Managing Resource (Mis)allocation*

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Abstract

Prior work has shown that the misallocation of capital and labor substantially lowers aggregate productivity. In this paper, we use Census microdata at the plant level to decompose how much aggregate productivity is lost due to misallocation across firms, and how much is lost because of misallocation within firms. When capital and labor are hypothetically reallocated to equalize marginal products across all plants, we find an increase in aggregate productivity of 42%, out of which 30% is due to misallocation within firms. Managerial quality explains a large part of the efficiency of internal capital and labor markets. In a counterfactual where all multi-unit companies are assigned the highest management score, aggregate productivity increases by 13% due to improvements in the allocation of internal resources. To ensure that our results are not driven by mismeasurement, we exploit the introduction of new airline routes that reduce the travel time between headquarters' ZIP code and the plant's ZIP code. We further document that companies that misallocate resources internally have lower profits and lower value.

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I Introduction

Large differences in capital and labor productivity across plants in the U.S. and around the world suggest that resources in these economies are not allocated efficiently. This misallocation substantially lowers aggregate productivity (Hsieh and Klenow, 2009).[1] We begin by observing that two broad mechanisms determine the allocation of resources to plants. First, firms acquire capital and labor in the market, and allocation is achieved through prices. Then managers choose how to allocate these resources within firms. The share of allocation that occurs within firms is substantial, with 88% of output being produced in multi-plant firms (Bernard and Jensen, 2007), which frequently span several industries. Therefore, it is natural to ask whether resources are misallocated in the economy because capital and labor markets are not functioning properly, or because managers do a poor job of allocating the resources they obtain. In other words, how much TFP is lost because resources flow to the wrong firms, and how much is due to firms misallocating the resources they have?

The distinction between allocations in markets and firms is important because they are subject to different distortions. Taxes, subsidies, regulations, or capital market frictions such as collateral constraints, distort resource allocation in markets. Within firms, the distortions in resource allocation are driven by management practices and incentives. In fact, resource allocation seems to be one of the primary tasks of management. McKinsey defines strategy at the corporate level as "primarily about deciding what businesses to be in, how to exploit potential synergies across business units, and how to allocate resources across businesses" (McKinsey & Company, 1994, p. 110). In this regard, a recent literature has shown that firms with better management practices have higher productivity, are more profitable, and more valuable (Bloom and Van Reenen, 2007; Bloom et al., 2019). We ask whether well managed firms experience superior performance partially because they allocate resources better, and quantify the contribution thereof to aggregate productivity.

Our first goal is to decompose how much aggregate TFP is lost because of misallocation within markets and how much is lost due to misallocation within firms. To quantify how within-firm frictions affect aggregate productivity and output, we build a simple model of monopolistic competition with heterogeneous plants based on Hsieh and Klenow (2009). The model allows us to decompose the wedges identified in Hsieh and Klenow (2009) into their market and firm components. We depart from standard models by explicitly modeling multi-plant firms. Plants are production units that cannot raise resources directly from the market. As in the McKinsey definition of strategy above, CEOs acquire capital and labor from the market, and allocate them to plants. Such allocations can be implemented directly, or CEOs

[1] See Hopenhayn (2014) and Restuccia and Rogerson (2017) for an overview of the literature.

can set budgets for plants and divisions, which in turn acquire resources within that budget. A central feature of the model is that distortions can arise in the allocation of resources to firms, as well as when firms allocate resources internally.

We estimate the model using plant-level data from the quinquennial Census of Manufacturing (CMF) of the U.S. Census Bureau. To see the intuition of how the model disentangles resource misallocation in the market from resource misallocation within firms, consider the following example. A firm consists of two plants with equal marginal revenue product of capital (MRPK) that exceeds their rental rate. Because the firm's MRPK exceeds the rental rate of capital we can conclude that this firm does not obtain enough capital, i.e. the capital allocation across firms in the market is distorted. However, the firm equalizes MRPKs across plants, so it efficiently allocates the limited capital that it does obtain across plants. In other words, there are no distortions within the firm. Conversely, if we observe large differences in MRPK across plants within the firm, but the MRPK of the overall firm is close to the rental rate of capital, we would conclude that capital is allocated appropriately to the firm, but that there are within-firm distortions. The model formalizes this intuition, and allows us to quantify how within-firm distortions affect firm, industry, and economy-wide TFP.

We find substantial differences in capital and labor productivity across firms, as well as across plants of the same firm, suggestive of resource misallocation both across and within firms. Overall, distortions are substantial, and removing them would lead to aggregate TFP increases of 42%, consistent with the estimates found in Hsieh and Klenow (2009). Within-firm distortions account for approximately 30% of the overall potential gains. To some degree, these estimates understate the amount of resource misallocation that takes place within firms, because single-plant firms by definition have no within-firm distortions. Once we focus on multi-plant firms, the share of within-firm distortions rises to approximately 50%. For these firms, on average, half of the productivity losses arise due to resources flowing to wrong firms, and the other half because firms mismanage the resources they acquire in the market.

Misallocations of capital and labor play a quantitatively similar role in within-firm misallocation and their allocation is highly correlated. In other words, plants, which on average obtain too much capital, are also flush in labor. Plants, which are allocated too little capital, are on average also starved of labor. This result suggests that some plants are generally better at obtaining resources from firm headquarters; a result, which we explore in more depth below. Interestingly, most of the within-firm resource misallocation occurs because firms misallocate resources among plants in the same sector, rather than across sectors. In other words, firms are better at allocating resources across sectors than within.

Misallocation of firm resources implies that firms use too much capital and labor for a given level of output, because they allocate too many resources to some plants, at the expense of others. Such within-firm misallocation should result in lower productivity, and consequently lower profits and value. For a subset of firms, matched with Compustat, we observe profits, as well as market values. We find that firms that have larger within-firm distortions are less profitable, have a lower return on assets, as well as lower market values (Tobin's Q).

If management is indeed about "how to allocate resources across businesses," as McKinsey claims, then better managed firms should excel at allocating resources. We measure the quality of management using data from the Management and Organizational Practices Survey from the Annual Survey of Manufacturing. We find that firms with better structured management exhibit lower distortions in within-firm resource allocation, both across plants within the same industry, as well as across different industries. In other words, poorly managed firms allocate too much capital and labor to unproductive plants at the expense of productive plants. This misallocation leads to lower factor productivity. This result is consistent with Bloom and Van Reenen (2007) and Bloom et al. (2019), who find that better managed firms achieve higher productivity and profitability. Our findings suggest that one channel through which management contributes to superior performance is through better resource allocation.

One way to evaluate the quantitative importance of high quality management is to measure the increase in TFP that would result from firms improving their management scores to those of the best managed firm in their industry. We find an aggregate gain in TFP of approximately seven percentage points, suggesting that better management would reduce the overall losses from resource misallocation by approximately 17%. Given that firm distortions account for approximately 30% of these losses, better management can substantially reduce the losses from resource misallocation. The benefits of better management are not due to one particular dimension of management. Both improvements in the management of targets and incentives, as well as monitoring, reduce within-firm frictions.

The methodology we employ uses model-implied marginal products of capital and labor to identify distortions. Because these distortions are recovered from model residuals, they may be incorrectly interpreted as inefficiencies if the model is misspecified (Haltiwanger, Kulick, and Syverson, 2018). In particular, distortions in the data could reflect measurement error (White, Reiter, and Petrin, 2018; Rotemberg and White, 2019; Blis, Klenow, and Ruane, 2021), adjustment costs (Asker, Collard-Wexler, and De Loecker, 2014; Kehrig and Vincent, 2019), overhead costs (Bartelsman, Haltiwanger, and Scarpetta, 2013), or other forms of model misspecification. We conduct several tests that suggest this is unlikely to be a first-order concern in our setting.

First, we measure resource misallocation within firms using only data on the relative amounts of capital, labor, and shipments across plants. We do not use market values or operating performance to arrive at our estimates. Nevertheless, our estimates of within-firm misallocation are associated with worse operating performance and lower market values, consistent with the notion that these firms are mismanaging resources. Second, we exploit exogenous variation in travel time between a plant and its headquarters due to the introduction of new airline routes. Our estimates of a plant's ability to obtain resources increase when the travel time between a plant and its headquarters exogenously decreases. Unless the introduction of a new airline route is correlated with changes in measurement error, fixed costs of investment, or any other model misspecification, these tests suggest that the distortions we identify in the data are indeed indicative of plants' ability to capture resources internally. Third, we find that better managed firms have lower estimates of within-firm misallocation. While this is consistent with our model and interpretation, it is difficult to explain this pattern if our results were purely driven by measurement error or model misspecification. One potential reason why the concerns raised by Haltiwanger, Kulick, and Syverson (2018) do not seem to be first-order in our setting is that, if deviations from the model assumptions occur at the firm level, our methodology would still allow us to accurately recover within-firm distortions—which are the focus of our paper—even if across-firm distortions could be biased.[2]

Our paper contributes to several strands of the literature. First, it contributes to the literature that examines the aggregate implications of misallocation (e.g., Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Bartelsman, Haltiwanger, and Scarpetta, 2013). While most of this literature focuses on the misallocation of resources in the economy, little is known of the aggregate implications of misallocation *within firms*. In this paper, we not only separate out the misallocation across and within firms, and quantify their respective importance, but also quantify the role of geographical distance and managerial quality as determinants of within-firm distortions. Second, our paper is related to the large literature on internal capital markets that studies the costs and benefits of multi-unit organization (e.g., Rajan, Servaes, and Zingales, 2000; Maksimovic and Phillips, 2002; Ozbas and Scharfstein, 2010; Matvos and Seru, 2014; Seru, 2014; Giroud and Mueller, 2015; Matvos, Seru, and Silva, 2018; Silva, 2021).[3] We contribute to this literature by quantifying the TFP losses due to the misallocation of resources within firms—one potential "dark" side of multi-unit organizations. Finally, our paper is related to the growing literature that studies the benefits from structured management practices. In particular, recent articles study how management practices affect productivity (Bloom et al., 2019, 2022) and the adoption of information technologies (Brynjolfsson and McElheran, 2016). Our paper identifies a novel channel through which better management

[2]For example, if the model assumption that all firms face a common (undistorted) cost of capital is wrong, the methodology would interpret across-firm differences in the cost of capital as signs of inefficiency. However, as long as the cost of capital is common across plants within the firm (which is arguably more plausible), our methodology would not lead to mismeasured within-firm distortions.

[3]For reviews of the literature on internal capital markets, see Stein (2003) and Maksimovic and Phillips (2013).

practices benefit companies, namely through the reduction of resource misallocation within firms.

This paper is organized as follows. Section II describes the model. Section III describes the data and provides a characterization of the resource misallocation within firms. Section IV presents the analysis of counterfactuals. Section V concludes.

II Model

We study an economy in which we distinguish between frictions that affect the allocation of resources within firms from those across firms in the market. We depart from standard models by explicitly modeling multi-plant firms, which can span several sectors. Plants cannot obtain resources directly from the market. Instead, firms raise resources and managers allocate them to plants within the firm. Managers lower in the hierarchy can engage in lobbying activities to obtain a larger share of resources, but doing so requires effort and is therefore costly. To explore how different types of frictions affect aggregate productivity and output, we build a simple model of monopolistic competition with heterogeneous plants based on Hsieh and Klenow (2009).

II.A Production and output

We first describe the production technology, and then describe how the different production units are organized within firms. The economy has S sectors, indexed by s. Each sector has M_s production units ("plants") that produce differentiated goods. Plant i in sector s,owned by firm f, produces output according to a Cobb-Douglas production function using capital and labor with industry-specific factor shares α_s:

$$Y_{fsi} = A_{fsi} K_{fsi}^{\alpha_s} L_{fsi}^{1-\alpha_s}. \tag{1}$$

Plants are price takers in the input markets, and input prices can differ across sectors. We denote the wage per unit of labor by w_s, and the rental rate of capital by r_s. Sector output Y_s is a constant elasticity of substitution (CES) aggregation of plant outputs in that sector:

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{fsi}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{2}$$

We aggregate sectoral output into a single final good Y, by combining the output of all sectors in the economy through a Cobb-Douglas production technology:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s}, \text{ where } \sum_{s=1}^{S} \theta_s = 1. \tag{3}$$

The final good market is perfectly competitive, and the price of aggregate output is normalized to one (numéraire).

Let P_{fsi} denote the price of the good produced by plant fsi, and P_s the price of the sector good. Firms interact in a monopolistic competition setting, that is, they maximize profits subject to their demand curve, but are price takers with respect to P_s. In Appendix A, we show that the demand for each differentiated good is given by

$$Y_{fsi} = P_{fsi}^{-\sigma} Y_s P_s^{\sigma}, \tag{4}$$

implying that a plant's share of industry sales is

$$\frac{P_{fsi} Y_{fsi}}{P_s Y_s} = P_{fsi}^{1-\sigma} P_s^{\sigma-1},$$

and the price of sector good s is obtained by aggregating prices across all plants in sector s

$$P_s = \left(\sum_{i=1}^{M_s} P_{fsi}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}.$$

II.B Influence activities within firms

Plants are production units that cannot raise resources directly from the market. Firms acquire resources, allocate these resources to divisions, which in turn allocate them to plants. Such hierarchical allocation occurs because headquarters sets budgets for divisions, which in turn set budgets for their plants.

We distinguish between distortions within markets and those within firms. We denote distortions that affect the marginal product of all plants within the firm by τ_{fY}. Such across-firm distortions may arise due to taxes or subsidies, or difficulties in accessing external financing, which in turn affect the overall output of the firm. Once resources are allocated across firms, they may be misallocated further within firms. Specifically, resources may be misallocated across divisions, and across plants within divisions. We denote division-level distortions by τ_{fsY}, and plant-level distortions by τ_{fsiY}, respectively.

