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CEO talent, CEO compensation, and product market competition☆

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ABSTRACT

We develop a structural industry equilibrium model to show how competitive chief executive officer (CEO)-firm matching and product markets jointly determine firm value and CEO pay. We analytically derive testable implications for the effects of product market characteristics on firm size, CEO pay, and CEO impact on firm value. CEO talent matters more in more competitive markets with greater product substitutabilities. Our CEO impact estimates are much higher than those obtained by previous structural approaches that abstract away from CEO market segmentation. The estimates differ across industries primarily due to variation in product market competition, rather than variation in the CEO talent distribution.

1. Introduction

The questions of whether CEOs make economically important contributions to firms, and whether CEO pay is commensurate with CEO contributions, have important positive and normative implications. A number of studies adopt reduced-form approaches to show significant effects of observed, but noisy, measures of CEO talent on firm value (e.g., Falato, Li, and Milbourn (2015)). In contrast, Gabaix and Landier (2008, hereafter GL) and Terviö (2008) indirectly infer the unobserved CEO talent

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distribution, and its effect on firm value differences, by calibrating structural models of CEO-firm matching to the observed firm size and CEO pay distributions at the aggregate level (across industries). Surprisingly, their analyses suggest that CEO talent dispersion has a negligible effect on firm value dispersion, and that CEO pay is almost entirely determined by firm size.

GL and Terviö (2008) both assume that CEO talent is perfectly transferable across industries, and abstract away from product market effects. In their frameworks, therefore, firm value and CEO pay are only affected by firm and CEO characteristics. There is, however, considerable evidence that CEO labor markets are segmented by industry, and that product market competition significantly influences CEO pay.[1] We develop a structural industry equilibrium model that incorporates the matching of CEOs to firms engaged in imperfect product market competition. In equilibrium, firm value (or firm size), CEO pay, and CEO impact on firm value are not just influenced by firm and CEO characteristics, but also by the product market environment. We estimate the model by matching moments of the intra-industry distributions of firm size and CEO pay as well as the industry profitability. Analogously to GL, we measure CEO impact as the change in the value of the median firm in the industry if its CEO were replaced with the industry's best CEO.

Our CEO impact estimates for different industries are over a hundred times higher than GL's estimate of 0.016%. The estimates are closer to the reduced-form estimates in Falato, Li, and Milbourn (2015) that range between 1.7% and 2.5%. We exploit our model to disentangle the effects of CEO talent and product market characteristics on CEO impact. Product market characteristics—specifically, the product substitutability—have a much bigger quantitative effect on the CEO impact estimates than the CEO talent dispersion. The impact estimates differ across industries largely due to variation in the product substitutability, rather than variation in the CEO talent distribution.

We develop a discrete-time, infinite horizon model of an industry in which firms are established by incurring sunk entry costs after which their random qualities are realized. In each period, firms hire CEOs with different talents in a competitive labor market. Firm qualities and CEO talents are observable, and complement each other multiplicatively in determining firms' productivities. Firms offer differentiated, imperfectly substitutable products, and are monopolistically competitive (Dixit and Stiglitz, 1977). Each firm enjoys a monopoly in its product and charges a markup over its marginal cost. Firms, however, also compete for consumers because consumer demand depends on the relative prices of the products. An increase in the product substitutability increases the intensity of product market competition because products become more homogeneous. The unique equilibrium features free entry by firms, product market clearing, and positive assortative matching (PAM), where more talented CEOs are efficiently matched to higher quality firms. By PAM, firm profit, firm value, and CEO pay all increase with firm rank (by productivity).

As products become more substitutable, consumer demand becomes more responsive to prices. More productive firms can, therefore, capture disproportionately higher market shares and rents by charging lower prices than less productive firms. Hence, firm profit increases more disproportionately with firm productivity as the product substitutability increases. Because firm productivity is determined by the product of firm quality and CEO talent, the above results also apply separately to the relations between firm profit and firm quality as well as firm profit and CEO talent. Further, firm profit is proportional to the product of firm-specific and CEO-specific factors. It then follows that the CEO (firm) factor increases with CEO talent (firm quality), with the relation becoming steeper as the product substitutability increases. The CEO factor, therefore, represents a CEO's influence on firm profit through the combined effects of CEO talent and the product substitutability.

The *CEO factor profile*—the variation of the CEO factor with firm rank—differs across industries because of variation in the CEO talent profile and the product substitutability.[2] Importantly, for the same talent profile, an increase in the product substitutability makes the CEO factor profile steeper. As our CEO impact measure is determined by the best to median CEO factor ratio, an increase in the product substitutability amplifies the impact measure. In other words, CEO talent matters more in a more competitive product market with greater product substitutability.

We estimate the model parameters that determine the unobserved firm quality and CEO talent profiles as well as the product substitutability, using observed moments of the intra-industry firm value and CEO pay distributions as well as the industry profitability. The profitability allows us to identify the product substitutability and, thereby, separate its effects on the CEO factor profile from those of the CEO talent profile. In support of our identifying assumption that our model is the "true" model, we show that it fits the data well. The predicted and actual moments are statistically indistinguishable in and out of sample. Our quantitative analysis shows that the product substitutability significantly increases the impact of CEO talent. On average, the best CEO in an industry is only 0.3% more talented than the median CEO, but the CEO impact estimate is about 2.2% due to the magnifying effect of the product substitutability. Further, the impact estimate ranges from 1.03% to 5.04% across industries, but the best to median CEO talent ratio varies by only 0.7%. Inter-industry differences in the impact estimates, therefore, stem largely from variation in the product substitutability rather than variation in the intra-industry CEO talent dispersion.

Our CEO impact estimates are significantly higher than GL's estimate of 0.016%. GL exogenously specify firm profit as being proportional to the product of a firm-specific factor and a CEO-specific factor that they refer to as "CEO talent." Hence, "CEO talent" in GL's model corresponds to our

[1] E.g., see Parrino (1997); Cuñat and Guadalupe (2009); Cremers and Grinstein (2014); Lewellen (2015).

[2] Hereafter, the "profile" of a quantity refers to its variation with firm rank (by productivity).

"CEO factor" that actually embodies the combined effects of CEO talent and the product substitutability. The CEO impact measure, however, depends directly on the CEO factor profile, and not on how the factor profile is separately affected by the talent profile and the product substitutability. The comparison between our and GL's estimates, therefore, hinges on differences between the factor profiles inferred by taking the models to the corresponding data. There are two main reasons why GL's analysis leads to a flatter factor profile and, therefore, a lower impact estimate: (i) misspecification in GL's model from not incorporating CEO market segmentation; and (ii) differing assumptions on the duration of CEO influence in our respective models.

Because GL assume a single aggregate CEO market, they infer the CEO factor profile by matching two moments in the *aggregate* data: the elasticities of CEO pay to firm size, and firm size to firm rank. As the product of the two elasticities is (roughly) the elasticity of CEO pay to firm rank, GL match the elasticity of the CEO pay profile in the data. Competitive CEO-firm matching ensures that the incremental pay of a CEO relative to her nearest (lower ranked) competitor—the slope of the CEO pay profile—is determined by her incremental (marginal) contribution to firm value relative to her competitor. As the marginal contribution increases with the difference in the CEO factors, a steeper factor profile leads to a steeper predicted pay profile. Conversely, a steeper observed pay profile, ceteris paribus, implies a steeper inferred factor profile and, therefore, a higher impact estimate. The impact estimate is, thereby, inferred from the two elasticities that GL match in their analysis. Given our premise of CEO market segmentation, we infer the CEO factor profiles at the industry level by matching the *industry-level* elasticities. GL's aggregate model is misspecified in two related aspects that are manifested in the aggregate and industry-level elasticities being different, thereby leading to a misspecification bias in GL's impact estimate.

First, GL assume that PAM holds at the aggregate level across industries. In the data, however, the correlation between the ranks of firms by size, and their ranks by CEO pay, is significantly higher at the industry level than at the aggregate level. The specification of a monotonic CEO pay-firm size relation is, therefore, more plausible at the industry level. Hence, the CEO pay-firm size elasticity is likely to differ at the aggregate and industry levels. Second, by specifying aggregate firm size and CEO pay profiles, GL assume that the corresponding industry-level profiles do not vary across industries, but our results show that they vary significantly. As the product substitutability influences the payoff profiles via its effects on the firm and CEO factors, inter-industry differences in the product substitutability are a key driver of the variation in the profiles and their elasticities. The variation in the elasticities across industries also implies that the aggregate and industry-level elasticities differ.

The wedges between the aggregate and industry-level elasticities depend on features of the data. We show that, depending on the data, and the industry composition of the aggregate sample, the aggregate elasticities could be above, below, or within the respective ranges of the industry-level elasticities. Hence, theoretical arguments alone cannot tell us even the direction of the misspecification bias in GL's aggregate estimate. We, therefore, empirically determine the bias by implementing their analysis at the industry level. We allow the firm and CEO factor profiles in their firm profit specification to differ across industries. Hence, the industry-level GL analysis incorporates industry segmentation, and serves as the appropriate benchmark to isolate the effects of the misspecification in GL's aggregate analysis. Because the CEO factor combines the effects of CEO talent and the product substitutability, the industry-level GL impact estimates implicitly embody product market effects. We show that the misspecification bias in GL's aggregate estimate is negative in the data. The industry-level elasticities are higher than the aggregate elasticities for all industries, and the corresponding impact estimates are an order of magnitude higher than GL's aggregate estimate.

The industry-level GL estimates are, however, significantly lower than our estimates. The discrepancies stem from differing assumptions on the duration of CEO influence in our respective models. In GL's framework, the CEO factor in each period proportionally affects earnings in *all future* periods. In our model, the CEO factor proportionally affects only the *current* period earnings. Hence, the marginal CEO contribution is proportional to firm value in GL's model, but is proportional to current period earnings in our model. For the same CEO factor profile, the dispersion in CEOs' marginal contributions is thus greater in GL's model, which implies that the predicted CEO pay profile is steeper. The industry-level GL analysis and our analysis use the same industry-level data to infer the respective factor profiles. It then follows that the inferred factor profile that matches the observed CEO pay profile is flatter in the industry-level GL analysis, thereby leading to a lower impact estimate. Our perspective on CEO influence relative to GL's perspective is supported by the fact that our estimates are more in line with those reported by reduced-form approaches that employ observed CEO talent measures (e.g., Falato, Li, and Milbourn (2015)).

The incorporation of product market competition in our industry equilibrium model plays two key related roles in our analysis. First, it provides an endogenous source of inter-industry variation in the firm and CEO factor profiles that is explicitly linked to the product market environment. The variation in the profiles contributes to the misspecification in GL's aggregate analysis. The industry-level GL analysis exogenously assumes this variation without being able to identify its sources (firm quality and CEO talent profiles as well as product market characteristics). Second, and more importantly, we determine the importance of CEO talent and product market characteristics in influencing CEO impact, firm size, and CEO pay. Relative to CEO talent, the product substitutability has a bigger quantitative effect on CEO impact, and its inter-industry variation. We also exploit our model to show that changes in product market characteristics significantly affect firm size and CEO pay. In contrast, GL's analysis attributes CEO impact entirely to CEO talent, and would predict that product market changes have no effects on firm size and CEO pay.

We develop and analyze several extensions of our model. (i) In reality, CEOs affect firms not just with their exogenous “talent,” but also by exerting endogenous “effort.” It is optimal for firms to tie CEO pay to firm performance so that CEO pay includes compensation for talent, and incentive compensation to induce effort. We show that our main implications for CEO impact hold in an extended model that incorporates moral hazard and incentive pay. (ii) CEOs could have long-term effects on earnings as GL assume, but it is plausible that their influence declines over time. We show that our quantitative results are robust to an extended model that incorporates long-term, but declining CEO effects on future earnings. (iii) Our results are also robust to the incorporation of (a) imperfect intra- and inter-industry transferability of CEO talent; (b) potential specification and/or measurement errors; (c) product market effects on CEO-firm matching; and (d) alternate CEO pay and profitability measures, as well as industry classifications.

2. The model

We develop a discrete-time, infinite horizon model of an industry with dates $t = 0, 1, 2, \ldots$. There are a continuum of heterogeneous firms, heterogeneous managers, and identical workers. At date 0, a group of (identical) entrepreneurs drawn from the pool of workers establish a firm. After entry, the firm's random quality is realized and remains constant through time. In each period after entry, each firm hires a CEO from a continuum of managers with different talents in a competitive executive labor market. Firm qualities and CEO talents are observable, and CEO talent is freely transferrable across firms in the industry. Firms have a common discount factor $\delta \in (0, 1)$.

2.1. Preferences, market demand, and production

The representative consumer has “constant elasticity of substitution” (CES) preferences for consumption of a continuum of goods produced by the industry in each period $t \equiv [t, t+1]$. The preferences are described by the utility function $U_t = \left[\int_\Omega q_t(\omega)^\rho d\omega\right]^{\frac{1}{\rho}}$, where $0 < \rho < 1$, Ω is the set of goods, and ω is a finite measure on the Borel sigma-algebra of Ω. Let R_t be the consumer's total expenditure in period t that can be interpreted as the industry (or market) size. We assume that

$$R_t = R_0 G_t, \tag{1}$$

where G is a random variable with a known distribution. The process G allows for stochastic evolution of the industry size. If $p_t(\omega)$ is the price of good ω, then the consumer's demand, $q_t(\omega)$, for the good is

$$q_t(\omega) = U_t\left[\frac{P_t}{p_t(\omega)}\right]^{1/(1-\rho)}. \tag{2}$$

P_t is a weighted average of the prices charged by all firms that we refer to as the *aggregate price index* as shown by

$$P_t = \left[\int_\Omega p_t(\omega)^{\frac{\rho}{\rho-1}} d\omega\right]^{\frac{\rho-1}{\rho}}, \tag{3}$$

and $R_t = P_t U_t$. By (2), the *elasticity of substitution* or *product substitutability* between any two goods in the market is given by $\sigma = \frac{1}{1-\rho} > 1$.

Production is driven by labor that is inelastically supplied by workers each of whom is endowed with one unit of labor and receives a wage of w_t in period t. The labor wage could also evolve stochastically so that $w_t = w_0 A_t$, where A_t is an industry-wide shock. A firm's quality and its CEO's talent together determine its productivity in a complementary manner. Suppose that the firm has quality $x \in R_+$ and its CEO has talent $y \in R_+$. The firm's productivity, which is defined as the inverse of its marginal cost of production (measured in units of labor), is

$$\theta_t(x, y) = xyB_t, \tag{4}$$

where B_t is an industry-wide productivity shock.[3]

In each period, the profit-maximizing firm optimally sets the product price to

$$p_t(x, y) = \frac{w_t}{\rho\theta_t(x, y)} = \frac{w_0 A_t}{\rho xy B_t} = \frac{w_0 \mu_t}{\rho xy}, \tag{5}$$

where $\mu_t = \frac{A_t}{B_t}$ is the relative wage shock. By (3) and (5), $P_t = P_0 \mu_t$, so that the aggregate price index also scales by the same stochastic factor, μ_t. By (2), (5), and the relation, $R_t = P_t U_t$, the firm's revenue and gross profit are

$$\begin{aligned} r_t(x, y) &= p_t(x, y) q_t(x, y) = R_t\left(P_t \frac{\rho xy}{w_0 \mu_t}\right)^{\sigma-1} \\ &= R_t((P_0/w_0)\rho xy)^{\sigma-1}, \end{aligned} \tag{6}$$

$$\begin{aligned} \Pi_t(x, y) &= p_t(x, y) q_t(x, y) - w_t \frac{q_t(x, y)}{\theta_t(x, y)} \\ &= \frac{R_t((P_0/w_0)\rho xy)^{\sigma-1}}{\sigma}. \end{aligned} \tag{7}$$

By (6) and (7), the firm's revenue and gross profit are increasing and convex in firm productivity and, therefore, in firm quality x and CEO talent y (as long as $\sigma > 2$ that we henceforth assume and later confirm in the data; see Section 4.3.2). The intuition is that the consumer demand for a product is decreasing and convex in its price. Consequently, more productive firms can exploit their greater efficiency to garner disproportionately higher proportions of the total consumer expenditure by charging lower prices. We also note that the convexities of firm payoffs in firm productivities increase with the product substitutability σ. As the elasticity of substitution between products increases, differences in productivities become even more important for firms' revenues and profits because the capacity of less productive firms to capture market shares through product differentiation declines. Hence, firms' payoffs become more convex or elastic in their productivities and, therefore, in firm quality and CEO talent as the product substitutability increases.

