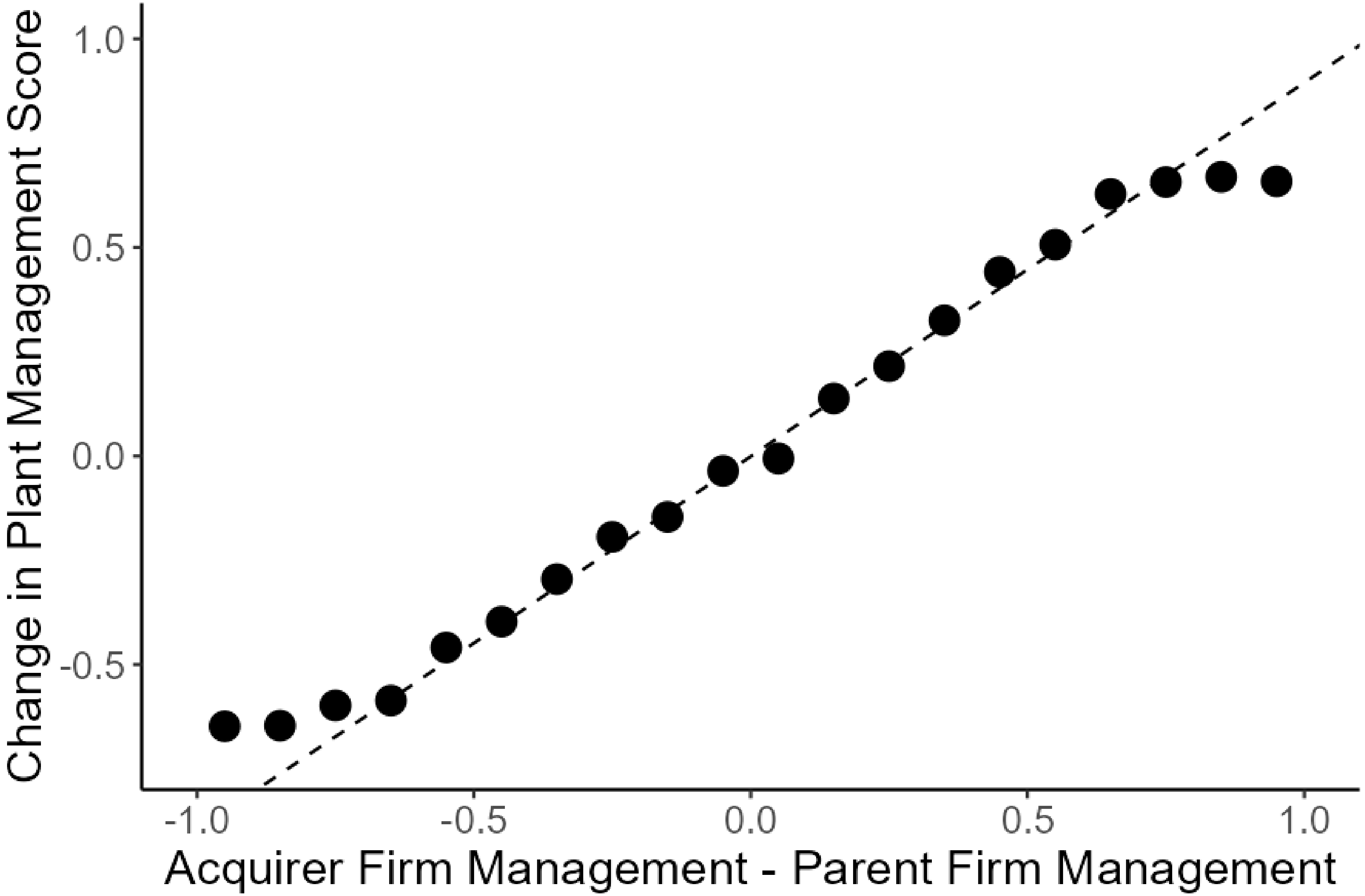
Notes: This Figure shows the relationship between binscattered management and various variables for approximately 65,000 plants at 28,000 firms per year for 50 simulated years. The acquisition (and disposal) rate is calculated as the number of plants that are acquired between period t+1 and t divided by the total number of plants at a firm in year t. The sample is limited to “stayer” firms, that is, firms that have at least one plant active in years t and t+1. Panel A plots management versus the acquisition rate of a firm. Panel B plots management versus the disposal rate of a firm. Panel C plots management versus the net brownfield acquisition rate of a firm. Management is positively related to acquisition, disposal, and net acquisitions rates.