The within-firm distortions differ from those within markets, as they are driven by frictions within the firm's hierarchy.[4] In this vein, a large literature argues that unit managers (that is, division and plant managers) engage in influence activities to channel more resources towards their units (e.g., Meyer, Milgrom, and Roberts, 1992; Milgrom, 1988; Milgrom and Roberts, 1988; Rajan, Servaes, and Zingales, 2000; Scharfstein and Stein, 2000). In these models, unit managers prefer larger resource allocations—due to "empire building" preferences (e.g., if managers enjoy the power and status of managing a large unit) or rent-seeking motives (e.g., if financial compensation, perquisite consumption, or outside job opportunities are linked to the size of the unit they manage)—and lobby the higher hierarchical level accordingly (i.e., division managers lobby headquarters, and plant managers lobby division managers). As a result, units run by more "powerful" managers may receive allocations that are larger than what would be justified by their investment opportunities.[5]

Plant manager's *optimization problem*

We start with the optimization problem of the plant managers. As in the models of influence activities, we assume that plant managers have empire building preferences and choose how much capital and labor to employ in order to maximize the size of their plants (captured by plant-level sales). The plant managers' ability to employ capital and labor is constrainted by the budget allocated to them by their division manager. B_{fsi} denotes the budget of plant i in division s of firm f. Plant managers can influence the size of the budget allocated to their plants by lobbying division managers. Lobbying requires effort, which we denote by μ_{fsi}. We assume that the effort cost of lobbying is given by the quadratic function $c_{fsi}\mu_{fsi}^2$.

Each plant manager chooses the lobbying effort (μ_{fsi}) as well as the amount of capital (K_{fsi}) and labor (L_{fsi}) to employ in order to maximize plant size net of the lobbying costs:

$$\max_{\left\{K_{fsi}, L_{fsi}, \mu_{fsi}\right\}} \quad P_{fsi}Y_{fsi} - c_{fsi}\mu_{fsi}^2$$
$$s.t. \quad (1+\tau_{fsiL})wL_{fsi} + rK_{fsi} = B_{fsi}.$$

Although our analysis focuses on the size distortions within firms, we also allow for distor-

[4] This notion can be traced back to Coase (1937, p. 388), who suggested that decisions within a hierarchy are determined by power considerations rather than relative prices.

[5] A vast empirical literature is consistent with this prediction. Glaser, Lopez-de Silanes, and Sautner (2013) find that, following cash windfalls, more powerful unit managers obtain larger capital allocations for their units than would be predicted by their fundamentals. This translates in overinvestment and lower ex post performance of their units. Similarly, Duchin and Sosyura (2013) find that divisional managers with better connections to the CEO (e.g., through education or prior employment) receive more generous capital allocations, which translates in overinvestment and lower performance among weakly governed firms. At a broader level, several studies find that multi-segment firms tend to overinvest in segments with low investment opportunities and underinvest in those with high investment opportunities (e.g., Shin and Stulz, 1998; Rajan, Servaes, and Zingales, 2000; Ozbas and Scharfstein, 2010), consistent with the presence of within-firm distortions in the resource allocation.

tions in relative input prices (τ_{fsiL}). These distortions could be due to, e.g., labor regulations or hiring and firing costs, which can vary by firm, location, and industry.

Division managers' optimization problem

Division managers engage in two activities: managing and lobbying. Managing refers to the allocation of budgets to the different plants under the division manager's supervision, subject to the divisional budget constraint (B_{fs}). Lobbying is the attempt to influence the headquarters' allocative process in the division's favor. Like plant managers, division managers have empire building preferences and face a quadratic cost of lobbying. In addition, the division managers' optimization problem is distorted by the lobbying of the plant managers. The higher the lobbying effort of a given plant (μ_{fsi}), the larger the weight that the division manager places on that plant in maximizing the division's size. The divisional manager's optimization problem can then be written as:

$$\left\{ \begin{array}{c} \max \\ \mu_{fs},\ B_{fsi} \\ s.t. \end{array} \right\} \begin{array}{c} \sum_{i\epsilon M_{fs}} [(1+\mu_{fsi})P_{fsi}Y_{fsi}] - c_{fs}\mu_{fs}^2 \\ \\ \sum_{i\epsilon M_{fs}} B_{fsi} = B_{fs}. \end{array}$$

Headquarters' optimization problem

The hierarchical level above the division managers is headquarters. Again, we assume that the headquarters' manager (that is, the CEO) has empire building preferences, and hence maximizes firm size by allocating the resources she obtains in the market across the different divisions of the firm. The allocation at the headquarters level is again distorted by influence activities at the lower level, that is, by the lobbying of division managers. Accordingly, the optimization problem of the CEO can be written as:

$$\max_{\{B_{fs}\}} \sum_{s\epsilon M_f} \left[(1+\mu_{fs}) \sum_{i\epsilon M_{fs}} P_{fsi}Y_{fsi} \right]$$
$$s.t. \sum_{s\epsilon M_f} B_{fs} = B_f.$$

External financiers' optimization problem

The last set of agents in our model are external financiers. While managers maximize firm, division, and plant *size*, capital markets allocate budgets with the goal of maximizing *profits*. Note that the allocation of resources across firms is subject to distortions as well (e.g., in the form of taxes and subsidies) that may vary by firm (τ_{fY}). Taking these across-firm distortions into account, the external financiers' optimization problem is as follows:

$$\max_{\{B_f\}}(1+\tau_{fY})\sum_{s\epsilon M_f}\sum_{i\epsilon M_{fs}}[P_{fsi}Y_{fsi}-(1+\tau_{fsiL})wL_{fsi}+rK_{fsi}]$$
$$s.t.\sum_f B_f = B.$$

II.C Equilibrium resource allocation

In equilibrium, the share of each plant's budget allocated to capital and labor is given by the factor shares α_s and $(1-\alpha_s)$, respectively:

$$K_{fsi}=\alpha_s\frac{B_{fsi}}{r}, \tag{5}$$

$$L_{fsi}=(1-\alpha_s)\frac{B_{fsi}}{(1+\tau_{fsiL})w}. \tag{6}$$

These two equations allow us to identify distortions in the capital-labor ratio of each plant:

$$(1+\tau_{fsiL})=\frac{(1-\alpha_s)}{\alpha_s}\frac{rK_{fsi}}{wL_{fsi}}. \tag{7}$$

A benefit of focusing on within-firm frictions in resource allocation is that all plants within a given firm are subject to the same firm-level distortions. For example, if a firm enjoys a favorable tax treatment, or has access to cheap borrowing, all plants within the firm benefit. Moreover, plants operating in the same sector are grouped in the same division. Thus, any division-level distortion—such as a division manager's successful lobbying of headquarters for more capital and labor—affects all plants within the division. Plants within the same division are subject to the same factor shares α_s, and the same factor costs w_s and r_s. Therefore, intuitively, the *relative* allocation of resources to these plants should be independent of firm- and division-level distortions, factor prices, and factor shares. This can be seen formally by considering the share of the divisional budget that plant fsi obtains:

$$\frac{B_{fsi}}{B_{fs}}=\frac{(1+\mu_{fsi})P_{fsi}Y_{fsi}}{\sum_{i\epsilon M_f}(1+\mu_{fsi})P_{fsi}Y_{fsi}}. \tag{8}$$

As is shown, firm- and division-level distortions do not appear in the equilibrium allocation of budgets across plants within a division. A plant will have a larger budget if it can generate more sales or if the plant manager puts more effort into lobbying the division manager. To capure the degree to which lobbying by plant managers (μ_{fsi}) can distort the allocation of divisional budgets across plants, we define plant-level distortions (which we denote by τ_{fsiY}) as the deviations from the allocation that would prevail in the absense of lobbying:

$$(1+\tau_{fsiY})=\frac{\frac{(1+\mu_{fsi})P_{fsi}Y_{fsi}}{\sum_{i\epsilon M_{fs}}(1+\mu_{fsi})P_{fsi}Y_{fsi}}}{\frac{P_{fsi}Y_{fsi}}{\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}}. \tag{9}$$

Summing across all plants i of division s of firm f, we obtain the intuitive result that, in equilibrium, lobbying by plant managers is a zero sum game. Since division managers have to operate within their budget, excessive generosity towards any given plant comes at the expense of the remaining plants of the division.

$$\frac{\sum_{i\epsilon M_{fs}}(1+\tau_{fsiY})P_{fsi}Y_{fsi}}{\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}=1. \tag{10}$$

Combining equations (8) and (9) provides us with the equation for plant-level distortions that we bring to the data:

$$(1+\tau_{fsiY})=\frac{\frac{B_{fsi}}{P_{fsi}Y_{fsi}}}{\frac{\sum_{j\epsilon M_{fs}}B_{fsj}}{\sum_{j\epsilon M_{fs}}P_{fsj}Y_{fsj}}}. \tag{11}$$

In addition to allocating budgets across plants, division managers also choose how much to lobby headquarters for additional resources. The inter-divisional resource allocation is determined by headquarters, who distributes divisional budgets taking into account how divisions subsequently allocate budgets across plants and how those plants use their budgets to generate sales. Like in the case of plants, lobbying at the division level is a zero sum game, and a division obtains a larger budget if it generates more sales or if the division manager puts more effort into lobbying the headquarters. Formally, the fraction of the firm's budget allocated to division s is given by:

$$\frac{B_{fs}}{B_f}=\frac{(1+\mu_{fs})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\sum_{s\epsilon M_f}(1+\mu_{fs})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}. \tag{12}$$

We further define division-level distortions (τ_{fsY}) as the deviations from what divisional budget allocations would be in the absence of lobbying:

$$(1+\tau_{fsY})=\frac{\frac{(1+\mu_{fsY})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\sum_{s\epsilon M_{fs}}(1+\mu_{fsY})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}}{\frac{\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\sum_{s\epsilon M_{fs}}\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}} \Leftrightarrow \frac{\sum_{s\epsilon M_{fs}}(1+\tau_{fsY})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\sum_{s\epsilon M_{fs}}\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}=1. \tag{13}$$

Combining equations (5) and (13) gives us the expression for division-level distortions that we use in our empirical analysis:

$$(1+\tau_{fsY})=\frac{\frac{B_{fs}}{\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}}{\frac{B_f}{\sum_{s\epsilon M_{fs}}\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}}. \tag{14}$$

Finally, we solve the problem of external financiers, who allocate budgets across firms to maximize profits. In equilibrium, the share of a firm's budget with respect to the economy-wide resources is given by:

$$\frac{B_f}{B}=\frac{(1+\tau_{fY})\sum_{s\epsilon M_f}\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\sum_f(1+\tau_{fY})\sum_{s\epsilon M_f}\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}. \tag{15}$$

In Appendix C, we show that our model is closely related to that of Hsieh and Klenow (2009), except that we explicitly model and decompose output distortions into their firm, division, and plant components. In our framework, a plant can have too much capital and labor because of output subsidies (high τ_{fY}), or due to influence activities at the division (high τ_{fsY}) and plant levels (high τ_{fsiY}). While Hsieh and Klenow (2009) treat each production establishment as an independent firm, we explicitly model the organizational structure of firms and characterize the nature of within-firm distortions. The resource allocation implied by our model is equivalent to each plant maximizing a distorted profit function, where distortions can occur not only across firms but also across divisions and plants within firms:[6]

$$\begin{aligned}\max_{K_{fsi},L_{fsi}}\ &(1+\tau_{fY})(1+\tau_{fsY})(1+\tau_{fsiY})P_{fsi}Y_{fsi}\\ &-w_s(1+\tau_{fsiL})L_{fsi}-r_sK_{fsi}.\end{aligned}$$

Finally, we can derive the price of differentiated good fsi:

$$P_{fsi}=\frac{\sigma}{\sigma-1}\left(\frac{w_s}{1-\alpha_s}\right)^{1-\alpha_s}\left(\frac{r_s}{\alpha_s}\right)^{\alpha_s}\frac{(1+\tau_{fsiL})^{1-\alpha_s}}{A_{fsi}(1+\tau_{fY})(1+\tau_{fsY})(1+\tau_{fsiY})}, \tag{16}$$

[6]Note that Hsieh and Klenow (2009) specify capital-labor distortions as a capital wedge, whereas we specify them as a labor wedge. This distinction is immaterial, since they both capture distortions that affect the marginal product of one factor relative to the other.

which is a fixed mark-up $(\frac{\sigma}{\sigma-1})$ over marginal costs. Note that a higher output distortion implies that the plant obtains more resources, produces more output, and therefore sells at a lower price. This is reflected in equation (16), as P_{fsi} decreases in $(1+\tau_{fY})(1+\tau_{fsY})(1+\tau_{fsiY})$.

II.D Sectoral and aggregate output and TFP

We are now ready to derive an expression for aggregate TFP, as a function of the firm-, division-, and plant-level distortions.