[3] For modeling convenience, we assume that a firm's productivity (the inverse of its marginal cost of production) is affected by the firm's quality and its CEO's talent. We can alter the model so that the representative consumer cares about product qualities (that appear as weights in the consumer's utility function). Firm quality and CEO talent directly affect product qualities and, therefore, firm revenues and profits. In other words, firms within the same industry may have different elasticities of product demand rather than different productivities. This framework is actually isomorphic to the one we consider in this paper (with a re-interpretation of variables) so that our main implications are not qualitatively or quantitatively affected.

2.2. CEO-firm matching and market entry

As in GL and Terviö (2008), the sets of firms and CEOs in the executive labor market have the same cardinality/measure. CEO talents and firm qualities are observable and constant through time. If a firm of quality x hires a CEO with talent y in period t by offering (endogenously determined) compensation u_t, the firm's net profit in the period is its gross profit Π_t in (7), net of the CEO's compensation u_t, that is, $\pi_t(x, y, u_t) = \Pi_t(x, y) - u_t$. It follows from (1), (6), and (7) that

$$r_t = r_0 G_t;\ \ \Pi_t = \Pi_0 G_t, \tag{8}$$

so that firm revenues and profits scale by the industry size shock G_t. G is a stationary Markov process with

$$E[G_s|G_t] = \beta^{s-t} G_t,\ \ \text{for } s > t. \tag{9}$$

To ensure that firm values are finite, we assume that $\beta\delta < 1$.

Let F_X and F_Y be the cumulative distribution functions of firm quality and CEO talent, respectively. The profiles of firm quality, $x[i]$, and CEO talent, $y[i]$, are the quantiles of their distribution functions. Consequently, $x'[i] > 0$ and $y'[i] > 0$ where $i \in [0, 1]$. The following proposition characterizes the CEO-firm matching equilibrium. We provide the proofs of all propositions in online Appendix A.

Proposition 1 (Matching equilibrium). *In equilibrium, we have positive assortative matching (PAM) between firms and CEOs. The equilibrium net profit of a firm ranked i in period t,* $\pi_t[i]$, *and the compensation of its matched CEO ranked i,* $u_t[i]$, *are, respectively, given by*

$$\pi_t[i] = \tilde{\pi}_t + \int_0^i R_t (P_0/w_0)^{\sigma-1} \rho^\sigma x[j]^{\sigma-2} y[j]^{\sigma-1} x'[j] dj, \tag{10}$$

$$u_t[i] = \tilde{u}_t + \int_0^i R_t (P_0/w_0)^{\sigma-1} \rho^\sigma x[j]^{\sigma-1} y[j]^{\sigma-2} y'[j] dj, \tag{11}$$

where $\tilde{\pi}_t$ *and* $\tilde{u}_t$ *are the payoffs from the outside options of firms and CEOs, respectively.*

Consistent with the scaling of all payoffs with the shock G_t, the payoffs of the lowest ranked firm and CEO also scale with G_t, that is,

$$\pi_t[0] = \tilde{\pi}_t = \tilde{\pi}_0 G_t;\ \ u_t[0] = \tilde{u}_t = \tilde{u}_0 G_t. \tag{12}$$

It then follows from (1), (10), (11), and (12) that

$$\pi_t[i] = \pi_0[i] G_t;\ \ u_t[i] = u_0[i] G_t. \tag{13}$$

Proposition 1 implies that, in equilibrium, all firms keep matching with a CEO of the same talent in every period because their qualities and, therefore, their ranks remain the same over time. Since firms have a common discount factor δ, firm i's market value (or firm size) at any date t—the expected present value of the firm's future net profits—is then

$$\mathcal{V}_t[i] = E_t\left[\sum_{s=t}^{\infty} \delta^{s-t} \pi_s[i]\right] = \sum_{s=t}^{\infty} \delta^{s-t} \beta^{s-t} \pi_t[i] = \frac{\pi_t[i]}{1-\beta\delta}, \tag{14}$$

where the second equality follows from (9) and (13).

The distributions of firm value and CEO pay after entry are rationally anticipated by prospective entrants into the market. Entry into the market requires fixed and sunk "investment labor" costs of $f_e > 0$. Since the quality of a newly established firm is determined *after* it enters the market, its quality is an unknown random variable with the cumulative distribution function F_X at the "market entry" stage. We, therefore, have the following free entry condition, which requires that the expected post-entry firm value equal the entry cost, that is,

$$E_0[\mathcal{V}_0[i]] = \int_0^1 \mathcal{V}_0[i] di = f_e, \tag{15}$$

where $\mathcal{V}_0[i]$ is given by (14).

3. Equilibrium

3.1. Equilibrium conditions

For given distributions of firm and CEO characteristics, an equilibrium is characterized by (i) a mass N of firms operating in the market; (ii) an aggregate price index P_t^* in each period t; and (iii) payoff profiles—the variation of CEO compensation $u_t[i]$ and firm net profit $\pi_t[i]$ with firm rank i—in each period t, such that the following conditions hold:

1. *Firm profit maximization*: In each period t, each firm i sets its price $p_t(i)$ and produces $q_t(i)$ units of its good to maximize its net profit, given the relative labor wage, $w_0\mu_t$, and the aggregate price index, P_t:

$$p_t(i) = \frac{w_0\mu_t}{\rho x[i] y[i]};\ \ q_t(i) = R_t (P_t^*)^{\sigma-1}\left(\frac{\rho x[i] y[i]}{w_0\mu_t}\right)^\sigma. \tag{16}$$

2. *CEO-firm matching and payoffs*: A CEO ranked i is assigned to the equally ranked firm i in each period. The equilibrium payoff profiles in period t satisfy

$$u_t[i] = \tilde{u}_t + \int_0^i R_t (P_0^*/w_0)^{\sigma-1} \rho^\sigma x[j]^{\sigma-1} y[j]^{\sigma-2} y'[j] dj, \tag{17}$$

$$\pi_t[i] = \Pi_t[i] - u_t[i] = \frac{R_t\left((P_0^*/w_0)\rho x[i] y[i]\right)^{\sigma-1}}{\sigma} - u_t[i]. \tag{18}$$

3. *Free entry*: At market entry at time zero, the expected post-entry firm value must equal the entry cost f_e. By (10), (14), (15), and (18), the following free entry condition must be satisfied:

$$\begin{aligned} R_0 (P_0^*/w_0)^{\sigma-1} \Bigg[& \frac{(\rho x[0] y[0])^{\sigma-1}}{\sigma} \\ & + \rho^\sigma \int_0^1 \left[\int_0^i x[j]^{\sigma-2} y[j]^{\sigma-1} x'[j] dj\right] di \Bigg] \\ = \tilde{u}_0 + & (1-\beta\delta) f_e. \end{aligned} \tag{19}$$

4. *Market clearing*: In each period t, the aggregate revenues of firms must equal the total consumer expenditure R_t. By (6),

$$N\int_0^1 r_t(x[i],y[i])di = R_t \Rightarrow$$
$$N = \left[\int_0^1 ((P_0^*/w_0)\rho x[i]y[i])^{\sigma-1}di\right]^{-1}. \tag{20}$$

The initial aggregate price index P_0^* is uniquely determined by (19), which also determines the price index P_t^* in any future period $t > 0$ as $P_t^* = P_0^*\mu_t$. The mass of firms operating in the market, N, is then determined by (20). Consequently, there is a unique market equilibrium determined by P_0^* and N. Notice from (20) that the aggregate price index and the mass of firms are inversely related. Indeed, a greater mass of firms has the effect of increasing product market competition and decreasing firms' monopoly power, thereby lowering the aggregate price level.

3.2. Effects of product market characteristics

We now analytically derive the effects of product market characteristics—the entry cost and product substitutability—on the equilibrium variables including firm value and CEO pay.

Proposition 2 (Effects of the entry cost). *(i) The price index P_t^* in any period $t \geq 0$ increases with the entry cost f_e. (ii) The mass of firms N declines with the entry cost f_e. (iii) Firm value and CEO pay increase with the entry cost f_e.*

Since the entry cost is sunk ex ante (that is, before firms enter the market and firm qualities are realized), it only influences payoffs in each period *indirectly* through its effects on the mass of firms and the aggregate price index. The mass of firms and the aggregate price index are determined in equilibrium by the entry condition (19) and the market clearing condition (20). A higher entry cost deters entry and reduces competition, thereby reducing the mass of firms and increasing their monopoly power. Consequently, the aggregate price index increases so that firm value increases. Since the equilibrium features PAM, CEO pay also increases.

Proposition 3 (Effects of the product substitutability). *(i) There exists a trigger $\bar{\imath}$ such that firm value decreases with a marginal increase in the product substitutability σ for $i < \bar{\imath}$, but increases for $i > \bar{\imath}$. (ii) There exists a trigger $\hat{\imath}$ such that CEO pay decreases with a marginal increase in the product substitutability σ for $i < \hat{\imath}$, but increases for $i > \hat{\imath}$. (iii) There exists a threshold level $\bar{f}_e(\sigma)$ of the entry cost such that the initial aggregate price index P_0^* increases with a marginal increase in the product substitutability σ if $f_e < \bar{f}_e(\sigma)$ and decreases if $f_e > \bar{f}_e(\sigma)$.*

In contrast with the entry cost, the product substitutability σ has *direct* effects on firm value and CEO pay. As discussed earlier at the end of Section 2.1, the convexities of firm size and CEO pay (due to PAM) in firm quality and CEO talent increase with the product substitutability. By the free entry condition, (15), however, the ex ante expectation of the post-entry firm value equals the entry cost. Because it coincides with the expectation of the post-entry firm value by the law of large numbers, the average firm value equals the entry cost, and is, therefore, unaffected by the product substitutability. Consequently, an increase in the convexities of the payoff profiles with the product substitutability, while keeping the average firm value unchanged, implies that large firms benefit at the expense of small firms. The differential effects of σ on large and small firms suggest that an increase in σ increases the intra-industry dispersions of firm value and CEO pay.

The intuition for the effects of the product substitutability on the aggregate price index is as follows. If the entry cost is below a threshold, the mass of firms is high and the price index is low due to high competition. A low price index, in turn, implies that there is a relatively large number of small firms compared with large firms. As discussed above, an increase in the product substitutability has a negative impact on small firms and a positive impact on large ones. It then follows that, for a fixed aggregate price index, an increase in the product substitutability in such a market with a large number of small firms has the effect of lowering average firm size. In other words, the direct effect of the product substitutability on average firm size is negative. By the entry condition, (15), however, the average firm size depends only on the entry cost and not on the product substitutability. The aggregate price index must, therefore, increase in equilibrium so that the indirect effect of the product substitutability on average firm size exactly offsets the direct effect. When the entry cost is above a threshold, competition is low so that the aggregate price index is high and there are relatively many large firms. In this case, an increase in σ (keeping the aggregate price index fixed) has a positive effect on average firm size, which, in turn, implies that the equilibrium aggregate price index must decrease with σ to offset the positive direct effect of σ.

3.3. Empirical implications

The results of Propositions 2 and 3 can be interpreted as predictions for changes in CEO pay and firm size as well as in the number of firms in the market in response to unanticipated (exogenous) variations in product market characteristics *within an industry*. They can also be interpreted as cross-sectional predictions for variations in these variables*across industries.* We summarize these predictions below as empirical implications of the model.

3.3.1. Intra-industry implications

1. Within an industry, an exogenous increase in the entry cost increases firm size and CEO pay, but decreases the number of firms operating in the industry, ceteris paribus.
2. Within an industry, an exogenous increase in the product substitutability, ceteris paribus, increases firm size and CEO pay for firms with ranks (by firm size) above a threshold, but decreases firm size and CEO pay for firms with ranks below the threshold.
3. An exogenous increase in the product substitutability, ceteris paribus, increases the intra-industry dispersions of CEO pay and firm size.

3.3.2. Inter-industry implications

1. Industries with higher entry costs have a smaller number of firms, ceteris paribus. Controlling for other determinants of firm size and CEO pay, firms with the same relative ranks within their industries are larger and have greater CEO pay in industries with higher entry costs.
2. Controlling for other determinants of firm size and CEO pay, firms with the same relative ranks within their industries that are above (below) a threshold are larger (smaller) and have greater (lower) CEO pay in industries with higher product substitutabilities.
3. Controlling for other determinants of firm size and CEO pay, industries with greater product substitutabilities feature greater intra-industry dispersions of firm size and CEO pay.

4. Quantitative analysis

We estimate the model to quantitatively investigate the extent to which CEO talent and product market characteristics affect firm size, CEO pay, and CEO impact on firm value.

4.1. Data

Our data include observations of U.S.-based firms from Compustat and Execucomp over the period 1993–2013.[4] We estimate the model using data over the period 1993–2010. We employ the data from the subsequent period 2011–2013 to perform out-of-sample tests. We measure annual CEO pay using Execucomp's variable, TDC1, which includes each year's salary, bonus, total value of stock and option grants, long-term incentive payouts, and all other payments. We obtain firm-specific variables such as firm value (debt plus equity), sales, operating costs, assets, and income from Compustat's Fundamentals Annual database, and Fama-French industry classifications from Kenneth French's website. We express all nominal variables in 2000 U.S. dollars (in millions) using the gross domestic product (GDP) deflator provided by the Bureau of Economic Analysis (BEA).

We use a firm's historical four-digit standard industrial classification (SIC) code from Compustat's Annual database or the SIC code of its largest segment from Compustat's Segment database (if the historical code is missing) to identify the firm's primary industry sector. Our analysis is based on the Fama-French 12 industries from which we exclude utilities (SIC 4900–4949), financial companies (SIC 6000–6999), and firms in miscellaneous industries classified as "Other." We also exclude the telecom industry (SIC 4800–4899) because the number of firm-CEO observations per year is not sufficient for a proper estimation of the model. After removing observations with missing variables, non-positive sales and operating costs, or negative book value of equity, our Compustat data set consists of 74,136 firm-year observations (including 9,422 firms) over the period 1993–2013. Our Execucomp data set for firm-CEO observations consists of 23,986 firm-year observations (including 2,150 firms). We group each of these two final data sets into eight different industry samples labeled as consumer nondurables, consumer durables, manufacturing, energy, chemicals, business equipment, shops, and healthcare.[5]

Table 1 provides cross-industry summary statistics for the variables in our samples. The relation between firm size and CEO pay is not perfectly monotonic in the data, especially at the aggregate level. Panel B in the table shows that differences in CEO pay levels across industries do not necessarily correspond to firm size differences. For instance, the market value of the average Standard and Poor's (S&P) 1500 firm is \$7.74 billion in the business equipment industry and \$12.77 billion in the consumer durable goods industry, whereas the average CEO earned \$4.36 million in the former, but earned only \$3.28 million in the latter industry. In other words, CEO pay does not increase with firm size *across industries*. The last column of Panel B shows that the time-series average (over the period 1993–2013) Pearson correlation between firm ranks by size and firm ranks by CEO pay within the industry ranges from 0.629 (shops) to 0.820 (chemicals). The correlations are substantially higher than the correlation for the top 500 firms across different industries (0.417). The stronger intra-industry correlation between firm size ranks and CEO pay ranks suggests that PAM between firms and CEOs is more plausible at the industry level, and that there is significant industry segmentation of the CEO labor market. These preliminary observations substantiate the central premise of our study, and support our subsequent analysis in which we estimate our industry equilibrium model using industry-level data.