Figure A4: Plants born to well-managed firms have higher management scores in model simulation



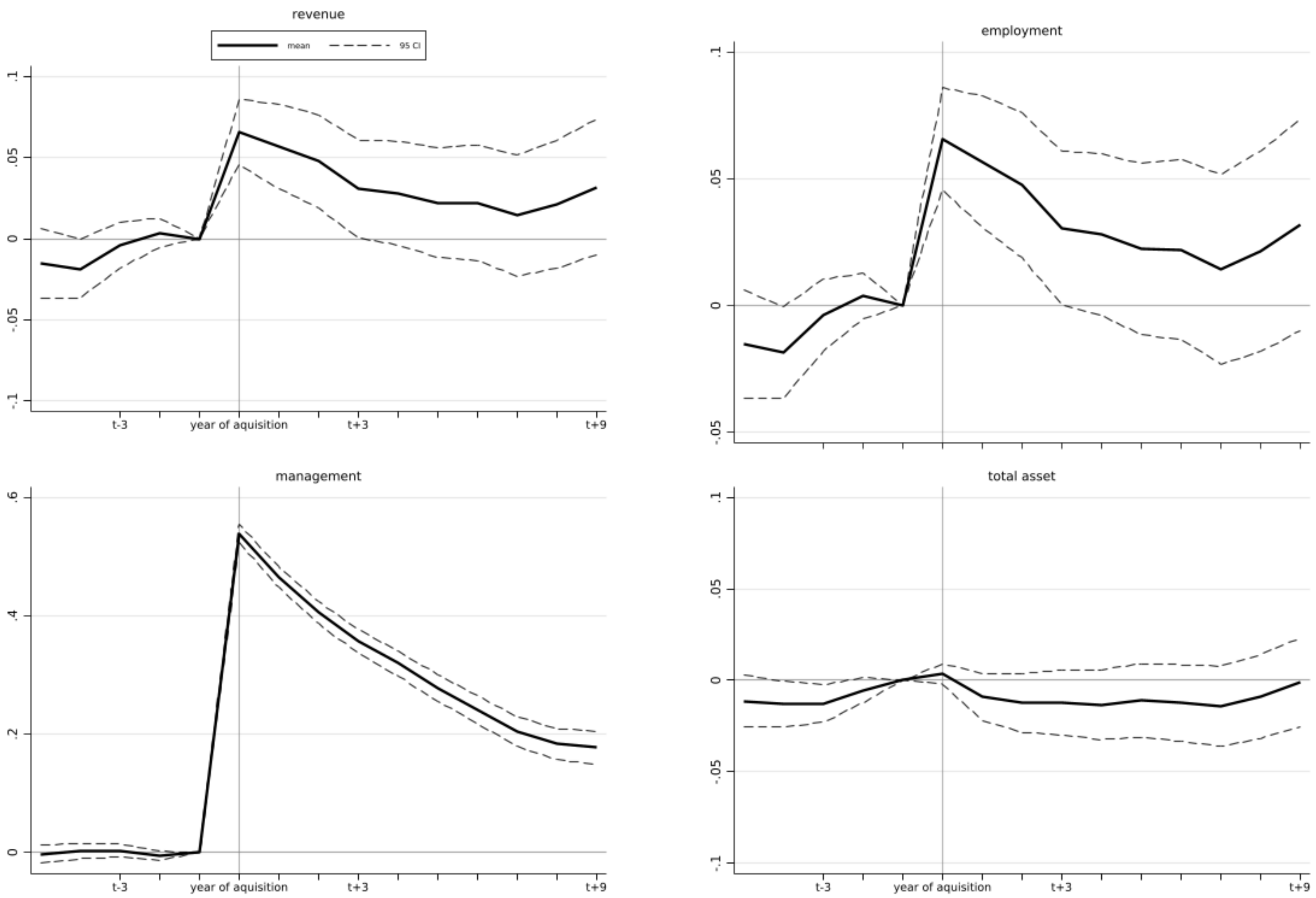
Notes: Figure shows the relationship between binscattered management of the firm and the management of the plants born to them for 28,000 simulated firms per year over 50 years. The management of firms is positively related to the management of plants born to them.