We can express total industry output as:

$$Y_s = TFP_s K_s^{\alpha_s} L_s^{1-\alpha_s},$$

where

$$TFP_s = \left(\sum_{i=1}^{M_s} \left[\left(\frac{A_{fsi}\left(1+\tau_Y\right)/\left(1+\tau_L\right)}{\left(1+\overline{\tau_Y}\right)/\left(1+\overline{\tau_L}\right)} \right)^{1-\alpha_s} \left(\frac{A_{fsi}\left(1+\tau_Y\right)}{\left(1+\overline{\tau_Y}\right)} \right)^{\alpha_s} \right]^{\sigma-1} \right)^{\frac{1}{\sigma-1}}, \tag{17}$$

and where

$$\left(1+\overline{\tau_Y}\right) \equiv \sum_{i=1}^{M_s} \left(1+\tau_{fY}\right)\left(1+\tau_{fsY}\right)\left(1+\tau_{fsiY}\right) \frac{P_{fsi}Y_{fsi}}{P_sY_s},$$

$$\left(1+\overline{\tau_Y}\right)/\left(1+\overline{\tau_L}\right) \equiv \sum_{i=1}^{M_s} \frac{\left(1+\tau_{fY}\right)\left(1+\tau_{fsY}\right)\left(1+\tau_{fsiY}\right)}{\left(1+\tau_{fsiL}\right)} \frac{P_{fsi}Y_{fsi}}{P_sY_s},$$

and

$$\left(1+\tau_Y\right) \equiv \left(1+\tau_{fY}\right)\left(1+\tau_{fsY}\right)\left(1+\tau_{fsiY}\right),$$

$$\left(1+\tau_L\right) \equiv \left(1+\tau_{fsiL}\right).$$

The derivations are provided in Appendix D. This expression for TFP_s is intuitive. Without distortions, industry TFP is simply a CES aggregate of TFP of individual plants (that is, $TFP_s = \left(\sum_{i=1}^{M_s} A_{fsi}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$). A positive distortion increases the weight of the plant in the TFP of its respective industry.

Finally, to obtain the economy-wide TFP, we use the Cobb-Douglas aggregator from equation (3):

$$TFP = \prod_{s=1}^{S} TFP_s^{\theta_s}. \tag{18}$$

Equations (17) and (18) are the key equations we use to estimate counterfactual gains in terms of aggregate TFP (see Section IV).

III Data and descriptive analysis

III.A Data sources and definition of variables

Plant-level data

The plant-level data are obtained from the Census of Manufactures (CMF) of the U.S. Census Bureau. The CMF covers all U.S. manufacturing plants with at least one paid employee. The CMF is conducted every five years in years ending with 2 and 7 (Census years). Our analysis uses the 1977, 1982, 1987, 1992, 1997, 2002, and 2007 CMF.[7] The CMF contains information about key plant variables such as the plant's industry, capital stock, employment, and shipments. We code industry sectors (and hence divisions within the firm) using 3-digit SIC codes until the 1992 CMF, and 4-digit NAICS codes as of the 1997 CMF.[8]

Following common practice in the literature (e.g., Foster, Haltiwanger, and Syverson, 2008), we exclude plants whose information is imputed from administrative records rather than directly collected. We also exclude plant-year observations for which physical capital, employment, and shipments are either zero or missing. These criteria lead to our final sample that consists of 1,262,000 plant-year observations.[9]

Plant- division- and firm-level distortions

To quantify the plant-level distortions $(1+\tau_{fsiY})$, we consider all plants in a given firm, division, and year. We then use information on the plant's capital (K_{fsi}), labor (L_{fsi}), and value added $(P_{fsi}Y_{fsi})$ to compute equation (11).[10]

Notice that the above calculation recovers plant-level distortions—that is, the extent to which too much capital and labor is allocated to a plant given its productivity. This follows from the structure of the model, where τ_{fsiY} captures distortions that affect both production factors

[7] In the non-Census years, Census collects information on manufacturing plants through the Annual Survey of Manufactures (ASM). However, the ASM covers only a subset of the plants in the CMF (approximately 15%), which is not suitable for our analysis.

[8] SIC codes were the basis for all Census Bureau publications until the 1992 Census. In 1997, the Census Bureau switched to the NAICS classification.

[9] Disclosure rules of the U.S. Census Bureau require us to round the number of observations to the nearest thousand.

[10] We compute capital as the average of the book value of the plant's machinery and buildings at the beginning and at the end of the year. Value added is computed as shipments (adjusted for inventory changes) minus the sum of the cost of materials and parts, cost of fuels, cost of purchased electricity, cost of resales, and cost of contract work.

(capital and labor), while any residual distortion in the relative allocation of the production factors is applied to the labor input (τ_{fsiL} in the model).

The division-level distortions $(1 + \tau_{fsY})$ are computed analogously. We use information on the budgets of each division of each firm, by computing the value of capital and labor used by all plants that belong to a division. We then use equation (14), which shows that a division consumes too many resources if it is allocated a budget that is too large given the amount of value added that it generates.

In the counterfactual analyses (see Section IV), we further compute the firm-level distortions $(1+\tau_{fY})$. This is done by comparing the amounts of capital and labor employed by each firm with the value added it creates.

Summary statistics

Table 1 provides summary statistics at the different levels of observation used in our analysis. Panel (A) shows the summary statistics at the plant-year level for all 1,262,000 plant-year observations in our sample, and separately for the plants of single- and multi-unit firms. Among the latter, we further distinguish between plants of single- and muti-division firms. For each characteristic, we report the mean and standard deviation (in parentheses).[11] To reduce the notational clutter, we denote the plant-level distortion by $1 + \tau_p \equiv 1 + \tau_{fsiY}$, and the division-level distortion by $1 + \tau_d \equiv 1 + \tau_{fsY}$.

The first variable is the plant-level distortion $1 + \tau_p$. By construction, the mean of $1 + \tau_p$ is very close to one, and only varies for multi-plant firms. In Figure 1, we plot the kernel density of $1 + \tau_p$ for companies with 2-4 plants and companies with 5+ plants, respectively. As can be seen, there is a fair amount of dispersion in plant-level distortions, and the dispersion is greater for companies with more plants.

The other variables in Panel (A) of Table 1 are as follows. *Employees* is the total number of employees at the plant. *Capital stock* is defined above. *Age* is the pseudo-age of the plant, which is computed as the number of years since the plant has coverage in the CMF. Finally, *Distance to HQ* is the great-circle distance between the plant's ZIP code and the ZIP code of the firm's headquarters (in miles).[12] We observe that plants of multi-unit firms are on average larger than plants of single-unit firms. Moreover, plants of multi-segment firms are on average larger, older, and located farther away from headquarters compared to plants of single-segment

[11] Due to the Census Bureau's disclosure policy, we cannot report medians or other quantile values.

[12] To identify the location of the firm's headquarters, we follow the procedure of Giroud (2013, pp. 909-911). This procedure exploits the information provided in two other datasets of the Census Bureau: the Auxiliary Establishment Survey (AES) and the Standard Statistical Establishment List (SSEL). The AES contains information on non-production (auxiliary) establishments, including information on headquarters. The SSEL contains the names and addresses of all U.S. business establishments.

firms.

Panel (B) shows summary statistics at the division-year level. The first variable is the division-level distortion $1+\tau_d$. Again, we note that, by construction, the mean of $1+\tau_d$ is very close to one, and only varies for multi-division firms. In Figure 2, we plot the kernel density of $1+\tau_d$ for companies with 2-4 divisions and companies with 5+ divisions, respectively. The pattern mirrors what we observed for plant-level distortions: there is a fair amount of dispersion in division-level distortions, and the dispersion is greater for companies with more divisions. Panel (B) of Table 1 further reports summary statistics for three measures of resource misallocation within divisions: i) the standard deviation of $1+\tau_p$ across all plants in the division, $\sigma(1+\tau_p)$; ii) the difference between the 90th and 10th percentiles of $1+\tau_p$ across all plants in the division; and iii) the difference between the 75th and 25th percentiles of $1+\tau_p$ across all plants in the division.[13] As can be seen, the degree of within-division misallocation is on average higher for single-division firms compared to multi-division firms. This could reflect the fact that single-division firms have on average more plants per division compared to multi-division firms (as shown in the last row of the panel), and hence more potential for misallocation.

Finally, Panel (C) reports summary statistics at the firm-year level. This panel provides statistics on the number of divisions and the number of plants, respectively, along with measures of resource misallocation across divisions within firms: $\sigma(1+\tau_d)$, the difference between the 90th and 10th percentiles of $1+\tau_d$, and the difference between the 75th and 25th percentiles of $1+\tau_d$. These measures are analogous to those in Panel (B), except that they are computed with respect to $1+\tau_d$.

III.B Plant and division power

Our measures of plant- and division-level distortions can be interpreted as measures of "power" within the organization, as more powerful plants (and divisions, respectively) are better able to tilt the allocation of resources in their favor. In the spirit of the model of "influence activities" presented in Section II, plant and division managers may lobby higher hierarchical levels (that is, division managers and headquarters, respectively) for more resources. Those with more political capital are likely to obtain a bigger share of resources compared to the optimal allocation. In this vein, plants or divisions that are flush with resources despite a relatively low productivity (i.e., plants and divisions with higher $1+\tau_p$ and $1+\tau_d$, respectively) are likely more "powerful" within the firm.

In Table 2, we provide evidence consistent with this interpretation. In Panel (A), we

[13] All three measures are commonly used in the literature to capture the misallocation of resources (e.g., Hsieh and Klenow, 2009).

regress our measure of plant-level distortion $(1+\tau_p)$ on two covariates that are likely related to plant power. The first covariate is the age of the plant, as seniority may help secure a larger share of resources. The second covariate is distance to headquarters. Arguably, proximity to headquarters makes it easier for plant managers to lobby headquarters for resources. In column (1), we regress $1+\tau_p$ on these two covariates, as well as year fixed effects. In column (2), we further include firm by division fixed effects. In both specifications, the sample is restricted to the plants of multi-unit firms, and standard errors are clustered at both the firm and year levels. As can be seen, the coefficient of age is positive and significant, whereas the coefficient of distance to headquarters is negative and significant. The fact that older plants and plants closer to headquarters are able to obtain more resources lends support to the power interpretation.

In Panel (B), we repeat the analysis in columns (1)-(2) of Panel (A) but at the division level, taking the average age and the average distance to headquarters across all plants within each division. The estimates mirror those in Panel (A). Older divisions and divisions located closer to headquarters are significantly more likely to obtain larger allocations of resources.

III.C Distortions versus measurement error? Evidence from exogenous changes in plant bargaining power

The results in columns (1) and (2) of Panel (A) of Table 2 indicate that characteristics such as age and distance to the headquarters correlate with plants' ability to obtain corporate resources at the expense of other plants within the same firm. However, we acknowledge that this evidence is merely suggestive. Indeed, there are other reasons—besides power and influence activities—as to why age and distance to headquarters may matter. For example, it could be that older plants, or plants located closer to headquarters, receive more generous allocations as they are of strategic importance to the firm's long-term plans. In this subsection, we refine the previous analysis by using (quasi-)exogenous variation in proximity to headquarters. Specifically, we follow the methodology of Giroud (2013), exploiting the introduction of new airline routes that reduce the travel time between the plant's ZIP code and the headquarters' ZIP code. We use these "treatments" in a difference-in-differences specification. Previous research has shown that physical proximity is one of the most important determinants of social connections (Marmaros and Sacerdote, 2006). In this spirit, closer proximity between the plant manager and the firm's senior management may give the plant manager an edge in lobbying for more resources. If this is the case, an exogenous decrease in distance to headquarters should increase the plant's ability to obtain resources relative to other plants, which in our model would manifest itself as an increase in $1+\tau_p$. Alternatively, if the above has no bearing in the data, or if $1+\tau_p$ merely captures measurement error or model misspecification, one would not expect $1+\tau_p$ to increase following an exogenous reduction in plant-headquarters distance.

In column (3) of Panel (A) of Table 2, we regress $1+\tau_p$ on the treatment dummy ("new airline route") as well as plant and year fixed effects. One appealing feature of this empirical setting is that the treatment is at the location-pair level (as opposed to the level of the plant location, and headquarters location, respectively). Accordingly, we can use other plants in the same location as the treated plant, but whose headquarters are not served by the new airline route, to account for unobservables at the plant location (e.g., shocks to local economic activity, local investment opportunities, or any other change in the local environment in which the plant operates) that may coincide with the introduction of the new airline route. Similarly, we can control for unobservables at the location of the plant's headquarters.[14] We do so in column (4) by including two sets of MSA (Metropolitan Statistical Area) by year fixed effects, with respect to the plant's MSA, and headquarters' MSA, respectively.

The results, presented in columns (3) and (4), show that the treatment effect is positive and significant in both specifications. This implies that the introduction of a new airline route that reduces the effective distance between the plant and its headquarters enhances the plant's ability to capture resources internally. Because these estimates are not driven by changes in local economic conditions (which are accounted for by the MSA by year fixed effects), they lend further support to the interpretation that our measures of within-firm distortion capture bargaining power within the firm. In contrast, it is difficult to think of these results as a manifestation of measurement error or model misspecification (e.g., due to adjustment costs) that would coincide with the the introduction of new airline routes.

III.D Resource misallocation and performance

Firms that misallocate resources use too much inputs for a given level of output, as they allocate too many resources to inefficient divisions (and plants, respectively) at the expense of more efficient ones. Accordingly, one would expect firms that misallocate resources to achieve lower profits and, ultimately, lower valuations. In Tables 3 and 4, we examine whether this is the case.

[14] Intuitively, if a new airline route is introduced between, say, a plant in Salt Lake City, UT, and the plant's headquarters in Boston, MA, not all Salt Lake City plants are affected. Accordingly, we can disentangle between the impact of the treatment (that affects only the Salt Lake City plants that have headquarters in Boston) and the impact of contemporaneous local shocks (that affect all plants in Salt Lake City). In terms of the regressions, this can be implemented by including location by year fixed effects with respect to the plant's location. We can also control for local shocks affecting all plants with headquarters in Boston by including location by year fixed effects with respect to the headquarters' location.