4.2. Model estimation

The equilibrium profiles of firm value and CEO pay within an industry depend on the profiles of firm quality and CEO talent as well as the product market parameters. We employ the simulated method of moments (SMM) to estimate the model parameters for each industry by matching relevant moments including those from the observed distributions of CEO pay and firm value.[6]

4.2.1. Model parameters and identification

We follow GL by specifying parametric forms for the firm quality and CEO talent distributions. Firm quality is

[4] To identify CEOs in Execucomp, we first use the CEOANN variable. In the absence of a CEO in a firm-year observation using this variable, we further infer the CEO's identity using the BECAMECEO (date when the executive became CEO) variable as usual in the literature (e.g., see the Internet Appendix of Taylor (2013)).

[5] List of industry sectors: (1) consumer nondurables—food, tobacco, textiles, apparel, leather, and toys; (2) consumer durables—cars, TV's, furniture, and household appliances; (3) manufacturing—machinery, trucks, planes, office furniture, paper, and commercial printing; (4) energy—oil, gas, and coal extraction and products; (5) chemicals—chemicals and allied products; (6) business equipment—computers, software, and electronic equipment; (7) shops—wholesale, retail, and some services (laundries, repair shops); (8) Healthcare—healthcare, medical equipment, and drugs.

[6] See Strebulaev and Whited (2012) for a review of the structural estimation literature in corporate finance.

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Table 1
Summary statistics.
This table shows cross-industry summary statistics for the samples of U.S. firms over the period 1993–2013 that we employ in our quantitative analysis. Panel A summarizes industry samples from the Compustat annual database, and Panel B summarizes those merged with the Execucomp database (S&P 1500 firms). In Panel B, we also include the summary statistics for the sample of the largest 500 firms across different industries over the same time period. We compute firm value (market value of equity plus debt) as common stock price ($PRCC_F$) times shares outstanding (CSHO) plus total assets (AT) minus book value of equity. Book value of equity is common equity (CEQ) plus balance sheet deferred taxes (TXDB). Sales are the net sales (SALE), and operating costs include costs of goods sold (COGS), selling, general, and administrative expenses (XSGA), as well as depreciation and amortization (DP). Income is earnings before interest and taxes (EBIT) that we compute as operating income before depreciation (OIBDP) minus depreciation and amortization (DP). CEO pay is Execucomp's TDC1, which includes each year's salary, bonus, total value of restricted stock granted, total value of stock options granted (using Black-Scholes), long-term incentive payouts, and all other payments. We report the means and standard deviations (in parentheses) of these firm and CEO variables. We also report the time-series average number of firms and Pearson correlation coefficient between firm ranks by firm value ($q_{\mathcal{V}}$) and firm ranks by CEO pay (q_u) along with their standard deviations over time (in parentheses). We convert all the nominal variables to 2000 U.S. dollars (in millions) using the GDP deflator from the BEA.

Panel A: Compustat samples

Industry sector	No. of firms (N)	Firm value	Sales	Operating costs	Assets	Income
Consumer nondurables	300	3,572	1,759	1,529	1,808	210
	(90.10)	(14,255)	(5,477)	(4,671)	(6,350)	(756)
Consumer durables	134	5,009	3,223	2,996	4,369	161
	(36.18)	(31,864)	(18,139)	(16,900)	(30,451)	(710)
Manufacturing	560	2,711	1,556	1,400	1,728	148
	(151.15)	(13,711)	(4,879)	(4,301)	(8,731)	(496)
Energy	212	5,498	3,749	3,350	3,771	271
	(18.17)	(27,743)	(20,909)	(18,507)	(16,604)	(1,082)
Chemicals	121	4,914	2,295	2,003	2,632	275
	(15.98)	(16,963)	(6,576)	(5,627)	(8,778)	(870)
Business equipment	1,060	2,492	805	706	1,013	87
	(255.81)	(15,818)	(4,704)	(4,004)	(5,595)	(599)
Shops	581	2,690	2,907	2,759	1,439	140
	(165.86)	(20,237)	(12,706)	(12,080)	(5,844)	(546)
Healthcare	562	2,618	654	528	1,007	116
	(77.54)	(14,647)	(3,233)	(2,438)	(6,025)	(689)

Panel B: Execucomp (S&P 1500) samples

Industry sector	No. of firms (n)	Firm value	Sales	Operating costs	Assets	Income	CEO pay	Corr($q_{\mathcal{V}}$, q_u)
Consumer nondurables	112	9,047	4,359	3,768	4,466	537	4.43	0.694
	(12.30)	(22,241)	(8,320)	(7,083)	(9,772)	(1,163)	(5.34)	(0.049)
Consumer durables	49	12,771	8,046	7,464	11,218	389	3.28	0.750
	(6.85)	(51,716)	(29,235)	(27,191)	(49,523)	(1,127)	(4.05)	(0.064)
Manufacturing	211	6,654	3,704	3,318	4,183	365	3.53	0.747
	(18.24)	(21,754)	(7,421)	(6,526)	(13,862)	(757)	(4.38)	(0.068)
Energy	64	16,264	11,442	10,194	11,163	821	5.09	0.762
	(5.51)	(48,526)	(36,749)	(32,507)	(28,717)	(1,837)	(6.34)	(0.060)
Chemicals	55	10,139	4,621	4,013	5,300	567	4.16	0.820
	(6.73)	(24,180)	(9,205)	(7,857)	(12,496)	(1,226)	(3.94)	(0.054)
Business equipment	309	7,744	2,505	2,161	3,123	298	4.36	0.649
	(46.56)	(28,546)	(8,449)	(7,186)	(10,005)	(1,077)	(8.19)	(0.084)
Shops	212	6,261	6,989	6,616	3,430	352	3.58	0.629
	(15.01)	(19,148)	(20,294)	(19,297)	(9,265)	(860)	(5.16)	(0.042)
Healthcare	131	10,380	2,567	2,012	3,960	507	4.32	0.756
	(11.19)	(28,965)	(6,312)	(4,737)	(12,000)	(1,350)	(5.19)	(0.073)
Top 500	500	49,394	12,989	11,014	38,432	1,554	8.11	0.417
		(125,746)	(24,244)	(21,561)	(119,005)	(2,003)	(9.37)	(0.037)

drawn from a Pareto distribution with exponent $\frac{1}{\alpha} > 0$ so that the relative firm quality profile $x[i]/x[0]$ is given by

$$\frac{x[i]}{x[0]} = [1 - c_1 i]^{-\alpha}, \tag{21}$$

where $c_1 > 0$ is an additional parameter that is greater than zero to ensure an increasing profile. As in GL, we assume that there is an upper bound y_{max} on the distribution of CEO talent, F_Y, and that its density is proportional to $(y_{max} - y)^{\frac{1}{\nu}-1}$ with $\nu > 0$ in the upper tail, that is, $F_Y(y) = 1 - B(y_{max} - y)^{\frac{1}{\nu}}$. The relative CEO talent profile is then expressed as

$$\frac{y[i]}{y[0]} = \frac{c_2 - (1-i)^{\nu}}{c_2 - 1}. \tag{22}$$

In the above, the parameter, $c_2 = B^{\nu} y_{max} > 1$, determines the highest CEO talent level relative to the lowest one. An increase in ν shifts the relative CEO talent profile upward, while keeping the ratio between the highest and lowest talent levels unchanged. The firm quality and CEO talent profiles are, therefore, determined by the four parameters, (α, ν, c_1, c_2). We refer to the first (last) two of the parameters as the tail indices (the coefficients) of the profiles. From (21) to (22), we note that the relative firm quality profile becomes more convex as either α or c_1 increases.

The relative CEO talent profile, however, becomes less convex as either ν or c_2 increases.

Next, note that (17), (18), and (14) relate the firm quality and CEO talent profiles to the payoff profiles. By (13), we scale the payoff profiles by the industry size shock, G_t, to obtain the following *normalized* payoff profiles:

$$u[i] = \frac{u_t[i]}{G_t} = \tilde{u} + \int_0^i \rho R\left(\widehat{P^*}\right)^{\sigma-1}\left(\frac{x[j]}{x[0]}\right)^{\sigma-1} \times \left(\frac{y[j]}{y[0]}\right)^{\sigma-2}\left(\frac{y'[j]}{y[0]}\right)dj, \quad (23)$$

$$\mathcal{V}[i] = \frac{\mathcal{V}_t[i]}{G_t} = \frac{1}{1-\beta\delta}\left[\frac{\Pi_t[i]-u_t[i]}{G_t}\right] = \frac{1}{1-\beta\delta}\left[\frac{R\left(\widehat{P^*}\frac{x[i]}{x[0]}\frac{y[i]}{y[0]}\right)^{\sigma-1}}{\sigma} - u[i]\right]. \quad (24)$$

In the above, $\tilde{u} \equiv \tilde{u}_t/G_t$ is the normalized CEO outside payoff, $R \equiv R_t/G_t$ is the normalized industry size, and $\widehat{P^*}$ is the *relative* aggregate price index defined as $\widehat{P^*} \equiv (P_0^*/w)\rho x[0]y[0]$. By (24), the product of the industry expected growth rate β and common discount factor δ, $\varphi \equiv \beta\delta$, which we refer to as the *effective discount factor*, determines firm value from firm profit. The relative aggregate price index $\widehat{P^*}$ can be rewritten as

$$\widehat{P^*} = \left[N\int_0^1\left(\frac{x[i]}{x[0]}\frac{y[i]}{y[0]}\right)^{\sigma-1}di\right]^{\frac{1}{1-\sigma}}, \quad (25)$$

using the market clearing equilibrium condition (20).[7]

From (23) to (24), we immediately note that

$$\frac{u_t[i]}{u_t[j]} = \frac{u[i]}{u[j]};\ \frac{\mathcal{V}_t[i]}{\mathcal{V}_t[j]} = \frac{\mathcal{V}[i]}{\mathcal{V}[j]}, \quad \text{for any } i \text{ and } j, \quad (26)$$

that is, the ratios of the pay of any two CEOs with given ranks, as well as the ratios of the sizes of any two firms with given ranks are *time-invariant*. Because our model is designed to explain intra-industry dispersions in CEO pay and firm value rather than their time-series variations, we use stationary moments from the normalized intra-industry payoff profiles in our estimation. The choice of stationary moments is also necessary for the SMM estimation approach (e.g., see Section 12 of Miao (2014)).

As shown in Table 1, CEO pay and firm value do not exhibit perfect rank correlation even at the industry level in the data. Consequently, we rank and partition firms in the same industry into five quintiles, $\mathcal{Q}_\infty - \mathcal{Q}_\nabla$, by firm value. We then compute the mean values of CEO pay and firm value within each quintile. The mean values are monotonically increasing from bottom to top quintiles. We compute eight ratios of the mean values of CEO pay and firm value in quintile Q_r to their corresponding mean values in quintile Q_{r-1} for $r \in \{2, 3, 4, 5\}$. These moments capture the shapes and, especially, the elasticities of the intra-industry payoff profiles. We select four additional moments to capture the covariation of CEO pay and firm value as well as their relative values: (i) the intercept and slope from the regression of log CEO pay on log firm value; (ii) the ratio of the mean value of CEO pay across firms to that of firm value; and (iii) the ratio of the differences between the mean values of CEO pay and firm value in the top and bottom deciles, respectively, which represents the ratio of the intra-industry CEO pay dispersion to the firm value dispersion. The last moment is the industry-level price-cost or operating margin that we measure by the ratio of industry sales to industry operating costs (e.g., Karuna (2007)).

Table 2
Model parameters.
This table provides the description of the model parameters that characterize the industry-level product market environment as well as the profiles of firm quality and CEO talent. We obtain the values of the parameters from SMM estimation except for $\tilde{u}$, which we set to the time-series average of the bottom 1% pay level among executives in S&P 1500 firms in the industry.

Parameter	Description
$\tilde{u}$	Normalized CEO outside payoff
φ	Effective discount factor ($\varphi = \beta\delta$)
σ	Product substitutability
α	Tail index of firm quality profile ($x[i]$)
ν	Tail index of CEO talent profile ($y[i]$)
c_1	Coefficient of firm quality profile ($x[i]$)
c_2	Coefficient of CEO talent profile ($y[i]$)

Table 2 lists the model parameters. As it only marginally affects most of the moments that we match in the estimation, we directly set the normalized CEO outside payoff $\tilde{u}$ in (23) to the time-series average of the bottom 1% pay level among executives in all Execucomp firms in the industry. The set of six parameters that we estimate using SMM, $\theta_0 = \{\varphi, \sigma, \alpha, \nu, c_1, c_2\}$, characterizes the industry-level product market environment and the profiles of firm quality and CEO talent.

Before proceeding to discuss our estimation approach, we provide intuition for how the selected moments discussed above help to identify the structural parameters. In Table 3, we show how the moments vary with a local change in each of the parameters around its baseline value (reported in Table 5).[8] First, the moments pertaining to the relative values of CEO pay to firm value—the intercept of the regression of log CEO pay on log firm value, the ratio of the average CEO pay to the average firm value, and the ratio of the CEO pay dispersion to the firm value dispersion—help to identify the effective discount factor (φ), which does not influence the other moments. Second, the last moment—the price-cost margin—is negatively associated with the product substitutability parameter (σ), but is insensitive to the other parameters. Note from the table that all moments except for the last moment vary in the same direction with the product substitutability pa-

[7] Our approach does not require us to estimate the entry cost so that we do not directly match the free entry condition (19). As we discuss later, however, we infer the entry cost f_e from the estimated model using (19) for our counterfactual experiments.

[8] In Table 3, a positive (negative) sign indicates that the particular moment increases (decreases) with the parameter for each industry. A question mark (?) indicates that the sign of the sensitivity is ambiguous (positive or negative depending on the industry) and its magnitude is small.

Table 3
Sensitivities of moments with respect to parameters.
This table shows the signs of the sensitivities of the moments used in SMM estimation with respect to the model parameters described in Table 2. The first two moments are the intercept and slope from the regression of log CEO pay on log firm value. The third moment is the ratio of the mean value of CEO pay (in millions) across firms to that of firm value (in billions). The next eight moments are the ratios of the mean values of CEO pay and firm value in quintile Q_r to their corresponding mean values in quintile Q_{r-1} for $r \in \{2, 3, 4, 5\}$. The next moment is the ratio of the intra-industry CEO pay dispersion (in millions) to the firm value dispersion (in billions) that we measure using the mean values of CEO pay and firm value in the top and bottom deciles. The last moment is the industry-level price-cost margin that we measure by the ratio of industry sales to industry operating costs.

	M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}	M_{13}
φ	−	0	−	0	0	0	0	0	0	0	0	−	0
σ	−	+	−	+	+	+	+	+	+	+	+	−	−
α	−	+	−	+	+	+	+	+	+	+	+	−	0
ν	+	−	−	−	−	−	−	?	?	?	?	−	0
c_1	−	−	−	+	+	+	+	+	+	+	+	−	0
c_2	−	−	−	−	−	−	−	?	?	?	?	−	0

rameter and the tail index (α) of the relative firm quality profile. Incorporating the price-cost margin as a moment in our estimation is, therefore, especially important as it helps to identify these two parameters separately.

We now discuss the identification of the remaining parameters (α, ν, c_1, c_2) that determine the relative firm quality and CEO talent profiles. The four quintile ratios of CEO pay—the ratios of the average CEO pay in successive quintiles—help to identify the tail index and coefficient parameter in the firm quality profile, (α, c_1), separately from those in the CEO talent profile, (ν, c_2). As noted earlier, the convexity of the firm quality profile *increases* with α and c_1, whereas the convexity of the CEO talent profile *decreases* with ν and c_2. Because the convexity of the CEO pay profile increases with the convexities of the firm quality and CEO talent profiles, the quintile ratios of CEO pay increase with α and c_1, but decrease with ν and c_2. The four quintile ratios of firm value—the ratios of the average firm value in successive quintiles—also help to identify the parameters in the firm quality profile separately from those in the CEO talent profile. That is, the parameters (α, c_1) increase the convexity of the firm quality profile and, therefore, that of the firm value profile, whereas the effects of the parameters (ν, c_2) on the convexity of the firm value profile are much less pronounced and ambiguous.