Figure A5: Plants purchased by better-managed firms improve their management scores



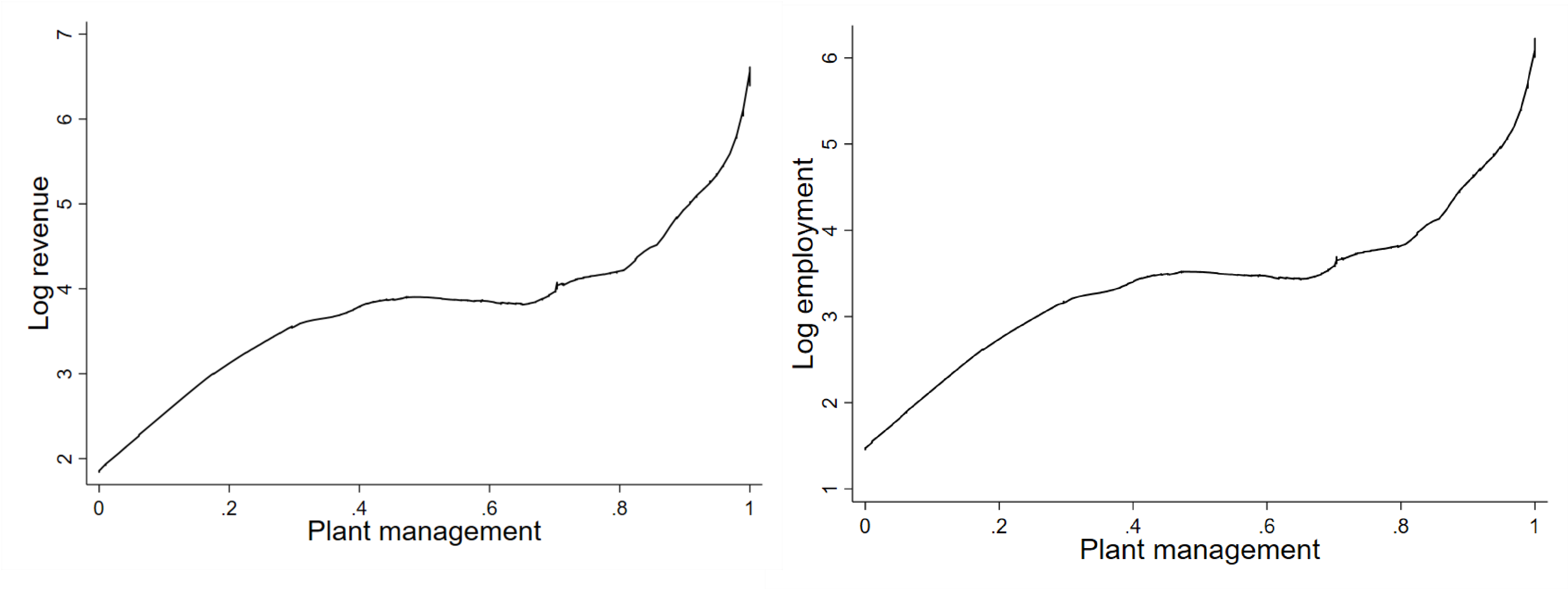
Notes: This figure shows the relationship between binscattered changes in management scores for 4400 acquired plants per year over 50 simulated years. Plant management is measured in the year before and year after acquisition. Parent firm management is the leave-out mean, and parent and acquirer firm management are measured in the year prior to acquisition. The difference in management scores between the acquirer and parent firm is positively related to the change in management at the acquired plant.

Figure A6: Performance rises after acquisition by well-managed firms



Notes: This Figure shows the results of event studies analyzing the effects of acquisition on revenue, employment, productivity and total assets of acquired plants for 10,000 simulated target plants per year over 50 simulated years. After acquisition, plant revenue, employment, management, and total assets tend to rise.

Figure A7: Firm revenue and employment increase in plant management in model simulation



Notes: This figure plots the lowest predicted values of log(revenue) and log(employment) against management (bandwidth=0.5). Sales is log(sales) in US$. Sample of 1% of approximately 65,000 plants at 28,000 firms per year for 50 simulated years.

Figure A8: Cross-Country Spread of Management Practices