Resource misallocation and division performance

In Table 3, we regress operating margin at the division level on each of the three measures of resource misallocation within divisions—that is, i) $\sigma(1+\tau_p)$, ii) the difference between the 90th and 10th percentiles of $1+\tau_p$, and iii) the difference between the 75th and 25th percentiles of $1+\tau_p$. We compute operating margin at the division level by taking the value added-weighted average of plant-level operating margin across all of the division's plants.[15]

In column (1), the coefficient of $\sigma(1+\tau_p)$ is negative and significant, that is, higher resource misallocation is associated with lower profits at the division level. Since the standard deviation of $\sigma(1+\tau_p)$ is 0.354 (see Table 1), the coefficient of -0.053 implies that a one-standard deviation increase in $\sigma(1+\tau_p)$ corresponds to a decrease in operating margin by $-0.053\times0.354 = -0.019$. Given that the mean of operating margin is 0.247, this corresponds to a decrease in profits by -7.7%. We obtain similar results when we use the two other measures of resource misallocation in columns (2) and (3).

Resource misallocation and firm performance

In columns (1)-(3) of Table 4, we repeat the analysis of Table 3 but at the firm level—that is, we regress firm-level operating margin on each of the three measures of misallocation across divisions.[16] The results mirror those in Table 3, as all three measures of misallocation are associated with lower profits. The coefficients are again economically significant. For example, the coefficient of -0.054 in column (1) implies that a one-standard deviation increase in $\sigma(1+\tau_d)$ corresponds to a decrease in operating margin by $-0.054 \times 0.233 = -0.013$. Since the mean of firm-level operating margin is 0.267, this corresponds to a -4.9% decrease in profits.

In columns (4)-(9) of Table 4, we study the subsample of public firms. We identify public firms by merging the CMF to Standard & Poor's Compustat using the Compustat-SSEL bridge maintained by the Census Bureau. For Compustat firms, we observe accounting measures of performance (such as the return on assets) as well as market values. We compute the return on assets (ROA) as the ratio of operating income before depreciation to total assets, and Tobin's Q as the ratio of the market value of total assets (computed as the book value of total assets plus the market value of common stock minus the sum of the book value of common stock and

[15] Plant-level operating margin is defined as the ratio of shipments minus labor and material costs divided by shipments. We winsorize this ratio at the 1st and 99th percentiles of its empirical distribution. The regressions are estimated using all division-year observations of multi-unit firms. Each regression includes year fixed effects and a control for size (the number of plants in the division). Standard errors are clustered at both the firm and year level.

[16] Firm-level operating margin is computed by taking the value added-weighted average of division-level operating margin across all of the firm's divisions. The regressions are estimated using all firm-year observations of multi-division firms. Each regression includes year fixed effects and a control for the number of divisions. Standard errors are clustered at both the firm and year level.

balance sheet deferred taxes) to the book value of total assets.[17]

In columns (4)-(6), we use ROA as dependent variable. In all three specifications, higher misallocation is associated with lower ROA. The estimates are again economically significant. For example, a one-standard deviation increase in $\sigma(1+\tau_d)$ corresponds to a decrease in ROA by $-0.017 \times 0.233 = -0.004$. At a mean ROA of 0.138, this corresponds to a decrease in ROA by -2.9%. Finally, in columns (7)-(9), the dependent variable is Tobin's Q. In line with the previous results, we find that higher misallocation is associated with a lower valuation. In particular, a one-standard deviation increase in $\sigma(1+\tau_d)$ corresponds to a decrease in Tobin's Q by $-0.130 \times 0.233 = -0.030$. Since the average Tobin's Q is 1.40, this corresponds to a decrease in firm value by -2.1%. Overall, the results in Table 4 indicate that firms that misallocate their resources internally are less profitable and less valuable.

The valuation results help mitigate typical pitfalls that arise in studies of misallocation. Indeed, one concern with misallocation measures based on the dispersion of marginal products is that dispersion in the data may arise due to measurement error or model misspecification (e.g., Asker, Collard-Wexler, and De Loecker, 2014; Haltiwanger, Kulick, and Syverson, 2018; Kehrig and Vincent, 2019; Blis, Klenow, and Ruane, 2021). In this study, we measure resource misallocation within firms using only data on the relative amounts of capital, labor, and value added across plants. Because we do not use market values to compute the extent of misallocation, the valuation results suggest that our measures of within-firm distortions do indeed capture resource misallocation, rather than measurement error or model misspecification.

III.E Management practices and resource misallocation

A recent literature shows that firms with better management practices achieve higher productivity (Bloom and Van Reenen, 2007; Bloom et al., 2019, 2022). One potential channel is that better managed firms might do a better job at allocating resources internally. We examine this question in Table 5.

We obtain data on management practices from the MOPS (Management and Organizational Practices Survey), which is included as a supplement to the 2010 Annual Survey of Manufacturing (ASM). Although the survey was only conducted in conjunction with the 2010 ASM, all of the questions asked respondents to report on the state of practices in 2005 as well. Hence, the MOPS contains data for both 2005 and 2010.

The MOPS is the first large-scale survey of management practices in the U.S.[18] It comprises 36 multiple-choice questions split into three sections. The first section, labeled "management practices," includes 16 questions that aim to characterize management practices along the di-

[17] We winsorize ROA and Tobin's Q at the 1st and 99th percentiles of their empirical distribution.
[18] For a description of the MOPS, see Buffington et al. (2016).

mensions of monitoring, targets, and incentives. Examples include the collection, review, and communication of performance indicators (e.g., production targets, on-time deliveries), the speed at with underperforming employees are reassigned or dismissed, and the basis for performance bonuses. The MOPS further includes a composite index of "structured management" proposed by Bloom et al. (2019) that is computed as the unweighted average of the score for each of the 16 questions, where each question is first normalized to be on a 0 to 1 scale. Hence, by construction, the composite index is scaled from 0 to 1, with 0 representing a plant in the bottom category (i.e., little structure around performance monitoring, targets, and incentives), and 1 representing a plant in the top category (i.e., an explicit focus on performance monitoring, detailed targets, and strong performance incentives). The MOPS also contains two subindices of the composite index based on the 6 questions pertaining to monitoring, and the 10 questions pertaining to targets and incentives. In the analysis, we use both the composite index and the two subindices.

To study the link between management practices and the misallocation of resources, we restrict our sample to the 2007 CMF (that is, the most recent CMF that was made available to us by the Census), which we merge with the 2005 MOPS data. We then aggregate the index of "structured management" (as well as the two subindices of "monitoring" and "targets and incentives") from the plant level into the division and firm level by taking the (value added-weighted) average across all plants in the division and firm, respectively.

In Panel (A) of Table 5, we regress our measures of resource misallocation at the division level on the division-level index of structured management (columns (1), (3), and (5)) and the two subindices of monitoring and targets and incentives (columns (2), (4), and (6)). In all regressions, we control for division size (the number of plants in the division), to account for the finding of Bloom et al. (2019) that structured management is more prevalent among larger businesses. As is shown, divisions with better structured management are less likely to misallocate resources. In column (1), a change from zero to one in the score of structured management is associated with a 0.13 decrease in $\sigma(1+\tau_p)$, corresponding to more than half of a standard deviation in $\sigma(1+\tau_p)$. In column (2), we decompose the index of structured management into the two subindices of monitoring and targets and incentives. We find that both dimensions contribute in roughly equal way to the baseline estimate. In columns (3)-(6), we obtain similar results when using the other two measures of misallocation.

In Panel (B), we conduct the same analysis, but at the firm level. That is, we regress our measures of resource misallocation at the firm level (capturing the extent to which resources are misallocated across divisions) on the firm-level index of structured management, as well as the corresponding subindices. As can be seen, the results mirror those at the division level. One potential nuance is that the point estimate is noticeably larger for the subindex of targets and incentives (compared to the subindex of monitoring), yet the difference is not significant in statistical terms.

Overall, the results in Table 5 indicate that firms (and divisions, respectively) with higher scores of structured management are less likely to misallocate resources internally. This finding is in line with Bloom and Van Reenen (2007) and Bloom et al. (2019), who find that firms with better structured management have higher productivity and profitability. Our results suggest that one channel through which better structured management achieves higher performance is through better internal resource allocation.

IV Counterfactuals

We now use the structure of the model to estimate several counterfactuals that assess the relative importance of internal and external frictions as determinants of economy-wide TFP. Specifically, we compute the aggregate TFP gains that would be achieved by sequentially eliminating the different frictions in the allocation of resources across firms, divisions, and plants. In what follows, we use the compact notation τ_f, τ_d, and τ_p to denote distortions at the firm, division, and plant level, respectively (that is, $\tau_f \equiv \tau_{fY}$, $\tau_d \equiv \tau_{fsY}$, and $\tau_p \equiv \tau_{fsiY}$).

Our counterfactuals hold fixed the distribution of TFPQ (i.e., "quantity TFP" denoted by A_{fsi} in the model) across plants. This guarantees that any improvement in overall TFP is a result of an improvement in the allocation of resources and is not due to an increase in the productivity of individual plants. An economy with less distortions is one where resources flow freely to their best use, resulting in a movement of capital and labor away from less productive plants towards more productive ones. This, in turn, is associated with an overall increase in the ability of the economy to transform inputs into finished goods.

The methodology we implement is as follows. We first calculate the actual aggregate total factor productivity that is observed in the data (TFP_{actual}). We then calculate a hypothetical counterfactual TFP that would be the result of the equilibrium allocation of resources in case a different distribution of distortions was in place ($TFP_{\text{counterfactual}}$). Finally, we divide the counterfactual TFP by the actual TFP to obtain a measure of the gain in productivity that would be achieved through reallocation of resources ($TFP_{\text{gain}} = TFP_{\text{counterfactual}}/TFP_{\text{actual}}$).[19]

[19] Aggregate TFP is computed using equations (17) and (18). We set the model parameters as in Hsieh and Klenow (2009). Specifically, we set $\sigma = 3$, $r = 0.1$, and $\alpha_s = 1 - 3/2 \times$ the labor share from the CES-NBER Productivity Database. The 3/2 adjustment addresses the well-known issue with the CES-NBER database that payments to labor omit fringe benefits and employers' social security contributions. (The CES-NBER labor share is about two-thirds what it is in manufacturing according to the National Income and Product Accounts, which incorporate non-wage forms of compensation; scaling up each industry's CES-NBER labor share by 3/2 accounts for this discrepancy.) θ_s is computed using the industry shares of value added in the economy. A_{fsi} is computed using equation (19) from Hsieh and Klenow (2009). Finally, since we focus on the allocation of resources (as opposed to the mix of resources), we set $\tau_L = 0$ in all counterfactuals.

IV.A Eliminating all distortions

We start by calculating the TFP gains associated with the elimination of all distortions in the economy. To do so, we set all wedges to zero (that is, $\tau_f = \tau_d = \tau_p = 0$), and calculate the counterfactual allocation of capital and labor in an economy in which marginal products are equalized across all plants. This experiment is the same as the one performed in Hsieh and Klenow (2009) and provides a benchmark that we can later use to understand the relative importance of the different types of distortions in the economy. In Table 6, we find that fully eliminating misallocation of resources in the economy would lead to a 42% increase in TFP across all years of our sample, with yearly estimates that range from 33.1% in 1992 to 48.9% in 1982. Our estimates are of similar magnitude as those in Hsieh and Klenow (2009) who report increases in productivity from full liberalization that reach 42.9% in 2005, but can be as low as 30.7% in 2001. Consistent with the view that intra-firm (mis)allocation of resources may have a significant impact on overall TFP, we find that the gains from no distortion are larger for firms with more extensive internal capital and labor markets. As can be seen in the last two columns of Table 6, these gains reach 57% for multi-unit firms and 59% for multi-division firms.

IV.B Eliminating plant-, division-, and firm-level distortions

Next, we turn to the task of quantifying the relative importance of resource misallocation at different levels: i) across firms, ii) across divisions within firms, and iii) across plants within divisions. We do so by sequentially and selectively eliminating some of the frictions in the economy, while keeping others active. In particular, we study the improvement in TFP that would arise if within-firm distortions were eliminated, but across-firm distortions were kept at the level we observe in the data. In the left-hand panel of Panel (A) of Table 7, we calculate the yearly gains in TFP that would be obtained if we set $\tau_p = 0$. In this alternative world, there is still potential for misallocation of capital and labor across firms, and across different divisions within firms. However, within a division of a firm, resources flow to their best uses, which in our model corresponds to having the marginal product of capital and labor equalized across plants within divisions. The average TFP gain across all years is 10.1%, and the yearly estimates are fairly stable, ranging from 9.3% in 1987 and 1997, to 10.8% in 1977 and 1992. This implies that, if we were to eliminate frictions in the within-division allocation of resources, overall productivity would increase by about one quarter of the overall increase we obtained in the no-distortion case. If in addition to eliminating within-division frictions we also eliminate frictions in the allocation of resources across divisions within firms (i.e., $\tau_p = 0$ and $\tau_d = 0$)—and hence impose full efficiency within the firm—the associated productivity gains would jump to 12.6%, which corresponds to 30.5% of the overall productivity gains in the no-distortion case.

Firms with a single plant are by definition unable to improve TFP by reallocating resources across plants. In Panel (B) we focus on multi-unit firms where internal resource reallocation is possible. In this sample, the TFP gains generated by eliminating all distortions are 57.3%, which is larger than in the full sample. The gains generated by eliminating distortions within divisions represent 37.9% of all possible TFP improvements in the economy. Eliminating distortions both within divisions and across divisions within the firm generates 48.3% of the TFP gains that can be achieved in the no-distortion case.