We now discuss how the tail index and coefficient parameter in each of the firm quality and CEO talent profiles are separately identified. As noted from Table 3, the slope of the regression of log CEO pay on log firm value increases with the tail index, α, but decreases with the coefficient parameter, c_1. Both parameters increase the convexities of firm value and CEO pay and, therefore, increase the firm value and CEO pay quintile ratios. However, α increases the levels of firm value more significantly than c_1 so that the percentage difference in firm value between any two firms *decreases* with α, but *increases* with c_1. As the slope of the regression of log CEO pay on log firm value is inversely related to the percentage difference in firm value, its inclusion in the set of moments helps to separately identify the parameters α and c_1. Similarly, the intercept of the log CEO pay–log firm value regression helps to separately identify the tail index, ν, and the coefficient parameter, c_2, in the CEO talent profile. An increase in ν increases the average CEO talent level, whereas an increase in c_2 decreases the average CEO talent level. As the average CEO talent is positively related to the average CEO pay, the regression intercept increases with ν, but decreases with c_2.

To supplement the above discussion, we verify that the Jacobian matrix—the matrix of the sensitivities of the moments with respect to the parameters (Table 3 displays their signs)—has full rank and is well-conditioned at the baseline parameter values for each industry. The necessary and sufficient conditions for local identification and numerical stability ensure reasonable standard errors for the parameters as shown in Table 5.

4.2.2. Estimation approach

Let $\widehat{M}_t$ be the vector of actual (empirical) moments in period t. Because the relative rank of a firm is constant through time in the model, and we choose stationary moments in our estimation as noted earlier, the theoretical (model-predicted) counterparts of the empirical moments are constant through time. The empirical moments are, of course, not constant because of unmodeled factors such as shocks to payoffs or relative firm ranks. In the spirit of generalized method of moments (GMM)/SMM estimation, if M is the vector of the theoretical moments, we assume that $\widehat{M}_t = M + \epsilon_t$, where the error terms ϵ_t are independent and identically distributed (i.i.d.) through time with mean zero. Hence, M is the expectation of the empirical moment vector, $\widehat{M}_t$. In our estimation approach, we incorporate the possibility of serial correlation of the errors. We match the time-series average of the empirical moment vector over the sample period 1993–2010 ($T = 18$), that is, $\widehat{M} = \frac{1}{T}\sum_{t=1}^{T}\widehat{M}_t$.

In Table 4, we report the time-series averages and standard deviations (in parentheses) of the empirical moments over the sample period. The standard deviations of the moments are small relative to their averages for most industries, thereby providing some support for the stationarity of the moments. Nevertheless, in Section 5, we extend the basic model to more explicitly incorporate potential sources of time variation in the empirical moments.

We now discuss the computation of the theoretical moments. As in GL and Terviö (2008), although the model involves a continuum of firm-CEO pairs, and thus generates continuous distributions of firm value and CEO pay, the data are only available for a sample of discrete firm-CEO observations. Further, the Compustat database does not include private firms, and CEO compensation data are only available for S&P 1500 firms. We do not a priori know the

Table 4
Actual and model-predicted moments from baseline estimation.
This table shows the actual and model-predicted values of the 13 moments that we match in the SMM estimation of our model. The definitions of the moments are in the description in Table 3. We compute the first 12 empirical moments from the Execucomp samples and the last moment from the Compustat samples for each year and then take their time-series averages and standard deviations (in parentheses) over the sample period 1993–2010. As we describe in Section 4.2.2, we generate the model-predicted moments using the baseline parameter estimates in Table 5. We also report the t-statistics for the tests of the null hypothesis that the actual and model-predicted values of each moment are equal. The last column shows the χ^2 statistics and corresponding p-values (in parentheses) for the J-test of the model's overidentifying restrictions.

Industry sector		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}	M_{11}	M_{12}	M_{13}	χ^2 (p-value)
Consumer nondurables	Actual	−2.41	0.43	0.50	1.49	1.61	1.49	2.01	2.78	2.28	2.67	6.00	0.19	1.15	8.36
		(0.30)	(0.04)	(0.06)	(0.37)	(0.32)	(0.41)	(0.56)	(0.30)	(0.26)	(0.25)	(0.66)	(0.04)	(0.01)	(0.30)
	Predicted	−2.31	0.44	0.49	1.66	1.51	1.52	1.98	2.83	2.36	2.57	6.10	0.21	1.16	
	t-statistics	0.10	0.03	−0.02	0.26	−0.15	0.05	−0.04	0.04	0.09	−0.09	0.04	0.04	0.02	
Consumer durables	Actual	−2.83	0.47	0.39	2.59	1.50	1.42	2.31	2.53	2.11	2.30	16.01	0.17	1.07	47.11
		(0.42)	(0.07)	(0.43)	(1.55)	(0.92)	(0.55)	(0.75)	(0.65)	(0.31)	(0.22)	(6.64)	(0.25)	(0.03)	(0.00)
	Predicted	−2.70	0.45	0.26	1.46	1.52	1.43	2.75	2.22	2.44	2.15	17.60	0.11	1.09	
	t-statistics	0.11	−0.07	−0.41	−1.01	0.03	0.02	0.47	−0.29	0.38	−0.15	0.24	−0.23	0.03	
Manufacturing	Actual	−2.81	0.47	0.54	1.45	1.41	1.66	1.91	2.28	1.92	2.35	6.59	0.21	1.11	40.26
		(0.30)	(0.05)	(0.13)	(0.30)	(0.25)	(0.30)	(0.44)	(0.25)	(0.21)	(0.18)	(1.21)	(0.07)	(0.02)	(0.00)
	Predicted	−2.87	0.50	0.60	1.56	1.39	1.52	2.28	2.30	1.87	2.32	6.39	0.27	1.12	
	t-statistics	−0.05	0.09	0.19	0.16	−0.02	−0.19	0.46	0.02	−0.07	−0.04	−0.07	0.25	0.02	
Energy	Actual	−3.02	0.49	0.32	1.47	1.76	1.55	2.16	2.46	2.34	2.56	8.07	0.13	1.11	21.79
		(0.53)	(0.08)	(0.06)	(0.52)	(0.39)	(0.51)	(0.64)	(0.44)	(0.36)	(0.34)	(0.95)	(0.05)	(0.04)	(0.00)
	Predicted	−2.67	0.47	0.32	1.60	1.55	1.54	2.21	2.59	2.43	2.42	7.72	0.14	1.11	
	t-statistics	0.28	−0.06	0.02	0.21	−0.29	−0.02	0.06	0.13	0.10	−0.14	−0.11	0.06	0.01	
Chemicals	Actual	−2.79	0.48	0.42	1.97	1.41	1.63	1.65	2.52	2.09	2.33	5.91	0.15	1.14	70.78
		(0.28)	(0.04)	(0.05)	(0.54)	(0.34)	(0.41)	(0.34)	(0.23)	(0.25)	(0.15)	(1.23)	(0.05)	(0.02)	(0.00)
	Predicted	−2.69	0.46	0.40	1.62	1.42	1.41	1.81	2.53	2.03	2.08	5.19	0.16	1.10	
	t-statistics	0.09	−0.04	−0.07	−0.42	0.02	−0.33	0.24	0.01	−0.07	−0.26	−0.30	0.03	−0.08	
Business equipment	Actual	−2.41	0.43	0.61	1.83	1.48	1.71	2.10	2.63	2.05	2.57	9.47	0.22	1.12	205.48
		(0.22)	(0.03)	(0.15)	(0.37)	(0.28)	(0.37)	(0.41)	(0.32)	(0.12)	(0.21)	(1.59)	(0.06)	(0.04)	(0.00)
	Predicted	−2.06	0.44	0.68	1.48	1.43	1.54	2.33	2.20	2.08	2.59	9.18	0.28	1.10	
	t-statistics	0.35	0.06	0.20	−0.46	−0.07	−0.24	0.25	−0.40	0.03	0.02	−0.07	0.21	−0.04	
Shops	Actual	−2.44	0.42	0.59	1.60	1.46	1.61	1.75	2.42	1.95	2.32	6.67	0.21	1.05	49.35
		(0.28)	(0.04)	(0.06)	(0.28)	(0.27)	(0.50)	(0.31)	(0.24)	(0.11)	(0.16)	(1.04)	(0.06)	(0.00)	(0.00)
	Predicted	−2.39	0.44	0.56	1.57	1.39	1.49	2.11	2.52	1.96	2.45	7.32	0.22	1.08	
	t-statistics	0.05	0.07	−0.10	−0.04	−0.11	−0.17	0.49	0.10	0.01	0.13	0.24	0.04	0.06	
Healthcare	Actual	−2.40	0.44	0.43	1.60	1.64	1.98	1.80	2.68	2.24	2.74	11.20	0.14	1.23	162.28
		(0.24)	(0.04)	(0.06)	(0.43)	(0.43)	(0.55)	(0.47)	(0.41)	(0.22)	(0.37)	(1.98)	(0.02)	(0.02)	(0.00)
	Predicted	−2.03	0.42	0.48	1.47	1.41	1.42	2.37	2.37	2.14	2.26	12.35	0.18	1.25	
	t-statistics	0.38	−0.05	0.17	−0.18	−0.34	−0.67	0.74	−0.28	−0.11	−0.43	0.26	0.16	0.03	

relative ranks of S&P 1500 firms within the set of all (public + private) firms. To compute the theoretical moments, therefore, we take the position that Compustat firms represent a random draw from the set of all firms, and S&P 1500 firms represent the largest firms among them. We also assume that the ranks of S&P 1500 firms remain the same through time. Indeed, in the data, S&P 1500 firms are usually the largest firms, and there is a high degree of persistence with an autoregressive coefficient higher than 0.95 in the ranks of S&P 1500 firms within each industry. Accordingly, we use simulations of the ranks of Compustat and S&P 1500 firms to compute the theoretical moments as detailed below.

First, as we discussed in Section 4.2.1, our theoretical moments are determined by the normalized CEO pay and firm value profiles, $u[\cdot]$ and $\mathcal{V}[\cdot]$, that are specified in (23) and (24). We use the time-series averages of the number of Compustat firms, and their total sales, as proxies for the mass of firms in the industry, N, and the normalized industry size, R, respectively. By plugging (25) into (23) and (24), we note that the normalized payoffs only depend on the ratio, R/N. Consequently, any downward biases in the measures of R and N due to the restriction to Compustat firms, as well as any potential mechanical effects of industry size, are likely to offset each other in the ratio, R/N, and, therefore, in the normalized payoffs.

Second, for each simulation $s \in \{1, 2,..., S\}$ with $S = 30,000$, we randomly draw and sort in ascending order N ranks from the unit interval [0, 1] that we denote by $\{i_1^s, \ldots, i_N^s\}$. These ranks represent the ranks of the simulated set of N Compustat firms in the industry. We compute their normalized payoffs using (23) and (24) in which we set the index i to their simulated ranks.

Third, the largest n firms with ranks $\{i_{N-n+1}^s, \ldots, i_N^s\}$ correspond to the simulated set of n S&P 1500 firms in the industry. For each candidate parameter vector θ and each simulation s, we use the normalized payoffs of the simulated set of S&P 1500 firms to compute 12 theoretical moments: the intercept and slope from the regression of log CEO pay on log firm value, the ratio of average CEO pay to average firm value, the quintile ratios of firm value and CEO pay, and the ratio of CEO pay dispersion to firm value dispersion. We compute the last moment—the industry price-cost margin—as the sum of the revenues of the simulated N Compustat firms divided by the sum of their operating costs.

Our estimates of the true parameter vector and the ranks of Compustat and S&P 1500 firms solve the following optimization program:

$$\min_{\theta,s} \; g^s(\theta)'\widehat{W}g^s(\theta). \tag{27}$$

In the above, given a candidate parameter vector θ and simulation s, $g^s(\theta) = (\widehat{M} - \widehat{m}^s(\theta))$, where $\widehat{M}$ is the time-series average of the vector of actual (empirical) moments from the data and $\widehat{m}^s(\theta)$ is the corresponding vector of moments obtained from the s^{th} simulation of the model. For the weighting matrix, $\widehat{W}$, we use the inverse of the variance-covariance matrix of the data moments $\widehat{M}_t$ after correcting for serial correlation using the Newey-West procedure with the Bartlett weights.[9]

4.3. Estimation results

4.3.1. Model fit and out-of-sample performance

Table 4 evaluates the quality of the model's fit to the data for each industry. The table contains the actual and model-predicted values of the 13 moments described in Section 4.2.1. We also include the t-statistics for the tests of the null hypothesis that the actual and model-predicted values of each moment are equal. The model does a good job matching the individual moments for all industries. The J-test of the model's overidentifying restrictions, however, rejects the joint hypothesis that all the 13 model-predicted moments equal the actual moments (except for the consumer nondurable goods sector).[10]

Fig. 1 displays the actual and model-predicted profiles of CEO pay for S&P 1500 firms in the manufacturing and healthcare industries. As noted in the figure, we simplify the notation by hereafter denoting the firm value quantile within the set of S&P 1500 firms in the industry by q, that is, $q = 1$ denotes the largest S&P 1500 firm in the industry, whereas $q = 0$ denotes the smallest one. Although the actual relation between CEO pay and firm rank by size is noisy, our model matches the smoothed monotonic pattern reasonably well.

Next, we examine the model's out-of-sample performance. The model does a good job matching the empirical moments over the time period 2011–2013 that is subsequent to the sample period employed in our parameter estimation (see Table H1 in online Appendix H). All the model-predicted moments are not significantly different from the actual moments at standard statistical confidence levels. In Fig. 2, we compare the actual and model-predicted values of additional moments associated with product market concentration—the four-firm concentration ratio (CR_4) and the Herfindahl-Hirschman index (HHI)—that are not matched by the model in the parameter estimation. We observe that the model fits the first moment, CR_4, quite well as most industries plot close to the 45-degree line. Although the model-predicted values of the second moment, HHI, are different from the corresponding actual values for a few industries, the industry rankings based on HHI are largely consistent with those based on CR_4 both in the data, and as implied by the model. Overall, the results of the additional tests taken together provide further validation of the model.

4.3.2. Baseline parameter estimates

Table 5 shows the baseline parameter estimates along with their standard errors that are generally reasonable for all industries. The estimated effective discount factor is higher in the chemicals, business equipment, and healthcare industries. By (14), the quantity $\frac{1}{1-\beta\delta} = \frac{1}{1-\varphi}$ is the ratio of firm value to profit and can, therefore, be interpreted as the price-earnings ratio. In this respect, our findings are consistent with empirical evidence that high-tech industries, which usually include the business equipment and healthcare sectors, have higher price-earnings ratios on average.

In support of our assumption in the theoretical analysis, the estimates of the product substitutability, σ, are all greater than 2 at standard statistical confidence levels. The product substitutability is lower in the consumer nondurables and healthcare industries, and higher in the consumer durables and retail (shops) industries, which reflects casual intuition that products are more homogeneous in the latter two industries. As the price elasticity of demand increases with σ, the lower level of σ in the healthcare industry is consistent with the finding of Tellis (1988) that the price elasticity for pharmaceutical products is lower than for any other product category.

4.3.3. Firm quality and CEO talent profiles

Given our baseline parameter estimates in Table 5, we obtain the firm quality and CEO talent profiles for each industry by evaluating the profiles (21) and (22) at their corresponding ranks. Table 5 shows the ratios of the highest to the lowest values of firm quality and CEO talent among the S&P 1500 firms in the industry. For all industries, the intra-industry firm quality dispersion is much larger than the CEO talent dispersion.The intra-industry dispersion of firm quality varies across industries. The industries of consumer nondurables and healthcare have higher relative values of firm quality than other industries, whereas the retail (shops) sector has a lower relative value of firm quality. According to our estimates of σ, the former two industries are low-substitutability industries, whereas the latter industry is a high-substitutability industry. The inverse relation between product substitutability and productivity dispersion (captured largely by firm quality dispersion because CEO talent dispersion is relatively small) is consistent with the main empirical finding of Syverson (2004).[11]

[9] See, for instance, Section 12 of Miao (2014) for details.