In Panel (C), we direct our attention to multi-division firms. We do so because firms with a single division are, by construction, unable to reallocate resources across divisions. In this smaller sample of about 253,00 plants, we estimate even larger TFP gains from internal relative to external reallocation of resources. In this case, having internal labor and capital markets operating in a fully efficient manner would lead to a 29.6% increase in overall TFP, which represents roughly 51% of the total possible gains from the reallocation of resources. This suggests that, for multi-division firms, frictions in internal capital and labor markets are of larger importance than frictions in external markets.

IV.C Eliminating extreme distortions

In the previous subsection we calculated the gains in TFP that are obtained by setting distortions at the plant, division, and firm level to zero. However, the full elimination of all distortions is unlikely to be realistic. Given that resources may not flow freely across plants, divisions, and firms due to transportation costs, information frictions, or other structural frictions, a distortion-free economy is a counterfactual that is likely too idealistic, and hence implausible in practice. To address this issue, we consider a more conservative—and arguably more realistic—counterfactual. Instead of fully eliminating the different distortions in the economy, we reduce extreme distortions to more moderate levels. Specifically, we compute TFP gains in two counterfactual economies in which we winsorize the within-firm distortions (i.e., τ_p and τ_d) at their 10th and 90th percentiles, and at their 25th and 75th percentiles, respectively. By eliminating the most extreme distortions without setting them to zero we are evaluating the potential gains in TFP obtained by reducing the most severe within-firm distortions to levels that are more in accordance with the rest of the economy.

In the left-hand panel of Panel (A) of Table 8, we calculate the TFP gains associated with setting the largest plant- and division-level distortions to the 10th and 90th percentiles of their respective distribution. Doing so yields a 2.5% increase in TFP. In the right-hand panel, we further improve the within-firm allocation by winsorizing the plant- and division-level distortions at their 25th and 75th percentiles. In that case TFP increases by 3.5%.

These productivity gains increase when we repeat this exercise in the subsample of firms with internal capital and labor markets. In Panel (B), where we consider multi-unit firms, we find that winsorizing the within-firm distortions to their 25th and 75th percentiles would lead to a 7.1% increase in TFP. In Panel (C), we focus on multi-unit firms with multiple divisions and find an 8.5% increase in TFP.

IV.D Improving management practices

Management practices have been shown to be an important determinant of productivity and profitability (Bloom and Van Reenen, 2007; Bloom et al., 2019). In our reduced form analysis, we observed that better structured management practices are associated with lower within-firm distortions (see Table 5). In this subsection, we build on this analysis and estimate counterfactuals that feature improvements in structured management and quantify their impact on overall productivity.

Specifically, we calculate the TFP gains that would be achieved if we were to improve the structured management score i) by one standard deviation, ii) by matching the score of the best-managed firm in the economy, and iii) by matching the score of the best-managed firm within the same industry. For each counterfactual, we use the reduced form estimates from Table 5 to determine the commensurate reduction in $\sigma(1+\tau_d)$ and $\sigma(1+\tau_d)$, respectively.

The results are provided in Table 9. We estimate large productivity gains associated with improvements in internal resource allocation that would be achieved through the adoption of better structured management. In Panel (A) of Table 9, we find that a one-standard deviation improvement in the structured management score yields a 2.9% increase in aggregate TFP. If instead of a one-standard deviation increase, we were able to have all managers mimic the resource allocation of the best-managed firm in the economy, productivity would be 7.5% higher, which represents about 18% of the overall TFP improvements that could be achieved if all distortions in the economy were eliminated. If instead of mimicking the resource allocation of the best-managed firm in the economy, each manager would allocate resources as efficiently as the best manager in their industry, overall productivity would increase by 7%.

As with the previous counterfactuals, a caveat of the analysis in Panel (A) is that it includes firms that, by construction, cannot improve their internal allocation of resources—firms with a single division cannot misallocate resources across divisions, and firms with a single plant cannot misallocate resources across plants. In Panels (B) and (C), we turn to the analysis of multi-unit firms and multi-division firms, respectively. We find that the improvements in TFP brought about by the adoption of better structured management are magnified in these firms. In the hypothetical scenario in which the managers of all multi-divisional firms mimic the resource allocation of the best-managed firm in the economy, TFP would increase by 13.4%.

In Tables 10 and 11, we refine the analysis by considering separately the two building blocks of structured management: monitoring (Table 10) and targets and incentives (Table 11). We start by considering improvements in monitoring practices, which Bloom and Van Reenen (2007, p. 1361) define as the "tracking of performance of individuals, reviewing performance (e.g., through regular appraisals and job plans), and consequence management (e.g., making sure that plans are kept and appropriate sanctions and rewards are in place)". As can be seen in Panel (A) of Table 10, a one-standard deviation increase in the monitoring score yields TFP gains of 1.9%, which represents about 5% of the overall TFP gains in the case of no distortion. If we instead assign to each company the monitoring score of the best-monitored firm in the economy and industry, we obtain TFP gains of 4.3% and 4%, respectively. In Panels (B) and (C), we repeat this analysis for multi-plant and multi-division firms, and find that TFP increases by up to 7.1% if all multi-divisional firms were to mimic the resource allocation of the best-monitored firm in the economy.

In Table 11, we study how improvements in targets and incentives practices affect TFP. Targets refers to "the type of targets (whether goals are simply financial or operational or more holistic), the realism of the targets (stretching, unrealistic, or nonbinding), the transparency of targets (simple or complex), and the range and interconnection of targets (e.g., whether they are given consistently throughout the organization)", while the incentives practices include "promotion criteria (e.g., purely tenure-based or including an element linked to individual performance), pay and bonuses, and fixing or firing bad performers, where best practice is deemed the approach that gives strong rewards to those with both ability and effort" (Bloom and Van Reenen, 2007, p. 1361). We find that a one-standard deviation improvement in the targets and incentives score yields TFP gains of 1.5% for all firms, and up to 3% for multi-division firms. Matching the targets and incentives score of all firms to the score of the best-managed firm in the economy yields TFP gains of 4% for all firms, and up to 6.7% for multi-division firms.

Overall, the results presented in this section indicate that the adoption of better structured management practices yields substantial TFP gains through improvements in the internal allocation of resources. A large literature has studied whether corporate executives create enough value to justify their pay (see Edmans, Gabaix, and Jenter, 2017, for a recent review of the executive compensation literature). Even though our data does not contain information on CEO compensation, our findings may be informative of the value of CEOs. In this regard, our results suggest that the value created by a competent CEO can be substantial, especially for large and complex organizations where resources have to be allocated across many divisions and establishments.

V Conclusion

Previous literature has shown that the misallocation of capital and labor substantially lowers aggregate productivity (e.g., Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Bartelsman, Haltiwanger, and Scarpetta, 2013). This paper examines how much aggregate productivity is lost because of misallocation across versus within firms. When capital and labor are hypothetically reallocated to equalize marginal products across all plants, we find an increase in aggregate productivity of 42%, out of which 30% is due to misallocation within firms. For multi-segment firms, the increase in aggregate productivity is 59%, out of which 51% is due to misallocation within firms. Hence, within-firm distortions—due to, e.g., influence activities or internal politics—give rise to large productivity losses in the aggregate.

We further document that companies that misallocate resources internally have lower profits and lower value, and that the misallocation of internal resources is mitigated for firms that have better structured management. In a counterfactual where all multi-unit companies are assigned the highest score of structured management, aggregate productivity increases by 13% due to improvements in the allocation of internal resources.

Our findings leave a number of important areas open for future research, of which we highlight three here. First, more work is needed to understand which organizational designs are effective in mitigating resource misallocation. Our paper takes a first step in this direction by identifying a set of management practices—namely structured management—that helps reduce the misallocation of resources. Future work could examine, e.g., which governance mechanisms and which corporate structures are effective in reducing the misallocation of capital and labor within firms. Second, while our analysis focuses on the misallocation of resources across the firm's existing plants, within-firm frictions may also affect the opening and closure (and, similarly, the acquisition and sale) of plants. More work is needed to study this margin. Doing so is a challenging task, as it would require a dynamic extension of our model. Third, and related, future work could examine the implications for the boundaries of the firm. For example, in Lucas (1978) span of control model, managers expand the boundaries of the firm until they are no longer able to effectively manage an incremental unit. From this perspective, the mismanagement of within-firm resources is a likely determinant of firms' boundaries. Future research could extend the model to consider the optimal firm scope.

Appendix

Appendix A. Demand for differentiated goods

The cost minimization problem is as follows:

$$P_s Y_s = \min_{Y_{fsi}} \sum_{i=1}^{M_s} P_{fsi} Y_{fsi} \quad \text{s.t.} \quad Y_s = \left(\sum_{i=1}^{M_s} Y_{fsi}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

The Lagrangian is given by

$$\mathcal{L}_s = \sum_{i=1}^{M_s} P_{fsi} Y_{fsi} + \lambda_s \left(Y_s^{\frac{\sigma-1}{\sigma}} - \sum_{i=1}^{M_s} Y_{fsi}^{\frac{\sigma-1}{\sigma}} \right),$$

where λ_s is the multiplier. The first-order condition (FOC) with respect to Y_{fsi} is then

$$P_{fsi} = \lambda_s \frac{\sigma - 1}{\sigma} Y_{fsi}^{-\frac{1}{\sigma}}.$$

Accordingly, total costs can be expressed as

$$\underbrace{\sum_{i=1}^{M_s} P_{fsi} Y_{fsi}}_{=P_s Y_s} = \lambda_s \frac{\sigma - 1}{\sigma} \underbrace{\sum_{i=1}^{M_s} Y_{fsi}^{\frac{\sigma-1}{\sigma}}}_{=Y_s^{\frac{\sigma-1}{\sigma}}} \quad \Rightarrow \quad \lambda_s = \frac{\sigma}{\sigma - 1} P_s Y_s^{\frac{1}{\sigma}}.$$

Plugging the expression for λ_s in the FOC yields

$$P_{fsi} = P_s Y_s^{\frac{1}{\sigma}} Y_{fsi}^{-\frac{1}{\sigma}},$$

which can be rearranged to obtain the demand function $Y_{fsi} = P_{fsi}^{-\sigma} Y_s P_s^{\sigma}$ provided in equation (4). Finally, aggregating the above expression yields

$$\sum_{i=1}^{M_s} P_{fsi}^{1-\sigma} = P_s^{1-\sigma} Y_s^{\frac{\sigma-1}{\sigma}} \underbrace{\sum_{i=1}^{M_s} Y_{fsi}^{\frac{\sigma-1}{\sigma}}}_{=Y_s^{\frac{\sigma-1}{\sigma}}} \quad \Rightarrow \quad P_s = \left(\sum_{i=1}^{M_s} P_{fsi}^{1-\sigma} \right)^{\frac{1}{1-\sigma}},$$

which is the expression for P_s provided in the main text.

Appendix B. Within-firm lobbying

Plant managers' optimization problem

To maximize their utility, plant managers choose how much capital and labor to employ in their plant as well as the amount of effort to devote to unproductive "influence activities," which consist of lobbying division managers for a larger budget. The first-order conditions (FOC) of the manager of plant i of division s of firm f with respect to capital (K_{fsi}), labor (L_{fsi}), and lobbying (μ_{fsi}), are given by the following equations:

$$\frac{\partial P_{fsi}Y_{fsi}}{\partial K_{fsi}} = \lambda_{fsi} r \Leftrightarrow \frac{\sigma - 1}{\sigma}\alpha_s \frac{P_{fsi}Y_{fsi}}{K_{fsi}} = \lambda_{fsi} r \tag{19}$$

$$\frac{\partial P_{fsi}Y_{fsi}}{\partial L_{fsi}} = \lambda_{fsi}(1+\tau_{fsiL})w \Leftrightarrow \frac{\sigma - 1}{\sigma}(1-\alpha_s) \frac{P_{fsi}Y_{fsi}}{L_{fsi}} = \lambda_{fsi}(1+\tau_{fsiL})w \tag{20}$$

$$\lambda_{fsi}\frac{\partial B_{fsi}}{\partial \mu_{fsi}} = 2c_{fsi}\mu_{fsi}, \tag{21}$$

where λ_{fsi} is the Lagrange multiplier associated with the budget constraint. Rearranging the first-order conditions with respect to capital and labor allows us to express λ_{fsi} as:

$$\lambda_{fsi} = \frac{\sigma - 1}{\sigma}\frac{P_{fsi}Y_{fsi}}{B_{fsi}}. \tag{22}$$

Plugging the equation for λ_{fsi} in the first order conditions for capital and labor yields the familiar expression for the demand of production inputs when the production function is Cobb-Douglas, where the share of the budget spent on each input is given by the production shares α_s and $(1-\alpha_s)$, respectively:

$$K_{fsi} = \alpha_s \frac{B_{fsi}}{r} \tag{23}$$

$$L_{fsi} = (1-\alpha_s)\frac{B_{fsi}}{(1+\tau_{fsiL})w}. \tag{24}$$

Division managers' optimization problem

We can then solve the problem of the division manager, who decides on how to allocate the divisional budget across plants and how much to lobby the headquarters for a larger budget. The FOC with respect to B_{fsi} is:

$$\frac{\partial(1+\mu_{fsi})P_{fsi}Y_{fsi}}{\partial B_{fsi}} = (1+\mu_{fsi})\left[\frac{\partial P_{fsi}Y_{fsi}}{\partial K_{fsi}}\frac{\partial K_{fsi}}{\partial B_{fsi}} + \frac{\partial P_{fsi}Y_{fsi}}{\partial L_{fsi}}\frac{\partial L_{fsi}}{\partial B_{fsi}}\right] = \lambda_{fs}, \tag{25}$$

where λ_{fs} is the lagrange multiplier on the divisional manager's budget constraint. Plugging in the expressions for $\frac{\partial P_{fsi}Y_{fsi}}{\partial K_{fsi}}$, $\frac{\partial P_{fsi}Y_{fsi}}{\partial L_{fsi}}$, $\frac{\partial K_{fsi}}{\partial B_{fsi}}$, and $\frac{\partial L_{fsi}}{\partial B_{fsi}}$, and rearranging, we obtain:

$$(1+\mu_{fsi})\frac{\sigma-1}{\sigma}\frac{P_{fsi}Y_{fsi}}{B_{fsi}} = \lambda_{fs}. \tag{26}$$

We can use this expression to obtain the share of the division budget that is allocated to plant i:

$$\frac{B_{fsi}}{B_{fs}} = \frac{(1+\mu_{fsi})P_{fsi}Y_{fsi}}{\sum_{i\epsilon M_f}(1+\mu_{fsi})P_{fsi}Y_{fsi}}. \tag{27}$$

This expression shows that resource misallocation is a product of *relative* lobbying efforts. In other words, a plant can only obtain excessive resources if it lobbies more than other plants. We denote plant-level distortions by τ_{fsiY}, which we define as the deviations from what budget allocations would be if there were no lobbying:

$$(1+\tau_{fsiY}) = \frac{\frac{(1+\mu_{fsi})P_{fsi}Y_{fsi}}{\sum_{i\epsilon M_{fs}}(1+\mu_{fsi})P_{fsi}Y_{fsi}}}{\frac{P_{fsi}Y_{fsi}}{\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}} \Leftrightarrow \frac{\sum_{i\epsilon M_{fs}}(1+\tau_{fsiY})P_{fsi}Y_{fsi}}{\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}} = 1. \tag{28}$$

It is easy to see that if we re-write the problem of the division manager as a product of distortions instead of a product of lobbying by replacing each μ_{fsi} with the respective τ_{fsi}, we obtain the same budget allocation.

In addition to allocating budgets across plants given the overall divisional budget, division managers can also lobby headquarters for a larger budget. The optimal lobbying effort weights the marginal cost of lobbying against its marginal benefit:

$$\lambda_{fs}\frac{\partial B_{fs}}{\partial \mu_{fs}} = 2c_{fs}\mu_{fs}. \tag{29}$$

Headquarters' optimization problem

We are now ready to solve the problem of the headquarters. The headquarters allocates budgets across divisions taking into account how divisions subsequently allocate budgets across plants and the marginal product of capital and labor of each plant. The headquarters' FOC with respect to the budget of division s is given by:

$$\frac{\partial(1+\mu_{fs})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\partial B_{fs}} = \lambda_f$$

$$(1+\mu_{fs})\sum_{i\epsilon M_{fs}}\left[\frac{\partial P_{fsi}Y_{fsi}}{\partial K_{fsi}}\frac{\partial K_{fsi}}{\partial B_{fsi}}\frac{\partial B_{fsi}}{\partial B_{fs}}+\frac{\partial P_{fsi}Y_{fsi}}{\partial L_{fsi}}\frac{\partial L_{fsi}}{\partial B_{fsi}}\frac{\partial B_{fsi}}{\partial B_{fs}}\right]=\lambda_f, \tag{30}$$

where λ_f is the lagrange multiplier of the headquarters' budget constraint. Since the headquarters correctly anticipates the marginal allocation of each budget across plants and knows the production technology of each plant, we can write this equation as:

$$(1+\mu_{fs})\frac{\sigma-1}{\sigma}\frac{\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{B_{fs}}=\lambda_f. \tag{31}$$

Like in the case of plant budget allocations, we can see that lobbying at the division level is also a zero sum game, as the share of resources allocated to each division is a function of the *relative* lobbying efforts of each division. The fraction of the firm's budget allocated to division s is given by:

$$\frac{B_{fs}}{B_f}=\frac{(1+\mu_{fs})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\sum_{s\epsilon M_f}(1+\mu_{fs})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}. \tag{32}$$

We define division-level distortions (τ_{fsY}) as deviations from what divisional budget allocations would be in the absence of lobbying:

$$(1+\tau_{fsY})=\frac{\frac{(1+\mu_{fsY})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\sum_{s\epsilon M_{fs}}(1+\mu_{fsY})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}}{\frac{\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\sum_{s\epsilon M_{fs}}\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}}\Leftrightarrow\frac{\sum_{s\epsilon M_{fs}}(1+\tau_{fsY})\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\sum_{s\epsilon M_{fs}}\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}=1. \tag{33}$$

Allocation of resources across firms

Finally, we solve the problem of external financiers, who allocate budgets across firms. Their first-order conditions are given by:

$$\frac{\partial(1+\tau_{fY})\sum_{s\epsilon M_f}\sum_{i\epsilon M_{fs}}[P_{fsi}Y_{fsi}-(1+\tau_{fsiL})wL_{fsi}+rK_{fsi}]}{\partial B_f}=0.$$

In equilibrium, the share of a firm's budget with respect to the economy-wide resources is given by:

$$\frac{(1+\tau_{fY})\sum_{s\epsilon M_f}\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}{\sum_f(1+\tau_{fY})\sum_{s\epsilon M_f}\sum_{i\epsilon M_{fs}}P_{fsi}Y_{fsi}}=\frac{B_f}{B}. \tag{34}$$

Appendix C. Mapping our model to a modified version of Hsieh and Klenow (2009)

The equilibrium allocation obtained in our model and the corresponding size and capital-labor wedges can be obtained by solving a modified version of the model of Hsieh and Klenow (2009), where each plant maximizes profits subject to distortions. The difference between our model and theirs is that the wedges faced by each plant compound distortions at different levels of the organization. More specifically, our framework results in equilibrium allocations that correspond to the input allocations obtained from the following modified Hsieh and Klenow (2009) plant profit maximization problem:

$$\max_{K_{fsi},L_{fsi}} (1+\tau_{fY})(1+\tau_{fsY})(1+\tau_{fsiY})P_{fsi}Y_{fsi} - rK_{fsi} - (1+\tau_{fsiL})wL_{fsi}.$$

In this setting, the FOCs with respect to the allocation of capital and labor are given by:

$$\frac{\sigma-1}{\sigma}\alpha_s\frac{P_{fsi}Y_{fsi}}{K_{fsi}} = \frac{1}{(1+\tau_{fY})\left(1+\tau_{fsY}\right)\left(1+\tau_{fsiY}\right)}r_s \tag{35}$$

$$\frac{\sigma-1}{\sigma}\left(1-\alpha_s\right)\frac{P_{fsi}Y_{fsi}}{L_{fsi}} = \frac{(1+\tau_{fsiL})}{(1+\tau_{fY})\left(1+\tau_{fsY}\right)\left(1+\tau_{fsiY}\right)}w_s. \tag{36}$$

The equilibrium budget for a given plant i in sector s of firm f is given by:

$$\left(1+\tau_{fY}\right)\left(1+\tau_{fsY}\right)\left(1+\tau_{fsiY}\right)\frac{\sigma-1}{\sigma}P_{fsi}Y_{fsi}.$$

Therefore, the share of a division's budget that is allocated to a given plant is given by:

$$\frac{\left(1+\tau_{fsiY}\right)P_{fsi}Y_{fsi}}{\sum_{i\epsilon M_{fs}}\left(1+\tau_{fsiY}\right)P_{fsi}Y_{fsi}}.$$

Thus, the plant distortions in our setup map directly to Hsieh and Klenow (2009), i.e., the expression above corresponds to the same distortions as those implied by equation (8). Note that, without loss of generality, we can have taus normalized such that equation (10) holds in the modified Hsieh and Klenow (2009) framework.

Following a similar approach, we can obtain the division-level distortions by measuring the equilibrium budget allocations across divisions within a firm. The budget for division s of firm f is given by:

$$\left(1+\tau_{fY}\right)\left(1+\tau_{fsY}\right)\sum_{i\epsilon M_{fs}}\frac{\sigma-1}{\sigma}P_{fsi}Y_{fsi}.$$

Therefore, the share of the firm's budget allocated to division s is given by:

$$\frac{(1+\tau_{fsY}) \sum_{i\epsilon M_{fs}} P_{fsi}Y_{fsi}}{\sum_{s\epsilon M_f} (1+\tau_{fsY}) \sum_{i\epsilon M_{fs}} P_{fsi}Y_{fsi}}.$$

The misallocations associated with this expression are equivalent to those implied by equation (12).

Finally, firm-level budgets are also determined by firm-level distortions, which we denote by τ_{fY}. In sum, our model is similar to that of Hsieh and Klenow (2009), except that we model within-firm distortions and decompose the amount of resources allocated to a given firm as the product of i) across-firm distortions, ii) within-firm, across-division distortions, and iii) within-division, across-plant distortions.

Appendix D. Aggregate TFP

From equation (35), we can express K_{fsi} as

$$K_{fsi} = \frac{\sigma-1}{\sigma}\frac{\alpha_s}{r_s} (1+\tau_{fY}) (1+\tau_{fsY}) (1+\tau_{fsiY}) P_{fsi}Y_{fsi}.$$

Aggregating across all plants in sector s, we obtain total capital at the sector level:

$$\begin{aligned} K_s \equiv \sum_{i=1}^{M_s} K_{fsi} &= \frac{\sigma-1}{\sigma}\frac{\alpha_s}{r_s} \sum_{i=1}^{M_s} (1+\tau_{fY}) (1+\tau_{fsY}) (1+\tau_{fsiY}) P_{fsi}Y_{fsi} \\ &= \frac{\sigma-1}{\sigma}\frac{\alpha_s}{r_s} P_sY_s \underbrace{\sum_{i=1}^{M_s} (1+\tau_{fY}) (1+\tau_{fsY}) (1+\tau_{fsiY}) \frac{P_{fsi}Y_{fsi}}{P_sY_s}}_{\equiv(1+\overline{\tau_Y})}. \end{aligned}$$

Similarly, aggregating L_{fsi} from equation (36) across all plants in sector s yields:

$$L_s \equiv \sum_{i=1}^{M_s} L_{fsi} = \frac{\sigma-1}{\sigma}\frac{1-\alpha_s}{w_s} P_sY_s \underbrace{\sum_{i=1}^{M_s} \frac{(1+\tau_{fY}) (1+\tau_{fsY}) (1+\tau_{fsiY})}{(1+\tau_{fsiL})} \frac{P_{fsi}Y_{fsi}}{P_sY_s}}_{\equiv\frac{(1+\overline{\tau_Y})}{(1+\overline{\tau_L})}}.$$

Using these expressions for K_s and L_s, we can express TFP_s as

$$TFP_s = \frac{Y_s}{K_s^{\alpha_s} L_s^{1-\alpha_s}} = \frac{1}{P_s}\frac{\sigma}{\sigma-1} \left(\frac{r_s}{\alpha_s}\right)^{\alpha_s} \left(\frac{w_s}{1-\alpha_s}\right)^{1-\alpha_s} \frac{(1+\overline{\tau_L})^{1-\alpha_s}}{(1+\overline{\tau_Y})}. \tag{37}$$

We know from above that $P_s = \left(\sum_{i=1}^{M_s} P_{fsi}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$. Inserting the expression for P_{fsi} from equation (16), we can write:

$$P_s = \frac{\sigma}{\sigma-1}\left(\frac{w_s}{1-\alpha_s}\right)^{1-\alpha_s}\left(\frac{r_s}{\alpha_s}\right)^{\alpha_s}\left(\sum_{i=1}^{M_s}\left(\frac{\left(\overbrace{(1+\tau_{fsiL})}^{\equiv(1+\tau_L)}\right)^{1-\alpha_s}}{A_{fsi}\underbrace{(1+\tau_{fY})(1+\tau_{fsY})(1+\tau_{fsiY})}_{\equiv(1+\tau_Y)}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}.$$

Inserting this expression in (37), we obtain:

$$\begin{aligned} TFP_s &= \left(\sum_{i=1}^{M_s}\left(\frac{A_{fsi}(1+\tau_Y)}{(1+\tau_L)^{1-\alpha_s}}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}}\frac{(1+\overline{\tau_L})^{1-\alpha_s}}{(1+\overline{\tau_Y})} \\ &= \left(\sum_{i=1}^{M_s}\left[\left(\frac{A_{fsi}(1+\tau_Y)/(1+\tau_L)}{(1+\overline{\tau_Y})/(1+\overline{\tau_L})}\right)^{1-\alpha_s}\left(\frac{A_{fsi}(1+\tau_Y)}{(1+\overline{\tau_Y})}\right)^{\alpha_s}\right]^{\sigma-1}\right)^{\frac{1}{\sigma-1}}, \end{aligned}$$

which is the expression in equation (17).