[10] As noted by related studies such as Taylor (2010; 2013), and by numerous studies in the broader economics literature on structural estimation, the J-test is a rather stringent test that often rejects models when there is a sufficiently large amount of data.

[11] In the model, firm quality and CEO talent influence firm productivity and, thereby, also affect earnings in each period. As we discussed in

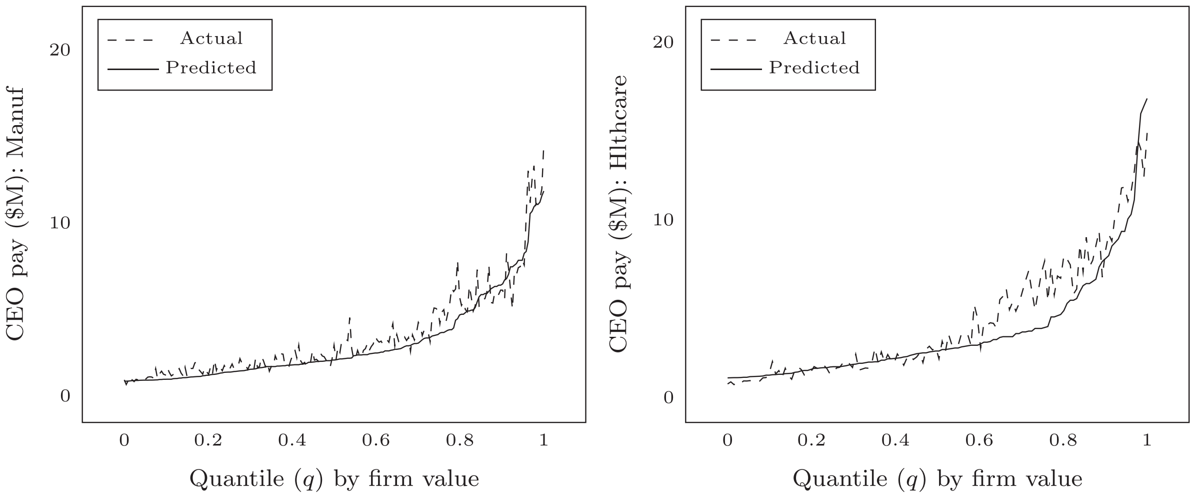

Fig. 1. Actual and model-predicted profiles of CEO pay. This figure plots the actual and model-predicted CEO pay profiles for S&P 1500 firms in the manufacturing and healthcare industries. The dashed lines plot the time-series average pay levels over the sample period 1993–2010 from the data, and the solid lines plot the monotonic relations of CEO pay and firm rank that the model generates at the baseline parameter estimates in Table 5.

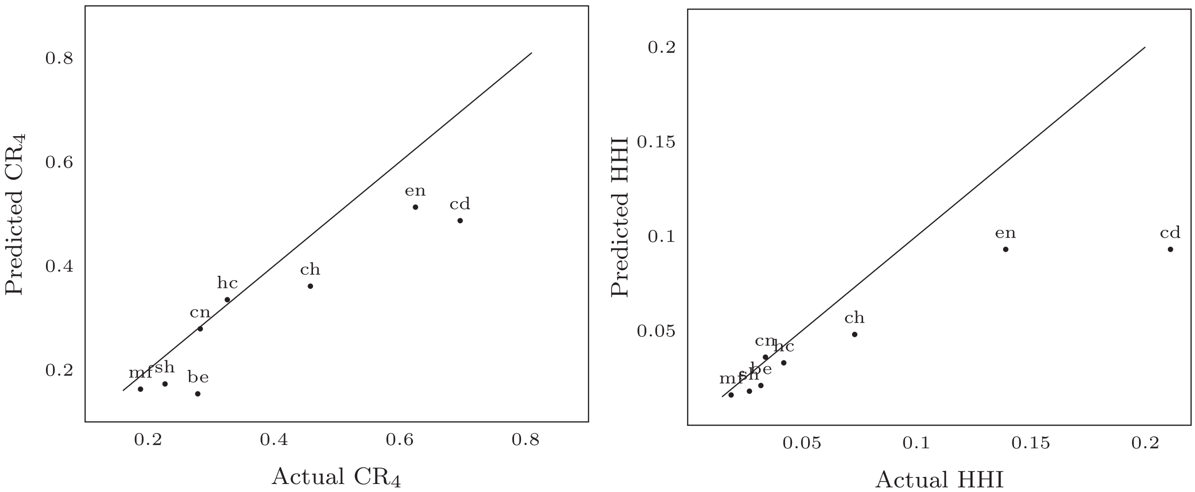

Fig. 2. Additional moments. This figure shows the actual and model-predicted values of additional moments—the four-firm concentration ratio (CR_4) and Herfindahl-Hirschman index (HHI)—that are not matched in the parameter estimation. We abbreviate the names of the eight Fama-French 12 industries with two letters. The model-predicted values generated using the baseline parameter estimates in Table 5 are on the vertical axis, and the actual values computed by taking the time-series averages of the moments over the sample period 1993–2010 are on the horizontal axis. We also include the 45-degree line to facilitate the comparison.

The intra-industry dispersion of CEO talent also varies across industries, but the variation is much smaller (in relative terms) than that of firm quality. In Fig. 3, we report the firm quality and talent profiles for the manufacturing, business equipment, and healthcare industries. Compared to the manufacturing industry, the healthcare and business equipment industries show relatively higher intra-industry CEO talent dispersions.

footnote [3], our framework also accommodates alternate channels through which firm and CEO characteristics affect earnings. It is plausible that these characteristics affect earnings through different channels as long as they complement each other in enhancing firm earnings. Our main implications would not be altered qualitatively or quantitatively because they hinge on the complementary effects of firm quality and CEO talent on earnings irrespective of the channels through which these effects manifest. The choice of interpretation, however, may be industry-specific and depend upon which channel is a first-order issue in generating payoff dispersions across firms within the industry.

4.3.4. Comparison with GL's factor profiles

We now relate our inferred firm quality and CEO talent profiles with those in GL. In their basic model, GL *exogenously specify* a firm's profit as being proportional to the product of "firm size" and "CEO talent," which represent the firm-specific and CEO-specific factors, respectively. In our model, it follows from (7) that a firm's (*endogenously derived*) profit in a particular industry is proportional to $(xy)^{\sigma-1}$ where x is firm quality and y is CEO talent. By (24), firm value $\mathcal{V}$ is roughly proportional to $(xy)^{\sigma-1}$ because CEO pay is typically small relative to a firm's gross profit (about 2–3% for the median-sized firm in the industry). As noted earlier, the variation in the CEO talent pro-

Table 5
Baseline parameter estimates, firm quality and CEO talent ratios, as well as firm size and CEO factor ratios.

This table shows the parameter estimates along with their standard errors (in parentheses) from our baseline estimation for each industry. We directly set $\tilde{u}$ to the time-series average of the bottom 1% pay level among executives in S&P 1500 firms in the industry. The next two columns report the ratios of the firm qualities and CEO talents of the largest and smallest S&P 1500 firms in the industry. The last two columns show the ratios of their sizes and CEO factors.

Industry sector	$\tilde{u}$	φ	σ	α	ν	c_1	c_2	$x[1]/x[0]$	$y[1]/y[0]$	$\tilde{x}[1]/\tilde{x}[0] = (x[1]/x[0])^{\sigma-1}$	$\tilde{y}[1]/\tilde{y}[0] = (y[1]/y[0])^{\sigma-1}$
Consumer nondurables	0.194	0.924	7.317	0.605	1.772	0.918	18.377	2.605	1.009	423.5	1.056
		(0.004)	(1.216)	(0.143)	(0.018)	(0.006)	(4.597)				
Consumer durables	0.151	0.948	12.267	0.252	1.530	0.973	38.278	1.825	1.006	879.4	1.064
		(0.019)	(6.175)	(0.163)	(0.053)	(0.010)	(16.549)				
Manufacturing	0.183	0.930	9.345	0.357	1.390	0.934	43.665	1.932	1.006	243.4	1.051
		(0.009)	(0.879)	(0.039)	(0.023)	(0.006)	(10.516)				
Energy	0.190	0.917	9.815	0.358	1.509	0.957	41.310	2.022	1.004	496.5	1.033
		(0.009)	(4.105)	(0.190)	(0.020)	(0.006)	(20.284)				
Chemicals	0.195	0.965	10.768	0.275	1.495	0.952	41.618	1.759	1.006	248.1	1.064
		(0.003)	(3.030)	(0.099)	(0.018)	(0.006)	(13.595)				
Business equipment	0.149	0.961	11.076	0.279	1.533	0.963	9.815	1.765	1.013	306.6	1.140
		(0.004)	(1.869)	(0.062)	(0.015)	(0.002)	(1.887)				
Shops	0.160	0.904	12.964	0.279	1.654	0.930	51.843	1.632	1.004	350.8	1.045
		(0.016)	(4.315)	(0.120)	(0.027)	(0.008)	(17.491)				
Healthcare	0.172	0.954	5.014	0.722	1.621	0.979	3.444	5.206	1.026	751.8	1.107
		(0.007)	(0.551)	(0.145)	(0.045)	(0.005)	(1.249)				

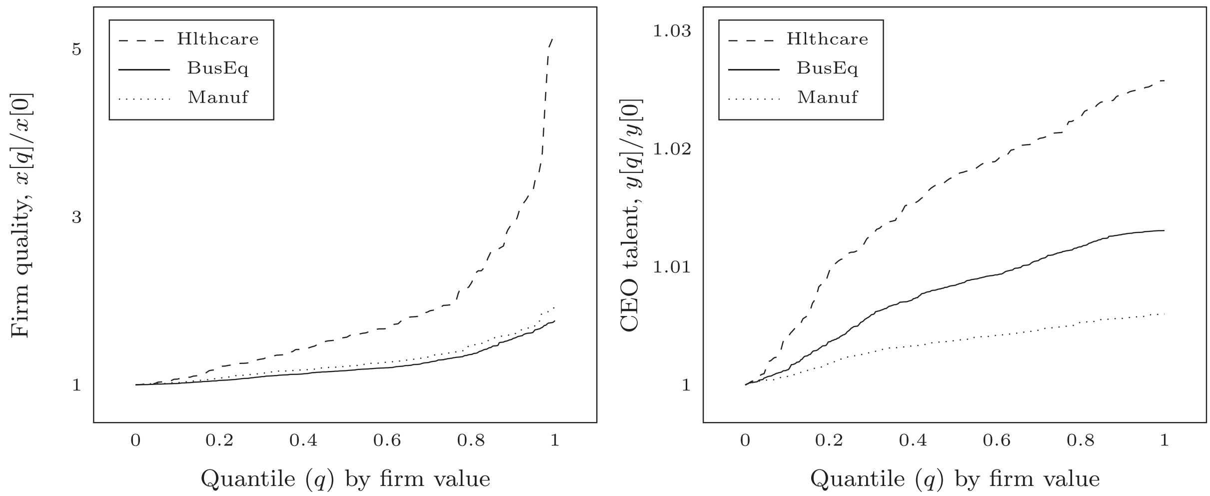

Fig. 3. Relative firm quality and CEO talent profiles from baseline estimation. Using the baseline estimates of the four parameters (α, ν, c_1, c_2) in Table 5, this figure plots the inferred intra-industry profiles of firm quality and CEO talent relative to their lowest values, $x[q]/x[0]$ and $y[q]/y[0]$, among S&P 1500 firms in the manufacturing, business equipment, and healthcare industries, respectively.

file, $y[\cdot]$, is much smaller than the variation in the firm quality profile, $x[\cdot]$. Hence, the firm size profile is mainly determined by the quantity $\tilde{x} \equiv x^{\sigma-1}$, which follows a power law with exponent $\alpha(\sigma-1)$ as shown in (21).

The estimates of α and σ across industries in Table 5 imply that, in sharp contrast with GL, firm size does not follow Zipf's law at the industry level. The second to last column of Table 5 shows the ratio of the sizes of the largest and smallest S&P 1500 firms in each industry. We compare the firm size ratio with the firm quality ratio, $x[1]/x[0]$ (reported in the same table). Note that the product substitutability, σ, significantly magnifies the effects of firm quality dispersion on the firm size dispersion. The table also shows that variation in the firm size ratio across industries is affected not only by inter-industry variation in the firm quality ratio, but also by variation in the product substitutability.

We refer to the quantity $\tilde{y} \equiv y^{\sigma-1}$ as the "CEO factor" because it determines a CEO's overall influence on firm profit. Importantly, the CEO factor reflects the *combined* effects of CEO talent, y, and the product substitutability, σ. In contrast, because they abstract away from product market effects, GL refer to the CEO factor in their profit function as "CEO talent." The "CEO factor profile," $\tilde{y}[\cdot]$, in our analysis is thus comparable to the "CEO talent profile" in GL's analysis. For the purpose of comparing their results with ours, we refer to the CEO talent profile in GL's model as the CEO factor profile. The last column of Table 5 shows the ratio of the best and worst CEO factors among S&P 1500 firms in each industry. As with the firm size ratios, the

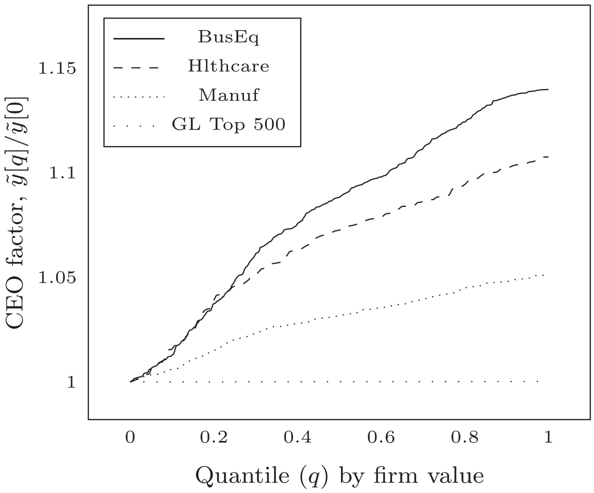

Fig. 4. Comparison of relative CEO factor profiles from baseline estimation with GL's aggregate profile. The first three lines plot the industry-level relative CEO factor profiles, $\tilde{y}[q]/\tilde{y}[0] = (y[q]/y[0])^{\sigma-1}$, for S&P 1500 firms in the business equipment, healthcare, and manufacturing industries, respectively, that we obtain from our baseline estimation results in Table 5. The last dotted line plots the relative CEO factor profile for the largest 500 firms (across different industries) that we obtain from the replication of GL's aggregate analysis (see online Appendix B.1 for details of the GL analysis).

product substitutability substantially amplifies the effects of CEO talent differences on the CEO factor ratio. Further, the magnifying effect of the product substitutability causes the CEO factor ratio to vary more significantly across industries than the CEO talent ratio, $y[1]/y[0]$ (displayed in the same table).

In Fig. 4, we display the relative CEO factor profiles, $\frac{\tilde{y}[q]}{\tilde{y}[0]} = (\frac{y[q]}{y[0]})^{\sigma-1}$, for the business equipment, healthcare, and manufacturing sectors. We compare them with the relative CEO factor profile inferred from GL's aggregate analysis (including the largest 500 firms operating in different industries). The inferred relative CEO factor profiles in our analysis are significantly steeper than the corresponding profile in GL. We summarize GL's aggregate analysis and describe how we obtain the CEO factor profile from their analysis in online Appendix B.1.

4.4. Counterfactual experiments

Using the baseline parameter estimates in Table 5, we now provide quantitative assessments of CEO impact on firm value, as well as the effects of product market characteristics on firm size, CEO pay, and CEO impact.

4.4.1. CEO impact

Suppose that the median-sized S&P 1500 firm ($q = 0.5$) could replace its CEO with the best (most talented) CEO at the largest S&P 1500 firm ($q = 1$) in the same industry.[12] Given that there is a continuum of firms in our model, the aggregate market structure is unchanged by this event associated with only one firm. First, we calculate the proportional increase in the normalized total surplus (gross earnings), $\Pi = \Pi_t/G_t$, at this reference firm as

$$\frac{\Delta\Pi}{\Pi[0.5]} = \frac{\Pi(x[0.5], y[1]) - \Pi(x[0.5], y[0.5])}{\Pi(x[0.5], y[0.5])} = \left(\frac{y[1]}{y[0.5]}\right)^{\sigma-1} - 1, \tag{28}$$

where the second equality follows from (7). The proportional increase only depends on the ratio of the best and median CEO factors, $\frac{\tilde{y}[1]}{\tilde{y}[0.5]} = (\frac{y[1]}{y[0.5]})^{\sigma-1}$ (recall the definition of the CEO factor, $\tilde{y}$, in Section 4.3.4). As shown by (28), the ratio of CEO factors depends on the ratio of the best and median CEOs' talents, $\frac{y[1]}{y[0.5]}$, and the product substitutability, σ. Because $\sigma > 2$, the ratio of CEO factors is significantly greater than the ratio of CEO talents, that is, the product substitutability magnifies the effects of replacing the median CEO with the best CEO on the median firm's profit.

Next, we use (24) to measure CEO impact by calculating how much the median firm's market value would change by hiring the best CEO through time (i.e., the present value of the increase in future earnings due to the CEO replacement). To be consistent with GL, we initially assume that there is no extra compensation payment incurred due to the replacement as shown below.

$$\begin{aligned}\frac{\Delta\mathcal{V}}{\mathcal{V}[0.5]} &= \frac{\frac{1}{1-\beta\delta}(\Pi(x[0.5], y[1]) - u[0.5]) - \frac{1}{1-\beta\delta}(\Pi(x[0.5], y[0.5]) - u[0.5])}{\mathcal{V}[0.5]} \\ &= \frac{\Pi[0.5]}{(1-\beta\delta)\mathcal{V}[0.5]} \times \frac{\Delta\Pi}{\Pi[0.5]} \\ &= \left(1 + \frac{u[0.5]}{(1-\beta\delta)\mathcal{V}[0.5]}\right)\left(\left(\frac{y[1]}{y[0.5]}\right)^{\sigma-1} - 1\right).\end{aligned} \tag{29}$$

In (29), the dominant term that determines the CEO impact measure is the second term, $(\frac{y[1]}{y[0.5]})^{\sigma-1} - 1$. This is because the first term is very close to one as the quantity $\frac{u[0.5]}{(1-\beta\delta)\mathcal{V}[0.5]}$ (that is, the median firm's ratio of CEO pay to its profit) is negligible.

For comparison, we also take into account the cost incurred by the firm if it were required to pay the best CEO her current compensation at the largest firm. We measure this cost as the ratio of the present value of extra compensation payments relative to its market value, that is,

$$\frac{\Delta u/(1-\beta\delta)}{\mathcal{V}[0.5]} = \frac{(u[1] - u[0.5])/(1-\beta\delta)}{\mathcal{V}[0.5]}. \tag{30}$$

Table 6 contains the results of this counterfactual experiment for each industry.[13] Panel A shows the ratio of the best CEO's talent to the median CEO's talent in each industry. On average across industries, the best CEO is only 0.3% more talented than the median CEO (see the second column of Panel A). As we show in the second column of Panel B, however, the estimates of CEO impact

[12] In addition to the median firm, we also consider the 75th percentile firm and the average firm as the reference firm, respectively. Our main implications for the CEO impact still hold for these different choices of the reference firm (see Table H2 in online Appendix H).

[13] When calculating the benefit and cost measures in (29) and (30), we also use the observed payoff levels instead of the model-predicted ones and find similar results. For brevity, we only report the results using the model-predicted ones.

Table 6
CEO impact.
This table shows the results of the counterfactual experiment of CEO replacement using the baseline parameter estimates in Table 5. Specifically, we consider the replacement of the median CEO at the median-sized firm ($q = 0.5$) with the best CEO at the largest firm ($q = 1$) among S&P 1500 firms in the industry. Panel A shows the ratios of the best and median CEOs' talents and their percentage differences. Panel B shows the percentage changes in gross earnings, firm value, and compensation costs due to the replacement (relative to the median firm's market value). Panel C reports the dollar changes in firm value (in millions) due to the replacement, and the difference in CEO pay between the largest and median-sized firms.

	Panel A: Talent dispersion		*Panel B: Percentage change*			*Panel C: Dollar change*	
Industry sector	$\frac{y[1]}{y[0.5]}$	$\left(\frac{y[1]}{y[0.5]}-1\right)(\%)$	$\frac{\Delta\Pi}{\Pi[0.5]}(\%)$	$\frac{\Delta\mathcal{V}}{\mathcal{V}[0.5]}(\%)$	$\frac{\Delta u/(1-\beta\delta)}{\mathcal{V}[0.5]}(\%)$	$\Delta\mathcal{V}$ (\$M)	Δu (\$M)
Consumer nondurables	1.002	0.19	1.22	1.25	5.60	26.03	8.84
Consumer durables	1.002	0.18	2.08	2.13	19.74	23.05	11.04
Manufacturing	1.002	0.22	1.88	1.93	10.95	24.58	9.77
Energy	1.001	0.12	1.02	1.03	6.75	26.35	14.26
Chemicals	1.002	0.19	1.84	1.89	9.44	57.92	10.04
Business equipment	1.005	0.46	4.72	5.04	28.47	54.70	12.13
Shops	1.001	0.10	1.25	1.27	6.36	15.34	7.40
Healthcare	1.008	0.80	3.24	3.40	26.52	39.89	14.22

defined in (29) are, on average, about 2.2% due to the magnifying effect of the product substitutability. Our impact estimates are two orders of magnitude greater than GL's estimate of 0.016% for all sectors. In addition, the CEO impact estimates significantly vary across industries (1.03–5.04%), whereas the ratio of the best and median CEOs' talents varies by only 0.7%. The dispersion in the CEO impact estimates across industries is, therefore, largely driven by variation in the product substitutability rather than variation in the intra-industry CEO talent dispersion. The first column of Panel C shows that the corresponding dollar changes in firm value due to the CEO replacement are also much larger than GL's dollar estimate of $4 million.

In the third column of Panel B, we report the additional compensation cost due to the replacement of the CEO at the median-sized firm in each industry with the industry's best CEO as a proportion of the firm's value. We see that the cost estimates in the third column are (on average across industries) about six times greater than the CEO impact estimates in the second column. In sharp contrast, the corresponding cost estimate in GL is about 2.65%, which is two orders of magnitude greater than their CEO impact estimate, 0.016%.

Our higher estimates of CEO impact are closer to the estimates reported by empirical studies that use reduced-form approaches to examine the impact of CEO talent. Falato, Li, and Milbourn (2015) use various observable proxies for CEO talent to show that replacing the CEO of median talent with the most talented CEO in their sample of S&P 1500 firms would increase firm performance by 1.7–2.5%. Hayes and Schaefer (1999) measure CEO impact by the difference between the stock price reactions when a CEO is hired away by another firm (high-talent CEO), and when a CEO dies suddenly (average-talent CEO). Their estimates of CEO impact range from $29.8 to $53.3 million for the median-sized firm. The estimates are in line with our estimates in dollar terms.

4.4.2. Comparison with GL's CEO impact estimate

We now discuss the main reasons why our CEO impact estimates are significantly higher than GL's estimate. As with all structural frameworks, we make the identifying assumption that our model is the "true" model. The assumption is supported by the in-sample and out-of-sample performance of the model as discussed in Section 4.3.1.

By (29), the CEO impact measure is determined by the relative CEO factor profile, $\frac{\tilde{y}[q]}{\tilde{y}[0]} = (\frac{y[q]}{y[0]})^{\sigma-1}$. Recall from Section 4.3.4 that the "CEO talent profile" in GL's model corresponds to the CEO factor profile in our model. The wedges between GL's and our impact estimates, therefore, hinge on differences between the inferred CEO factor profiles from the respective analyses. As noted earlier, Fig. 4 shows that the relative CEO factor profiles in our analysis are much steeper than the corresponding profile from GL's aggregate analysis. There are two main reasons why GL's analysis leads to a flatter CEO factor profile and, therefore, a lower impact estimate than our estimates: (i) misspecification in GL's model from not incorporating industry segmentation of CEO markets; and (ii) differing assumptions on the duration of CEO influence in our respective models.

Misspecification in GL's aggregate model. As they assume a single aggregate market for CEOs, GL infer the CEO factor profile in their model by matching two key moments in the *aggregate* data: the elasticities of CEO pay to firm size, and firm size to firm rank (see online Appendix B.1 for details). Because the product of the two elasticities is (roughly) the elasticity of CEO pay to firm rank, GL's calibration matches the elasticity of the CEO pay profile in the aggregate data. Competitive assignment and PAM together ensure that the incremental pay of a CEO relative to her nearest (lower ranked) competitor in any period—the slope of the CEO pay profile—is determined by the CEO's incremental (or marginal) contribution to firm value relative to her competitor (see Proposition 1). The CEO's marginal contribution relative to her competitor increases with the difference in their CEO factors. Hence, a steeper CEO factor profile leads to a steeper predicted CEO pay profile. Conversely, a more elastic or steeper observed pay profile, ceteris paribus, implies a steeper inferred factor profile and, therefore, a higher impact estimate. The CEO impact estimate is, thereby, inferred from the two elasticities that GL match in their calibration.

Because our premise is that CEO markets are segmented by industry, we match the *industry-level* elasticities to infer the CEO factor profiles at the industry level.[14] GL's aggregate model is misspecified in two related aspects that are manifested in the aggregate elasticities being different from the industry-level elasticities, thereby leading to a misspecification bias in GL's impact estimate.

First, GL assume that PAM holds at the aggregate level across industries. As noted earlier in Table 1, the rank correlation of firm size and CEO pay is significantly higher at the industry level than at the aggregate level in the data. The specification of a monotonic CEO pay-firm size relation is, therefore, more plausible at the industry level so that the CEO pay-firm size elasticity is likely to differ at the aggregate and industry levels. Second, because GL specify aggregate profiles of firm size and CEO pay, they effectively assume that the corresponding industry-level profiles do not vary across industries. Our estimation results in Table 5 show that the industry-level firm size and CEO factor profiles vary significantly across industries, especially due to variation in the product substitutability. As the CEO pay profile is determined by the firm size and CEO factor profiles (see (23)), the CEO pay profile also varies across industries. Inter-industry variation in the firm size and CEO pay profiles implies that the corresponding elasticities also vary. Hence, the aggregate and industry-level elasticities differ.

The differences between the aggregate and industry-level elasticities, and the resulting misspecification bias in GL's CEO impact estimate, depend on features of the data. In particular, the discrepancies depend on the extent to which PAM is violated in the aggregate sample relative to the industry samples. The discrepancies also depend on the shapes of the firm size and CEO pay profiles within each industry as well as how they vary across industries in the data. In addition, the differences between the elasticities are affected by the relative proportions of firms from different industries in the aggregate sample, and how their relative ranks change when they are grouped together to form the aggregate sample. In online Appendix B.2, we provide an example to show that, depending on the data, and how the aggregate sample is constituted from different industry samples, the aggregate elasticities could be above, below, or within the respective ranges of the industry-level elasticities. Consequently, theoretical arguments alone cannot tell us even the direction of the misspecification bias in GL's aggregate estimate. We, therefore, empirically determine the misspecification bias by implementing GL's analysis at the industry level as described in online Appendix B.1.

Addressing the misspecification: Industry-level GL analysis. We employ GL's exogenous specification of firm profit, but allow the firm and CEO factor profiles to vary across industries. Consequently, the industry-level GL analysis incorporates CEO market segmentation, and serves as the appropriate benchmark to isolate the effects of the misspecification in GL's aggregate model on their impact estimate. In particular, as we discussed in Section 4.3.4, the CEO factor reflects the combined effects of CEO talent and the product substitutability. Hence, the CEO impact estimates from the industry-level GL analysis *implicitly* embody product market effects, but the effects cannot be disentangled from those of CEO talent.

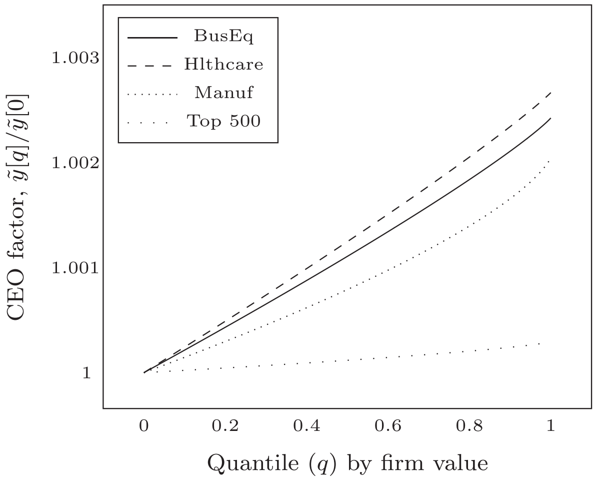

Fig. 5. Comparison of relative CEO factor profiles from aggregate and industry-level GL analyses. We implement the industry-level GL calibration analysis and infer the relative CEO factor profiles for S&P 1500 firms in the business equipment, healthcare, and manufacturing industries, respectively. For comparison, the last dotted line plots the relative CEO factor profile for the largest 500 firms (across different industries) that we obtain by replicating GL's aggregate analysis. We describe the aggregate and industry-level GL analyses in detail in online Appendix B.1.

Table H4 in online Appendix H reports the results of the aggregate and industry-level GL analyses in Panels A and B, respectively. The aggregate values of the firm size-firm rank elasticity ($\simeq 1$) and the CEO pay-firm size elasticity ($\simeq 1/3$) are lower than their respective values at the industry level. As we show in Fig. 5, the lower aggregate elasticities imply a flatter inferred CEO factor profile in GL's aggregate analysis relative to the factor profiles from the industry-level GL analysis. GL's aggregate estimate of 0.016% (Panel A) is about an order of magnitude lower than the estimates from the industry-level GL analysis (Panel B), which reflects the negative misspecification bias in GL's estimate from ignoring industry segmentation of CEO markets.

We show the statistical robustness of the negative misspecification bias in GL's aggregate analysis via a parametric boostrapping analysis. As we describe in detail in online Appendix B.3, we use ourestimated model (the "true" model by our identifying assumption) to simulate samples of firms in each industry. We then combine the industry samples to form aggregate samples with the relative proportions of firms from different industries being the same as in GL's aggregate sample. We compute the firm size-firm rank and CEO pay-firm size elasticities in the simulated industry and aggregate samples, and thereby obtain the aggregate and industry-level CEO impact estimates as in the GL analysis. Our results in Table H5 show that the differences between the GL impact estimates at the aggre-

[14] The quantile ratios of firm size and CEO pay that we match in our estimation effectively match the industry-level elasticities of the firm size and CEO pay profiles. In addition, we also directly match the CEO pay-firm size elasticity.

gate and industry levels are negative and statistically significant.

CEO influence in GL's model and our model. Comparing Figs. 4 and 5, we note that the inferred CEO factor profiles from the industry-level GL analysis are flatter than the profiles from our analysis. As shown in Table H4, the industry-level GL impact estimates are, therefore, substantially lower than our estimates in Table 6 for all industries. The discrepancies between the estimates stem from differing assumptions on the duration of CEO influence in our respective models. Our discussion below draws on the comparison between the CEO impact measure in our framework and the impact measure in the dynamic extension of the industry-level GL framework that we present in online Appendix B.4.