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Table 1. Summary Statistics

This table provides summary statistics for the main variables used in the analysis. $1 + \tau_p$ and $1 + \tau_d$ are the measures of plant- and division-level distortion, respectively. $\sigma(1 + \tau_p)$ is the standard deviation of $1 + \tau_p$ across all plants of a given division. 90 – 10 Pctl. $(1 + \tau_p)$ is the difference between the 90th and the 10th percentiles of $1 + \tau_p$ across all plants of a given division. 75 – 25 Pctl. $(1 + \tau_p)$ is the difference between the 75th and the 25th percentiles of $1 + \tau_p$ across all plants of a given division. $\sigma(1 + \tau_d)$, 90 – 10 Pctl. $(1 + \tau_d)$, and 75 – 25 Pctl. $(1 + \tau_d)$ are defined analogously with respect to $1 + \tau_d$ across all divisions of a given firm. *Employees* is the number of employees of the plant. *Capital stock* is the average of the plant's total assets (machinery and buildings) at the beginning and end of the year (expressed in millions of dollars). *Age* is the number of years since the plant has coverage in the Census of Manufactures (CMF). *Distance to HQ* is the great-circle distance between the plant's ZIP code and the ZIP code of the firm's headquarters (in miles). The sample consists of all plants in the CMF from 1977-2007. Divisions are partitioned according to 3-digit SIC codes (1977-1992) and 4-digit NAICS codes (1997-2007). All figures are sample means. Standard deviations are in parentheses.

Panel (A): Plant-year observations

	All firms	Single-unit firms	Multi-unit firms		
			All	Single-division	Multi-division
$1 + \tau_p$	1.007	1	1.024	1.025	1.023
	(0.296)	(0)	(0.550)	(0.538)	(0.555)
Employees	83	38	192	106	230
	(311)	(87)	(547)	(230)	(635)
Capital stock	6.13	1.61	17.24	8.43	21.16
	(56.56)	(13.74)	(102.1)	(61.56)	(115.4)
Age	13.69	13.20	14.91	13.94	15.34
	(9.33)	(9.10)	(9.76)	(9.86)	(9.69)
Distance to HQ	144	0	498	313	581
	(412)	(0)	(641)	(552)	(661)
N	1,262,000	897,000	365,000	112,000	253,000

Panel (B): Division-year observations

	All firms	Single-unit firms	Multi-unit firms		
			All	Single-division	Multi-division
$1+\tau_d$	1.001	1	1.007	1	1.010
	(0.145)	(0)	(0.393)	(0)	(0.459)
$\sigma(1+\tau_p)$	0.033	0	0.242	0.399	0.185
	(0.155)	(0)	(0.354)	(0.378)	(0.327)
$90-10$ Pctl. $(1+\tau_p)$	0.061	0	0.448	0.680	0.364
	(0.291)	(0)	(0.673)	(0.698)	(0.658)
$75-25$ Pctl. $(1+\tau_p)$	0.047	0	0.349	0.585	0.263
	(0.230)	(0)	(0.535)	(0.577)	(0.491)
# Plants in division	1.22	1	2.59	3.00	2.45
	(1.77)	(0)	(4.56)	(3.14)	(4.97)
N	1,038,000	897,000	141,000	38,000	103,000

Panel (C): Firm-year observations

	All firms	Single-unit firms	Multi-unit firms		
			All	Single-division	Multi-division
$\sigma(1+\tau_d)$	0.014	0	0.194	0	0.409
	(0.087)	(0)	(0.259)	(0)	(0.233)
$90-10$ Pctl. $(1+\tau_d)$	0.024	0	0.329	0	0.693
	(0.149)	(0)	(0.451)	(0)	(0.420)
$75-25$ Pctl. $(1+\tau_d)$	0.021	0	0.289	0	0.609
	(0.131)	(0)	(0.396)	(0)	(0.368)
# Divisions	1.07	1	1.97	1	3.05
	(0.62)	(0)	(2.05)	(0)	(2.65)
# Plants	1.30	1	5.12	3.00	7.46
	(3.08)	(0)	(10.64)	(3.14)	(14.74)
N	968,000	897,000	71,000	37,000	34,000

Table 2. Plant and Division Power

In Panel (A), the dependent variable is the plant-level distortion $1 + \tau_p$. *Log(distance to HQ)* is the logarithm of one plus the great-circle distance between the plant's ZIP code and the ZIP code of headquarters. *Age* is the number of years since the plant has coverage in the CMF. The regressions are estimated using all plant-year observations of multi-unit firms. *New airline route* is a dummy variable indicating whether a new airline route that reduces the travel time between the plant and its headquarters has been introduced. In Panel (B), the dependent variable is the division-level distortion $1 + \tau_d$. *Log(distance to HQ, division)* is the logarithm of one plus the average distance to headquarters across all plants of the division. *Age (division)* is the average age across all plants of the division. The regressions are estimated using all division-year observations of multi-division firms. Standard errors (in parentheses) are clustered at both the firm and year level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Plant power

	$1 + \tau_p$	$1 + \tau_p$	$1 + \tau_p$	$1 + \tau_p$
	(1)	(2)	(3)	(4)
Log(distance to HQ)	-0.0015***	-0.0029***		
	(0.0006)	(0.0008)		
Age	0.0011***	0.0016***		
	(0.0002)	(0.0003)		
New airline route			0.0172***	0.0159**
			(0.0056)	(0.0066)
Year FE	Yes	Yes	Yes	–
Firm × division FE	No	Yes	–	–
Plant FE	No	No	Yes	Yes
MSA_{HQ} × year FE	No	No	No	Yes
MSA_{Plant} × year FE	No	No	No	Yes
R-squared	0.00	0.15	0.40	0.42
Observations	365,000	365,000	365,000	365,000

Panel (B): Division power

	$1 + \tau_d$	$1 + \tau_d$
	(1)	(2)
Log(distance to HQ, division)	-0.0042***	-0.0043***
	(0.0011)	(0.0012)
Age (division)	0.0037***	0.0043***
	(0.0006)	(0.0007)
Year FE	Yes	Yes
Firm FE	No	Yes
R-squared	0.00	0.16
Observations	103,000	103,000

Table 3. Resource Misallocation and Division Performance

The dependent variable is operating margin (OM) at the division level, which is the value added-weighted average of plant-level OM across all of the division's plants, where plant-level OM is defined as the ratio of shipments minus labor and material costs divided by shipments. OM is winsorized at the 1st and 99th percentiles of its empirical distribution. All other variables are described in Table 1. The regressions are estimated using all division-year observations of multi-unit firms. Standard errors (in parentheses) are clustered at both the firm and year level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	Operating margin (division level)		
	(1)	(2)	(3)
$\sigma(1+\tau_p)$	-0.053***		
	(0.002)		
$90-10$ Pctl. $(1+\tau_p)$		-0.032***	
		(0.001)	
$75-25$ Pctl. $(1+\tau_p)$			-0.034***
			(0.001)
# Plants in division	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)
Year FE	Yes	Yes	Yes
R-squared	0.03	0.03	0.03
Observations	141,000	141,000	141,000

Table 4. Resource Misallocation and Firm Performance

In columns (1)-(3), the dependent variable is operating margin (OM) at the firm level. Firm-level OM is computed by taking the value added-weighted average of division-level OM across all of the firm's divisions. In columns (4)-(9), the sample is restricted to Compustat firms. The CMF is matched to Compustat using the SSEL-Compustat Bridge maintained by the U.S. Census Bureau. The dependent variables are the return on assets (ROA) and Tobin's Q in columns (4)-(6) and (7)-(9), respectively. ROA and Tobin's Q are computed using Compustat data. ROA is the ratio of operating income before depreciation to total assets. Tobin's Q is the ratio of the market value of total assets (computed as the book value of total assets plus the market value of common stock minus the sum of the book value of common stock and balance sheet deferred taxes) to the book value of total assets. OM, ROA, and Tobin's Q are winsorized at the 1st and 99th percentiles of their empirical distribution. All other variables are described in Table 1. The regressions are estimated using firm-year observations of multi-division firms. Standard errors (in parentheses) are clustered at both the firm and year level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

				Public firms					
	Operating margin (firm level)			Return on assets			Tobin's Q		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\sigma(1+\tau_d)$	-0.054***			-0.017***			-0.130**		
	(0.004)			(0.004)			(0.058)		
$90-10$ Pctl. $(1+\tau_d)$		-0.041***			-0.012***			-0.081**	
		(0.002)			(0.002)			(0.033)	
$75-25$ Pctl. $(1+\tau_d)$			-0.037***			-0.010***			-0.086***
			(0.002)			(0.002)			(0.032)
# Divisions	0.005***	0.003***	0.005***	0.001***	0.001***	0.001***	-0.005**	-0.006**	-0.005**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.003)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.04	0.04	0.04	0.03	0.03	0.03	0.12	0.12	0.12
Observations	34,000	34,000	34,000	5,000	5,000	5,000	5,000	5,000	5,000

Table 5. Management Practices and Resource Misallocation

The sample is restricted to the 2007 CMF, merged with the Management and Organizational Practices Survey (MOPS). *Structured management* is the index of structured management at the division (Panel (A)) and firm level (Panel (B)), respectively. Division- and firm-level indices are constructed by computing the (value added-weighted) average of the plant-level index across all plants in the division and firm, respectively. *Monitoring* and *targets and incentives* are constructed similarly with respect to the corresponding subindices of structured management. All other variables are described in Table 1. Standard errors (in parentheses) are clustered at the firm level. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel (A): Division level

	$\sigma(1+\tau_p)$		90 – 10 Pctl. $(1+\tau_p)$		75 – 25 Pctl. $(1+\tau_p)$	
	(1)	(2)	(3)	(4)	(5)	(6)
Structured management	-0.130***		-0.385***		-0.186***	
	(0.034)		(0.071)		(0.054)	
Monitoring		-0.070**		-0.207***		-0.086*
		(0.029)		(0.061)		(0.047)
Targets and incentives		-0.060*		-0.178**		-0.100*
		(0.033)		(0.070)		(0.053)
# Plants in division	0.001***	0.001***	0.003***	0.003***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.01	0.01	0.03	0.03	0.01	0.01
Observations	6,000	6,000	6,000	6,000	6,000	6,000

Panel (B): Firm level

	$\sigma(1+\tau_d)$		90 – 10 Pctl. $(1+\tau_d)$		75 – 25 Pctl. $(1+\tau_d)$	
	(1)	(2)	(3)	(4)	(5)	(6)
Structured management	-0.141***		-0.250***		-0.216***	
	(0.035)		(0.057)		(0.054)	
Monitoring		-0.050*		-0.089*		-0.079*
		(0.031)		(0.050)		(0.047)
Targets and incentives		-0.091***		-0.161***		-0.137**
		(0.034)		(0.056)		(0.053)
# Divisions	0.008***	0.008***	0.042***	0.043***	0.012***	0.012***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
R-squared	0.01	0.01	0.08	0.08	0.01	0.01
Observations	3,000	3,000	3,000	3,000	3,000	3,000

Table 6. Counterfactual Analysis—No Distortion

This table reports TFP counterfactual gains that would be achieved in the absence of distortions. Counterfactual gains are reported separately for all plants, plants of multi-unit firms, and plants of multi-division firms.

Census year	TFP counterfactual gain		
	All plants (N = 1,262,000)	Plants of multi-unit firms (N = 365,000)	Plants of multi-division firms (N = 253,000)
1977	1.471	1.574	1.604
1982	1.489	1.609	1.654
1987	1.379	1.491	1.521
1992	1.331	1.414	1.416
1997	1.439	1.679	1.697
2002	1.438	1.640	1.597
2007	1.386	1.606	1.628
All years	1.419	1.573	1.588

Table 7. Counterfactual Analysis—Closing Plant-, Division-, and Firm-Level Distortions

This table reports TFP counterfactual gains that would be achieved by sequentially closing plant-, division-, and firm-level distortions. Counterfactual gains are reported separately for all plants, plants of multi-unit firms, and plants of multi-division firms.

Panel (A): All plants (N = 1,262,000)

	Setting $\tau_p = 0$ (closing plant-level distortions)		Setting $\tau_p = 0$ and $\tau_d = 0$ (closing plant- and division-level distortions)		Setting $\tau_p = 0$ and $\tau_d = 0$ and $\tau_f = 0$ (closing plant-, division, and firm-level distortions)	
Census year	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.108	0.229	1.138	0.293	1.471	1.000
1982	1.107	0.219	1.137	0.280	1.489	1.000
1987	1.093	0.245	1.112	0.296	1.379	1.000
1992	1.108	0.326	1.127	0.384	1.331	1.000
1997	1.093	0.212	1.124	0.282	1.439	1.000
2002	1.096	0.219	1.123	0.281	1.438	1.000
2007	1.099	0.256	1.122	0.316	1.386	1.000
All years	1.101	0.244	1.126	0.305	1.419	1.000

Panel (B): Plants of multi-unit firms (N = 365,000)

Census year	Setting $\tau_p = 0$ (closing plant-level distortions)		Setting $\tau_p = 0$ and $\tau_d = 0$ (closing plant- and division-level distortions)		Setting $\tau_p = 0$ and $\tau_d = 0$ and $\tau_f = 0$ (closing plant-, division, and firm-level distortions)	
	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.202	0.352	1.264	0.460	1.574	1.000
1982	1.207	0.340	1.279	0.458	1.609	1.000
1987	1.173	0.352	1.215	0.438	1.491	1.000
1992	1.203	0.490	1.238	0.575	1.414	1.000
1997	1.236	0.348	1.322	0.474	1.679	1.000
2002	1.233	0.364	1.303	0.473	1.640	1.000
2007	1.246	0.406	1.306	0.505	1.606	1.000
All years	1.214	0.379	1.275	0.483	1.573	1.000

Panel (C): Plants of multi-division firms (N = 253,000)

Census year	Setting $\tau_p = 0$ (closing plant-level distortions)		Setting $\tau_p = 0$ and $\tau_d = 0$ (closing plant- and division-level distortions)		Setting $\tau_p = 0$ and $\tau_d = 0$ and $\tau_f = 0$ (closing plant-, division, and firm-level distortions)	
	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.205	0.339	1.288	0.477	1.604	1.000
1982	1.215	0.329	1.309	0.472	1.654	1.000
1987	1.168	0.322	1.228	0.438	1.521	1.000
1992	1.197	0.474	1.252	0.606	1.416	1.000
1997	1.228	0.327	1.348	0.499	1.697	1.000
2002	1.219	0.367	1.318	0.533	1.597	1.000
2007	1.249	0.396	1.328	0.522	1.628	1.000
All years	1.212	0.365	1.296	0.507	1.588	1.000

Table 8. Counterfactual Analysis—Reduction of Within-Firm Distortions

This table reports TFP counterfactual gains that would be achieved by winsorizing τ_p and τ_d at their 10th and 90th percentiles (and 25th and 75th percentiles, respectively) within division and firm, respectively. Counterfactual gains are reported separately for all plants, plants of multi-unit firms, and plants of multi-division firms.