In GL's framework, the CEO factor in each period proportionally affects the firm's earnings in *all future* periods. In our framework, the CEO factor in each period proportionally affects the firm's earnings only during *that* period. It then follows that, in GL's model, a given difference in CEO factors in each period generates a proportional difference in firm values, rather than a proportional difference in current period earnings as in our model. In other words, given the CEO factor profile, the marginal contribution of a CEO in any period is proportional to firm value in GL's model, but is proportional to current period earnings in our model.[15] The dispersion in CEOs' marginal contributions across firms is, therefore, greater in GL's model. As we mentioned earlier, competitive assignment and PAM together ensure that the slope of the CEO pay profile in any period increases with the dispersion in CEOs' marginal contributions. Hence, GL's model predicts a steeper CEO pay profile for the same CEO factor profile. The industry-level GL analysis and our analysis use the same industry-level data to infer the respective factor profiles. It then follows that the inferred CEO factor profile that matches the observed CEO pay profile is flatter in the industry-level GL analysis, ceteris paribus. As a result, the CEO impact estimates from the industry-level GL analysis are lower than our estimates.

As we show in online Appendix B.4, because the marginal contribution of a CEO is proportional to current period earnings in our model, but is proportional to firm value in GL's model, the following simple (approximate) relation holds between the industry-level GL estimates and our estimates:

$$\text{Industry-level GL estimate} \approx (1-\varphi) \times \text{Our estimate}. \tag{31}$$

In the above, $\varphi = \beta\delta$ is the industry effective discount factor used to compute firm value as the expected present value of earnings.[16] It follows from the preceding discussion that the industry-level GL estimates would approximately coincide with our estimates if we were to modify GL's model so that the CEO factor affects earnings "period by period" as in our model.

Neither our perspective nor GL's on the duration of CEO influence corresponds perfectly to reality. CEOs could affect earnings in future periods as GL assume. However, it is plausible that their long-term effects decline over time instead of affecting all future earnings by the same proportion. Our estimates are, however, in line with those reported by reduced-form approaches that employ observed measures of CEO talent (e.g., Falato, Li, and Milbourn (2015)), which provides more support for our perspective on CEO influence. Nevertheless, in Section 6.1 and online Appendix D, we show that our quantitative results regarding CEO impact are robust to an extension of our model that incorporates long-term, but declining CEO effects on future earnings.

It is worth emphasizing here that the above discussion only pertains to the comparison between our estimates and the industry-level GL estimates. The misspecification bias in GL's aggregate impact estimate from not incorporating industry segmentation is present regardless of how one models CEO influence. This also further clarifies why the industry-level GL analysis is the appropriate intermediate benchmark that allows us to disentangle the effects of the (i) misspecification in GL's aggregate model; and (ii) differences in the modeling of CEO influence; on the wedges between our estimates and GL's aggregate estimate. The reason is that we compare GL's model implemented at the aggregate and industry levels. Consequently, the differences between the aggregate and industry-level GL estimates stem purely from the misspecification in GL's aggregate model, and not from differences in the modeling of CEO influence. The wedges between the industry-level GL estimates and our estimates then arise from the differences in the modeling of CEO influence.

The role of product market competition. The incorporation of product market competition in our industry equilibrium model plays two key related roles in our analysis. First, it provides an endogenous source of inter-industry variation in the firm size and CEO factor profiles that is explicitly linked to the product market environment, especially the product substitutability. The variation in the profiles contributes to misspecification in GL's aggregate analysis. In contrast, the industry-level GL analysis exogenously assumes this variation without being able to identify the different sources of the variation, that is, the CEO talent and firm quality profiles as well as product market characteristics.

Second, and more importantly, we can determine the relative importance of CEO talent and product market characteristics in influencing CEO impact and market outcomes.

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[15] The proportionality constant is the same in our and GL's frameworks (see online Appendix B.4).

[16] The relation between the estimates is approximate because we employ different econometric approaches to take our respective models to the data, which lead to differences in the inferred factor profiles. GL adopt a calibration approach that matches the aforementioned two elasticities in the data. In contrast, we carry out a structural estimation in which we match additional moments (specifically, the quantiles of the firm size and CEO pay distributions) that facilitate a better match to the payoff distributions. Further, we match the industry profitability to identify the product substitutability that, in turn, influences the inferred factor profiles from our analysis. The differing econometric approaches, however, lead to quantitatively similar estimates.

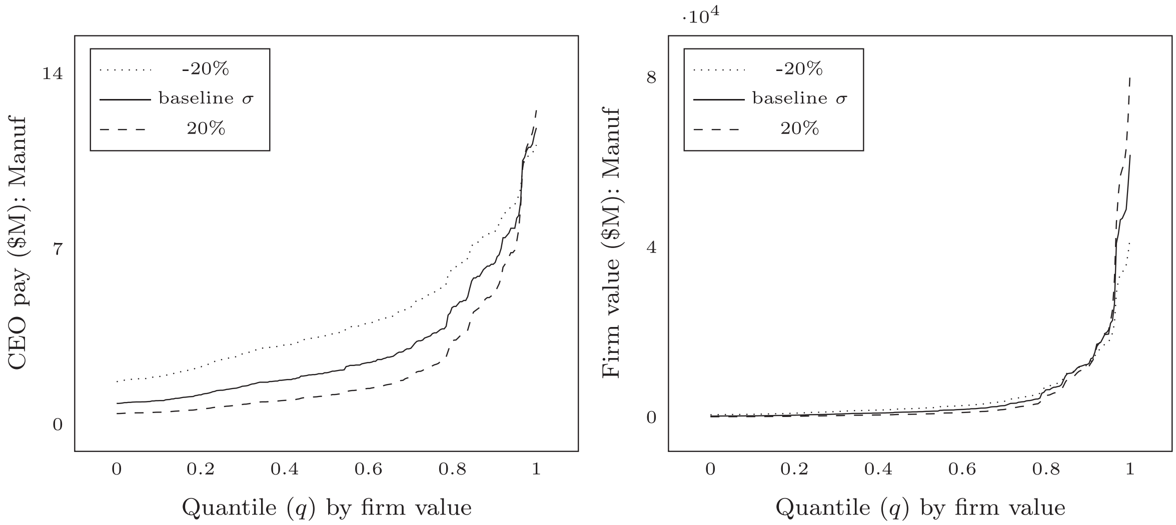

Fig. 6. Shifts in CEO pay and firm value profiles due to changes in the product substitutability. This figure shows the effects of varying the product substitutability (σ) on the intra-industry profiles of CEO pay (left) and firm value (right) for the manufacturing industry. The solid line plots the payoff profiles that we generate using the baseline parameter estimates in Table 5. The dotted and dashed lines plot the payoff profiles generated by decreasing and increasing the value of σ by 20% from its baseline value while keeping other parameter values the same.

As discussed in Section 4.4.1, relative to the CEO talent dispersion, the product substitutability has a much more significant quantitative influence on CEO impact, and its variation across industries. In contrast, GL's analysis attributes CEO impact entirely to CEO talent. Further, it would predict that product market changes have no effects at all on firm size and CEO pay.

4.4.3. Product market effects. We now quantitatively assess how the distributions of firm value and CEO pay within an industry and the impact of CEOs are influenced by changes in product market characteristics: the product substitutability (σ) and the entry cost (f_e). We use the free entry condition, (19), to infer the entry cost from the baseline equilibrium for each industry (see Table 8).[17] We then examine the effects of a change in each of the product market parameters on the equilibrium keeping other model primitives—in particular, the inferred factor profiles—unchanged. Fig. 6 and Table 7 show the effects of varying the product substitutability on the intra-industry distributions of firm value and CEO pay. Fig. 6 confirms our analytical result of Proposition 3 that the firm size and CEO pay profiles become more convex as the product substitutability increases. As shown in the left graph of Fig. 6 for the manufacturing industry, an increase in the product substitutability increases the pay of very talented CEOs, but decreases the pay of the other CEOs. Table 7 shows that the average CEO pay declines with the product substitutability for all industries. In particular, CEO pay levels in the consumer durable goods and healthcare industries are affected most with the average CEOs in these industries facing a 14.97% and 16.95% pay cut, respectively, in response to a 5% increase in the product substitutability. Table 7 also shows that the average firm value is marginally sensitive to changes in the product substitutability because the differential effects of the product substitutability on higher-ranked and lower-ranked firms almost offset each other as shown in Fig. 6. Fig. 8 confirms that the CEO factor profile, $\tilde{y} = y^{\sigma-1}$, becomes steeper as σ increases, thereby increasing the CEO impact estimate.[18]

As discussed in Section 3.2, the entry cost affects the firm size and CEO pay of all firms by the same proportion. Table 8 shows that an increase in the entry cost significantly increases the mean values of firm size and CEO pay. Fig. 7 shows that the intra-industry payoff profiles shift upward (downward) with an increase (decrease) in the entry cost without altering their shapes. Recall that the CEO impact measure is determined by the proportional change in firm value. Hence, the identical proportional effects of the entry cost on the payoffs of all firms imply that the quantitative impact of the CEO replacement is insensitive to variations in the entry cost, as we see in Fig. 8.

[17] To infer the entry cost f_e from the estimated baseline equilibrium, we rewrite the entry condition (19), along with the definitions of the normalized market variables in Section 4.2.1, as follows:

$$R(\widehat{P}^*)^{\sigma-1}\left[\frac{1}{\sigma} + \rho\int_0^1\left[\int_0^i\left(\frac{x[j]}{x[0]}\right)^{\sigma-2}\left(\frac{y[j]}{y[0]}\right)^{\sigma-1}\left(\frac{x'[j]}{x[0]}\right)dj\right]di\right]$$
$$= \tilde{u} + (1-\beta\delta)f_e,$$

where we set R to the average industry sales over the sample period, and σ, $\tilde{u}$, $\beta\delta$, relative factor profiles, as well as $\widehat{P}^*$, are obtained using the baseline parameter estimates in Table 5.

[18] The amplifying effect of the product substitutability on CEO impact is in line with recent empirical evidence by Li, Lu, and Phillips (2016). They report that CEO power, as represented by a CEO' s ability to influence and direct corporate policies, increases firm value only in a dynamic and competitive product market.

Table 7
Effects of the product substitutability.
This table shows the effects of varying the product substitutability (σ) on the equilibrium variables for each industry, including the relative aggregate price index, the mass of operating firms, and the mean values of CEO pay and firm value. Specifically, we vary the level of σ about its baseline value reported in Table 5 and determine the new set of equilibrium aggregate variables (the aggregate price index and the mass of operating firms) by assuming that the other parameter values are kept in place. Using the new aggregate variables and the new value of σ, we generate the intra-industry profiles of CEO pay and firm value. We then compare the new equilibrium variables with those from the baseline equilibrium.

Industry sector	$\Delta\widehat{P}^*/\widehat{P}^*$(%)				$\Delta N/N$(%)				$\Delta E[u]/E[u]$(%)				$\Delta E[\mathcal{V}]/E[\mathcal{V}]$(%)			
(Change in σ)	−10%	−5%	5%	10%	−10%	−5%	5%	10%	−10%	−5%	5%	10%	−10%	−5%	5%	10%
Consumer nondurables	−9.20	−4.35	3.92	7.44	11.01	5.03	−4.72	−9.12	27.67	12.39	−11.03	−20.11	0.90	0.10	−0.70	-1.10
Consumer durables	−3.55	−1.64	1.42	2.65	10.87	5.07	−5.07	−8.70	40.21	17.02	−14.97	−26.15	0.08	−1.41	−2.84	-4.10
Manufacturing	−8.03	−3.80	3.43	6.52	11.02	5.25	−4.75	−8.98	19.20	9.30	−8.26	−15.67	−0.41	0.00	−0.22	-0.38
Energy	−5.50	−2.57	2.26	4.25	11.00	5.26	−4.78	−9.09	27.61	13.16	−10.60	−19.56	−1.36	−0.27	0.18	0.93
Chemicals	−4.82	−2.25	1.97	3.70	11.29	4.84	−4.84	−8.87	27.20	12.27	−10.64	−20.79	4.51	1.56	−1.21	-3.32
Business equipment	−6.72	−3.18	2.85	5.43	10.39	4.93	−4.57	−8.69	25.49	11.84	−10.14	−18.69	−2.62	−1.20	1.10	2.27
Shops	−5.38	−2.54	2.27	4.31	10.89	5.20	−4.72	−8.94	24.06	11.40	−9.89	−18.42	−0.79	−0.17	0.07	0.12
Healthcare	−14.31	−6.80	6.15	11.72	10.65	5.15	−4.64	−8.93	49.54	21.60	−16.95	−30.13	3.22	1.31	−1.96	-3.36

Table 8
Effects of the entry cost.
This table shows the entry cost (f_e) inferred from our baseline estimation results for each industry, and the results of the sensitivity analysis that examines the effects of varying the entry cost on the equilibrium variables.

Industry sector	f_e	$\Delta\widehat{P}^*/\widehat{P}^*$(%)				$\Delta N/N$(%)				$\Delta E[u]/E[u]$(%)				$\Delta E[\mathcal{V}]/E[\mathcal{V}]$(%)			
(Change in f_e)		−10%	−5%	5%	10%	−10%	−5%	5%	10%	−10%	−5%	5%	10%	−10%	−5%	5%	10%
Consumer nondurables	2,946	−1.65	−0.81	0.77	1.52	11.01	5.35	−4.72	−9.12	−9.83	−4.76	4.45	9.25	−10.77	−5.17	4.91	10.16
Consumer durables	4,927	−0.93	−0.45	0.43	0.85	10.87	5.07	−5.07	−9.42	−9.32	−5.47	4.16	8.79	−12.95	−7.76	3.49	7.77
Manufacturing	2,198	−1.25	−0.61	0.59	1.15	11.02	5.25	−4.75	−9.15	−9.55	−4.63	4.71	9.59	−10.44	−5.09	4.95	10.35
Energy	4,119	−1.19	−0.58	0.55	1.09	11.00	5.26	−4.78	−9.09	−9.69	−4.46	5.09	10.27	−11.65	−5.42	5.29	11.19
Chemicals	5,671	−1.07	−0.52	0.50	0.98	11.29	5.65	−4.84	−8.87	−9.55	−4.72	5.53	10.06	−11.22	−5.67	6.63	12.23
Business equipment	1,592	−1.04	−0.51	0.48	0.95	11.11	5.29	−4.75	−9.05	−9.57	−4.77	4.91	9.63	−10.07	−4.99	5.17	10.14
Shops	2,057	−0.88	−0.43	0.41	0.80	11.06	5.20	−4.72	−9.11	−9.57	−4.70	4.72	9.73	−10.35	−5.07	5.04	10.49
Healthcare	2,571	−2.59	−1.27	1.22	2.40	11.17	5.33	−4.81	−9.11	−9.74	−4.70	4.67	9.74	−11.37	−5.65	4.80	10.22

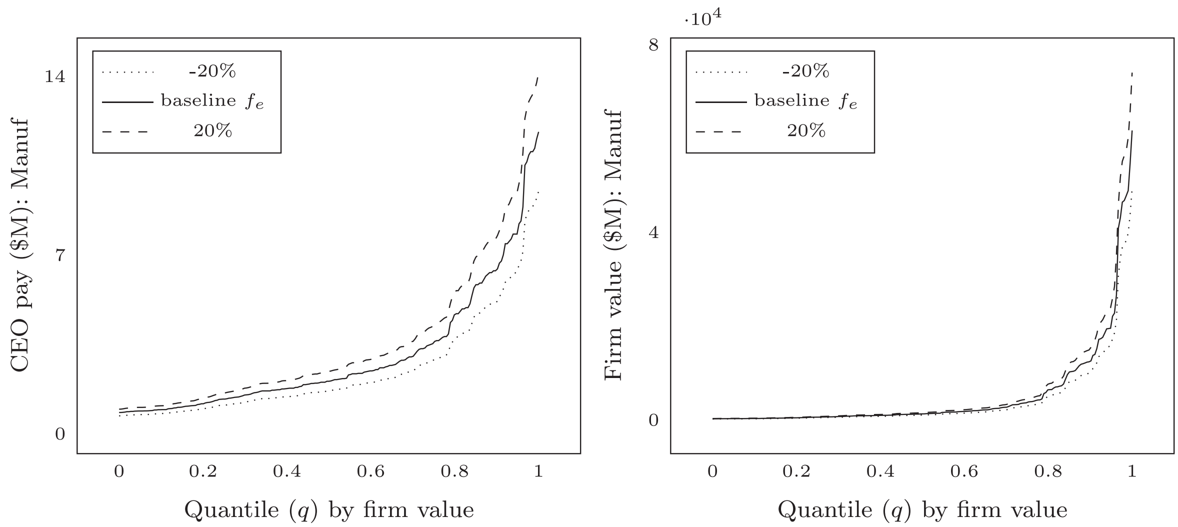

Fig. 7. Shifts in CEO pay and firm value profiles due to changes in the entry cost. Table 8 shows the level of the entry cost (f_e) inferred from our baseline estimation results. This figure shows the shifts in the intra-industry CEO pay (left) and firm value (right) profiles in response to a 20% increase and a 20% decrease in f_e for the manufacturing industry.