Panel (A): All plants (N = 1,262,000)

	Winsorizing τ_p and τ_d at their 10th and 90th pctl.		Winsorizing τ_p and τ_d at their 25th and 75th pctl.	
Census year	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.029	0.062	1.038	0.081
1982	1.028	0.057	1.039	0.080
1987	1.030	0.079	1.041	0.108
1992	1.033	0.100	1.041	0.124
1997	1.020	0.046	1.028	0.064
2002	1.017	0.039	1.025	0.057
2007	1.021	0.054	1.030	0.078
All years	1.025	0.062	1.035	0.084

Panel (B): Plants of multi-unit firms (N = 365,000)

Census year	Winsorizing τ_p and τ_d at their 10th and 90th pctl.		Winsorizing τ_p and τ_d at their 25th and 75th pctl.	
	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.052	0.091	1.071	0.123
1982	1.048	0.079	1.076	0.124
1987	1.054	0.111	1.083	0.168
1992	1.054	0.131	1.070	0.168
1997	1.038	0.056	1.067	0.098
2002	1.030	0.047	1.058	0.091
2007	1.040	0.067	1.071	0.117
All years	1.045	0.083	1.071	0.127

Panel (C): Plants of multi-division firms (N = 253,000)

Census year	Winsorizing τ_p and τ_d at their 10th and 90th pctl.		Winsorizing τ_p and τ_d at their 25th and 75th pctl.	
	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.059	0.098	1.083	0.137
1982	1.054	0.083	1.090	0.137
1987	1.062	0.118	1.096	0.184
1992	1.059	0.143	1.080	0.192
1997	1.048	0.069	1.085	0.122
2002	1.041	0.069	1.069	0.115
2007	1.052	0.083	1.095	0.151
All years	1.054	0.095	1.085	0.148

Table 9. Counterfactual Analysis—Improvements in Structured Management

This table reports TFP counterfactual gains that would be achieved by reducing the dispersion in $1 + \tau_p$ and $1 + \tau_d$ corresponding to an improvement in the structured management score i) by one standard deviation, ii) by matching the score of the best-managed firm in the economy, and iii) by matching the score of the best-managed firm within the same industry. Counterfactual gains are reported separately for all plants, plants of multi-unit firms, and plants of multi-division firms.

Panel (A): All plants (N = 1,262,000)

	One standard deviation improvement		Matching best-managed firm		Matching best-managed firm in same industry	
Census year	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.033	0.070	1.086	0.183	1.080	0.170
1982	1.034	0.070	1.088	0.180	1.082	0.168
1987	1.029	0.077	1.075	0.198	1.070	0.185
1992	1.027	0.082	1.070	0.211	1.065	0.196
1997	1.028	0.064	1.073	0.166	1.068	0.155
2002	1.027	0.062	1.071	0.162	1.066	0.151
2007	1.025	0.065	1.065	0.168	1.060	0.155
All years	1.029	0.070	1.075	0.181	1.070	0.169

Panel (B): Plants of multi-unit firms (N = 365,000)

	One standard deviation improvement		Matching best-managed firm		Matching best-managed firm in same industry	
Census year	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.055	0.095	1.129	0.225	1.122	0.212
1982	1.057	0.093	1.135	0.222	1.127	0.209
1987	1.052	0.105	1.119	0.242	1.113	0.229
1992	1.048	0.115	1.108	0.262	1.103	0.250
1997	1.055	0.081	1.131	0.193	1.124	0.183
2002	1.054	0.084	1.136	0.213	1.120	0.187
2007	1.053	0.087	1.124	0.205	1.117	0.193
All years	1.053	0.094	1.126	0.223	1.118	0.209

Panel (C): Plants of multi-division firms (N = 253,000)

	One standard deviation improvement		Matching best-managed firm		Matching best-managed firm in same industry	
Census year	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.062	0.102	1.139	0.230	1.132	0.218
1982	1.065	0.099	1.147	0.225	1.140	0.214
1987	1.059	0.113	1.129	0.248	1.123	0.236
1992	1.053	0.127	1.114	0.274	1.110	0.264
1997	1.063	0.090	1.143	0.205	1.136	0.195
2002	1.058	0.097	1.130	0.219	1.124	0.208
2007	1.060	0.095	1.135	0.214	1.128	0.204
All years	1.060	0.103	1.134	0.231	1.128	0.220

Table 10. Counterfactual Analysis—Improvements in Monitoring

This table reports TFP counterfactual gains that would be achieved by reducing the dispersion in $1 + \tau_p$ and $1 + \tau_d$ corresponding to an improvement in the monitoring score i) by one standard deviation, ii) by matching the score of the best-managed firm in the economy, and iii) by matching the score of the best-managed firm within the same industry. Counterfactual gains are reported separately for all plants, plants of multi-unit firms, and plants of multi-division firms.

Panel (A): All plants (N = 1,262,000)

	One standard deviation improvement		Matching best-managed firm		Matching best-managed firm in same industry	
Census year	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.022	0.047	1.049	0.104	1.046	0.098
1982	1.022	0.045	1.051	0.104	1.047	0.096
1987	1.019	0.050	1.043	0.113	1.040	0.106
1992	1.018	0.054	1.040	0.121	1.038	0.115
1997	1.018	0.041	1.041	0.093	1.039	0.089
2002	1.018	0.041	1.040	0.091	1.038	0.087
2007	1.016	0.041	1.037	0.096	1.034	0.088
All years	1.019	0.046	1.043	0.103	1.040	0.097

Panel (B): Plants of multi-unit firms (N = 365,000)

	One standard deviation improvement		Matching best-managed firm		Matching best-managed firm in same industry	
Census year	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.032	0.056	1.069	0.121	1.066	0.116
1982	1.034	0.056	1.072	0.119	1.069	0.114
1987	1.030	0.062	1.064	0.131	1.061	0.125
1992	1.027	0.066	1.058	0.141	1.055	0.133
1997	1.032	0.047	1.069	0.102	1.066	0.098
2002	1.031	0.049	1.067	0.105	1.064	0.100
2007	1.030	0.050	1.065	0.108	1.062	0.103
All years	1.031	0.055	1.067	0.118	1.064	0.113

Panel (C): Plants of multi-division firms (N = 253,000)

	One standard deviation improvement		Matching best-managed firm		Matching best-managed firm in same industry	
Census year	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.036	0.059	1.074	0.123	1.071	0.118
1982	1.038	0.058	1.079	0.121	1.075	0.115
1987	1.034	0.065	1.069	0.132	1.066	0.126
1992	1.031	0.074	1.061	0.146	1.059	0.141
1997	1.037	0.053	1.076	0.109	1.072	0.103
2002	1.034	0.057	1.070	0.117	1.066	0.110
2007	1.035	0.055	1.071	0.113	1.068	0.108
All years	1.035	0.060	1.071	0.123	1.068	0.117

Table 11. Counterfactual Analysis—Improvements in Targets and Incentives

This table reports TFP counterfactual gains that would be achieved by reducing the dispersion in $1 + \tau_p$ and $1 + \tau_d$ corresponding to an improvement in the targets and incentives score i) by one standard deviation, ii) by matching the score of the best-managed firm in the economy, and iii) by matching the score of the best-managed firm within the same industry. Counterfactual gains are reported separately for all plants, plants of multi-unit firms, and plants of multi-division firms.

Panel (A): All plants (N = 1,262,000)

	One standard deviation improvement		Matching best-managed firm		Matching best-managed firm in same industry	
Census year	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.017	0.036	1.045	0.096	1.042	0.089
1982	1.018	0.037	1.046	0.094	1.043	0.088
1987	1.015	0.040	1.040	0.106	1.037	0.098
1992	1.014	0.042	1.037	0.112	1.034	0.103
1997	1.014	0.032	1.038	0.087	1.035	0.080
2002	1.014	0.032	1.037	0.084	1.034	0.078
2007	1.013	0.034	1.034	0.088	1.031	0.080
All years	1.015	0.036	1.040	0.095	1.037	0.088

Panel (B): Plants of multi-unit firms (N = 365,000)

Census year	One standard deviation improvement		Matching best-managed firm		Matching best-managed firm in same industry	
	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.028	0.049	1.065	0.114	1.061	0.107
1982	1.029	0.048	1.068	0.112	1.064	0.106
1987	1.026	0.053	1.060	0.123	1.057	0.116
1992	1.024	0.058	1.054	0.131	1.052	0.126
1997	1.027	0.040	1.065	0.096	1.061	0.090
2002	1.027	0.042	1.062	0.097	1.059	0.093
2007	1.026	0.043	1.061	0.101	1.058	0.096
All years	1.027	0.048	1.062	0.111	1.059	0.105

Panel (C): Plants of multi-division firms (N = 253,000)

Census year	One standard deviation improvement		Matching best-managed firm		Matching best-managed firm in same industry	
	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain	TFP counterfactual gain	Gain as share of no-distortion gain
1977	1.031	0.051	1.070	0.116	1.066	0.109
1982	1.033	0.050	1.074	0.113	1.070	0.107
1987	1.030	0.057	1.065	0.125	1.062	0.119
1992	1.027	0.064	1.058	0.139	1.055	0.131
1997	1.032	0.046	1.071	0.102	1.068	0.097
2002	1.030	0.050	1.065	0.109	1.062	0.104
2007	1.030	0.047	1.067	0.107	1.064	0.102
All years	1.030	0.052	1.067	0.116	1.064	0.110

Figure 1. Density of Plant-Level Distortions $1 + \tau_p$

This figure plots the density of $1 + \tau_p$ among plants of multi-unit firms. The tails of the density have been trimmed in accordance with the disclosure rules of the Census Bureau.

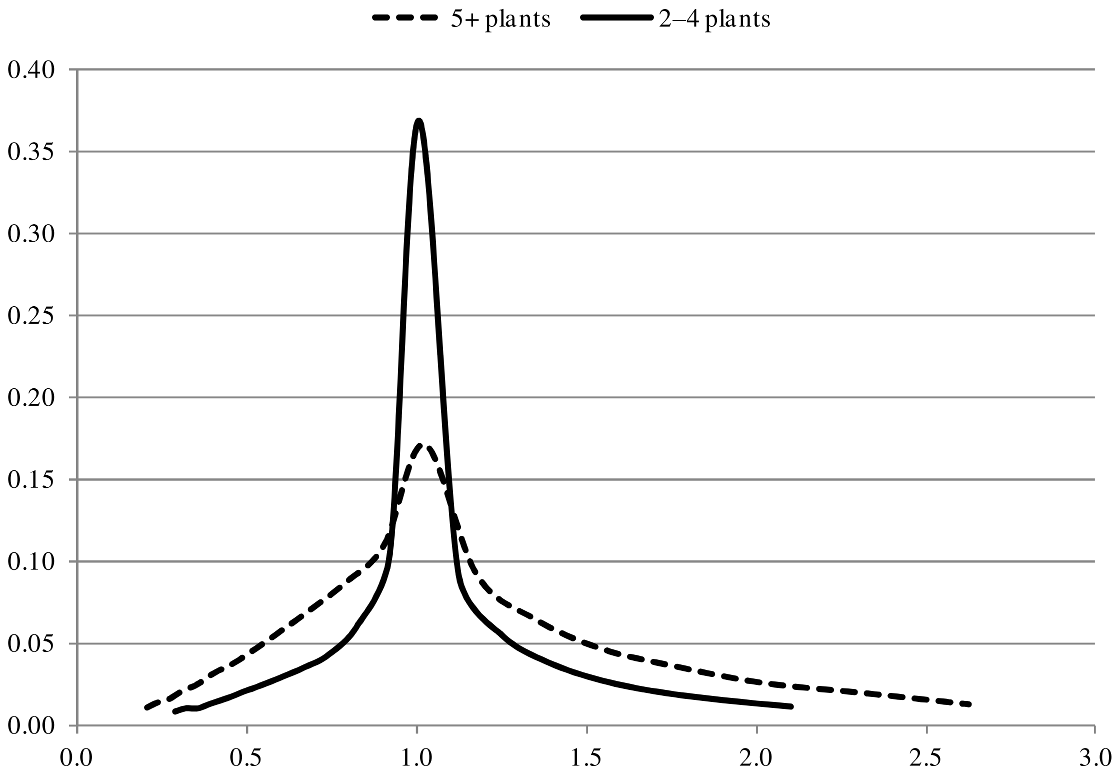

Figure 2. Density of Division-Level Distortions 1 + τ_d

This figure plots the density of 1 + τ_d among divisions of multi-division firms. The tails of the density have been trimmed in accordance with the disclosure rules of the Census Bureau.