5. Moral hazard

CEOs affect firms not just through exogenous attributes such as "talent," but also by endogenous actions such as "effort." It is optimal for firms to tie CEO pay to firm performance so that CEO pay includes compensation for talent, and incentive compensation to induce effort. Ignoring the separate effects of CEO talent and effort on firm value as well as the structure of CEO pay could incorrectly attribute CEO impact and CEO pay differences entirely to differences in CEO talent, thereby exaggerating the importance of CEO talent. To address these potential biases, we

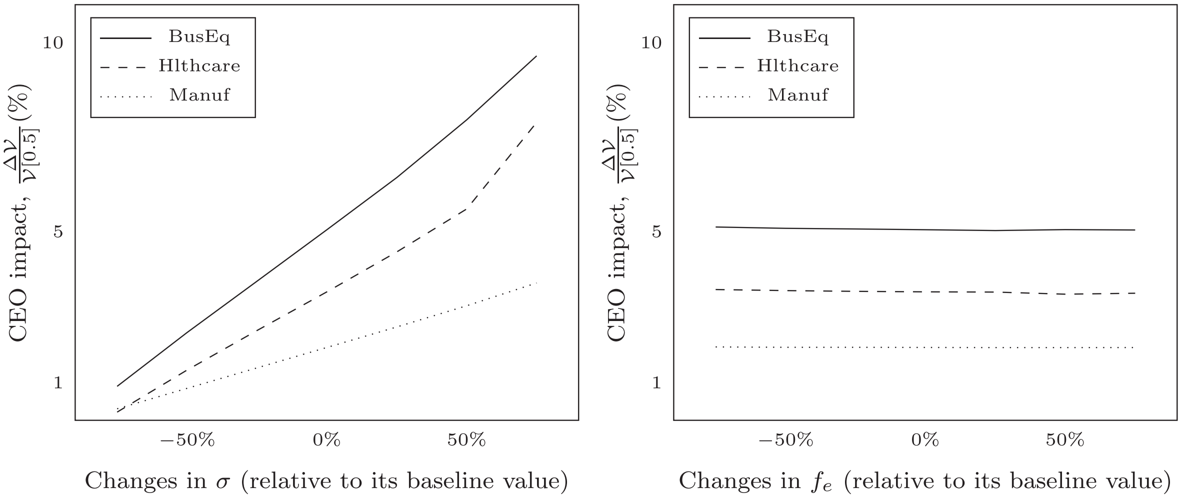

Fig. 8. CEO impact for different values of the product substitutability and the entry cost. This figure shows the CEO impact estimates for different values of the product substitutability (σ) and the entry cost (f_e) in the manufacturing, business equipment, and healthcare industries. We derive a new equilibrium by varying the value of each of the parameters (σ and f_e) from its baseline value (reported in Tables 5 and 8, respectively), while keeping other parameter values the same. Using the new set of equilibrium variables, we carry out the counterfactual experiment of CEO replacement at the median-sized firm.

extend our model to incorporate moral hazard and incentive compensation for CEOs, and show that our main implications are robust. Recent studies extend the competitive CEO assignment models by incorporating moral hazard (e.g., Baranchuk, MacDonald, and Yang (2011); Edmans and Gabaix (2011); Chen (2016)). Our model, which builds on the framework in Subramanian (2013), complements these models by incorporating product market competition.

In online Appendix C.1, we alter the basic model to allow for firms to experience idiosyncratic productivity shocks in each period after matching occurs whose distributions depend on CEOs' costly effort choices. A CEO's total compensation comprises a base salary that is endogenously determined in the equilibrium of the CEO-firm competitive matching process, and additional incentive pay to mitigate the effects of moral hazard. In equilibrium, PAM holds, that is, more talented CEOs are matched to higher quality firms. More talented CEOs also exert greater effort, generate greater profits, and receive greater expected total compensation. Consistent with evidence, there is a negative relation between CEO pay-performance sensitivity (PPS) and firm size (e.g., Baker and Hall (2004)).

Our estimation strategy is similar to our main analysis described in Section 4.2 except for additional parameters and moments. The additional parameters include the two possible values (h, l) of firms' idiosyncratic productivity shocks and the coefficient parameter (κ) in the CEO effort cost function. The additional moments, which are relevant for the identification of these parameters, capture the profile of CEO dollar-dollar incentives (see Table H6 in online Appendix H). Table H6 shows that the model-predicted moments are not statistically distinguishable from the actual moments at the 1% level across all industries. Table H7 shows that the estimates of the parameters that also appear in the basic model change slightly, but their variations across industries are largely similar to what we observe from the baseline parameter estimates in Table 5.

Table H9 shows the results of the counterfactual experiment to measure CEO impact. In the experiment, we assume that the median firm needs to guarantee the best CEO's base pay at the largest firm as the talent premium, but her optimal effort and incentive pay are determined through the firm-specific contract after matching takes place. The CEO impact estimates in the second column of the table are slightly smaller than the corresponding estimates in Table 6. Although the difference may imply some bias from ignoring the distinction between CEO talent (exogenous human capital) and effort (endogenous human capital), our main implications for CEO impact continue to hold. Further, the estimates of the additional compensation cost are much smaller than the estimates from the basic model in Table 6 mainly because we disentangle incentive pay from total pay. The results suggest that the cost estimates from the analysis of the basic model are actually biased upward because the basic model does not incorporate the impact of moral hazard, and the presence of incentive pay to mitigate it. By correcting the bias through the extended model, we conclude that CEO compensation is more in line with CEO impact on firm value. In sum, our main implications from the estimation of the basic model are robust to the incorporation of moral hazard and incentive compensation.

To further examine the robustness of our results, we modify the basic model to incorporate moral hazard and CEO risk aversion in online Appendix C.2. We adopt a "CARA-normal" specification where firms' ex post (after matching) idiosyncratic productivity shocks are normally distributed, and CEOs have constant absolute risk aversion (CARA) preferences. CEO incentive pay now reflects compensation for effort costs and a risk premium for bearing firm-specific risk.

Table H11 shows the parameter estimates along with their standard errors from the estimation of the extended model. The coefficient of absolute risk aversion (multiplied by the variance of firm idiosyncratic risk) is significantly different from zero, thereby resulting in a sizeable risk premium that is greater for larger firms as shown in Table H12. Although the talent premium still predominantly explains the difference in total CEO pay between the best and median CEOs, the difference in incentive pay is also significant especially in the business equipment and healthcare industries. The CEO impact estimates reported in Table H13 are again quite similar to those from our main analysis in Table 6.

6. Additional robustness tests

In this section, we discuss the results of several additional tests that we carry out to examine the robustness of our main implications.

6.1. Long-term effects of CEOs

In online Appendix D, we extend the basic model by allowing CEOs to have long-term effects on firms' earnings as in Terviö (2008). In the extended model, the equilibrium payoff profiles are affected by an additional parameter, $\lambda > 0$, which represents the rate at which a CEO's influence on earnings fades over time. A lower value of λ implies longer-term effects of the CEO. The extended model reduces to the basic model in which CEOs have an effect only on contemporaneous earnings as $\lambda \to \infty$. The results of our analysis of the extended model, which we report in Tables H14–H17 in online Appendix H, suggest that the CEO impact estimates are actually *higher* when CEOs are assumed to have longer-term effects on firms' earnings.

As the duration of CEO influence increases (that is, as λ decreases), the effect of the CEO factor in the current period on future earnings increases. By the same logic, however, the effect of the CEO factor on current period earnings decreases because the earnings are also influenced by the CEO factors in previous periods. Because CEO influence declines over time, and earnings in any period are additively affected by the CEO factors in previous periods, the second effect actually outweighs the first. Consequently, in any period, the marginal contribution of a CEO to firm value decreases as λ decreases (see online Appendix D for the formal analysis). As a result, for a given CEO factor profile, the dispersion in CEOs' marginal contributions across firms and, therefore, the CEO pay dispersion decrease as λ decreases. Conversely, given the CEO pay profile in the data, the inferred CEO factor profile that matches the observed pay profile becomes steeper as λ decreases. Hence, the CEO impact estimate increases as the duration of CEO influence increases.

Although both models incorporate long-term CEO effects, our extended model differs significantly from GL's framework described in online Appendix B.4 in two respects. First, in each period, CEOs *additively,* rather than *multiplicatively,* affect earnings in future periods. Second, a CEO's influence on future earnings declines over time. The two distinctions combine to create *increasing* returns to the CEO factor over time in GL's model, but *decreasing* returns in our extended model. Consequently, for the same CEO factor profile, the dispersion in CEOs' marginal contributions to their firms and, therefore, the CEO pay dispersion are greater in GL's model than in our extended model (for any $\lambda > 0$). By arguments similar to those we described earlier, the inferred CEO factor profile that matches the observed pay profile in the data is flatter in the industry-level GL analysis. Consequently, the CEO impact estimates from the industry-level GL analysis are lower than those from our extended model.

6.2. Transferability of CEO ability

In our main analysis, we assume that CEO ability is perfectly transferable across firms within the industry, but is non-transferable across industries. To the extent that CEOs develop firm-specific human capital, CEO ability may not be perfectly transferable to other firms even within the same industry. Further, in addition to "industry-specific" ability, CEOs could also have "general" ability that is transferable across industries. We now show that our results are robust to relaxing our assumptions on transferability of CEO ability within and across industries.

6.2.1. Imperfect intra-industry transferability of CEO ability

In online Appendix E.1, we modify the basic model to incorporate imperfect intra-industry transferability of CEO ability across firms that affects the division of firm earnings generated by a firm-CEO match and, therefore, firm value and CEO pay. The degree of imperfect transferability of CEO ability is captured by a parameter τ with $\tau = 0$ corresponding to perfect transferability.

Table H19 in online Appendix H shows the parameter estimates, including the estimates of τ, along with their standard errors. The parameter τ is significantly different from zero for the consumer nondurable goods, energy, business equipment (weakly), and healthcare sectors. For other industries, we cannot reject the null hypothesis that CEO talent is perfectly transferable across firms within the industry. Other parameter estimates and intra-industry dispersions of firm quality and CEO talent are similar to the baseline estimation results in Table 5.

Table H20 shows that the CEO impact estimates are similar to the baseline estimates in Table 6, but the cost estimates tend to be much larger. Relative to the basic model, a firm would be even worse off by choosing a new CEO over the current CEO because the new CEO's ability is only partially transferable. Consequently, the incumbent CEO is able to capture a larger fraction of the total surplus in equilibrium so that the implicit cost of CEO replacement is higher.

6.2.2. Imperfect inter-industry transferability of CEO ability

In online Appendix E.2, we modify the basic model to incorporate "general" and "industry-specific" components of CEO ability. The general talent component is perfectly transferable across industries, but the industry-specific component is perfectly transferable only within the industry. We estimate the parameters of the extended model by *jointly matching* the moments across industries. Table H24 in online Appendix H shows the parameter estimates, including those that characterize the distributions of general and industry-specific talent components. The intra-industry firm quality and CEO talent dispersions are similar to those from the baseline model (see Table 5). Table H25 shows that CEO impact continues to be significant. The estimate for the business equipment sector, however, is twice as large as the baseline estimate in Table 6 because the inferred intra-industry dispersion of CEO ability is greater than in the baseline case.

6.3. Parametric and non-parametric bootstrapping

Unmodeled features that drive the discrepancy between model-predicted and empirical payoff distributions and/or the possibility of measurement errors could lead to incorrect parameter estimates and inferences. We address these issues using bootstrapping analyses.

We run a placebo analysis in which we use our model to generate 5,000 bootstrapped samples by injecting idiosyncratic random shocks in each period (see online Appendix F.1 for details of the analysis). These shocks can also be interpreted as ex post (after matching occurs) match quality shocks that have multiplicative effects on CEO pay levels. We choose the distribution of these shocks to match the distributions of the residuals in the regression of log CEO pay on log firm value in each period. The first column of Table H26 in online Appendix H shows that the mean correlation between firm size ranks and CEO pay ranks across the bootstrapped samples is close to the actual correlation from the data for each industry, which validates the identification of the variance of the noise injected in the bootstrap samples. The parameter estimates as well as intra-industry dispersions of firm quality and CEO talent across industries are largely similar to the baseline estimates in Table 5. Table H27 shows that our estimates of CEO impact are quite robust.

To further address the possibilities that specification errors could lead to distorted inferences, and that our parametric bootstrapping model could itself be misspecified, we also employ non-parametric bootstrapping. Instead of simulating from the model, we generate fictitious panels by re-sampling from the data and re-run the estimation on each resampled data panel (see online Appendix F.2 for details of the analysis). Table H29 in online Appendix H shows that our implications for CEO impact continue to hold, but the impact estimates are larger than in the baseline case for all industries mainly because the estimates of the product substitutability are higher than its baseline values.

6.4. CEO-firm matching and the product market

In the basic model, the firm quality and CEO talent profiles are exogenous so that there is no direct link between the CEO-firm matching process and the product market. In online Appendix G, we extend the model to allow for CEO-firm matching and, therefore, the intra-industry profiles of firm and CEO characteristics to be influenced by the product market. Specifically, the mass of potential CEOs could exceed the mass of actual CEOs who successfully match with firms. Under reasonable assumptions, there is a unique equilibrium in which only CEOs with abilities above a cutoff level are employed. We thereby endogenize the talent profile of actual CEOs, that is, the ex post talent profile. Fig. H1 in online Appendix H reports how the ex post talent dispersion varies as either of the product market characteristics (σ and f_e) changes. If we perform the experiment to measure CEO impact with the ex ante pool of *potential* CEOs rather than the ex post pool of matched CEOs, the CEO impact estimates would be much larger than those obtained from the basic model in which the potential and actual CEO pools are identical.

6.5. Alternate CEO pay measure, price-cost margin measure, and industry classification

We carry out a robustness check in which we repeat the analysis of our basic model using an alternate measure of annual CEO pay that includes stock and options in the year *vested*, rather than the year granted (Taylor, 2013). Execucomp's annual pay variable (TDC1) that we use for our main analysis includes stock and option grants in the year they are granted. However, instead of making annual grants, firms often offer large grants every few years that vest gradually over time (typically over a four-year period). The "lumpy" nature of grants could distort the correspondence between CEO pay in our model and the original CEO pay measure. In this respect, the alternate CEO pay measure might be a better proxy for the annual flow compensation for CEOs. Table H31 in online Appendix H shows that the alternate annual pay measure leads to CEO impact estimates that are quantitatively similar to the estimates we obtain using the original pay measure (TDC1) in Table 6.

Following the suggestion of recent literature (e.g., Eisfeldt and Papanikolaou (2013)) that selling, general, and administrative (SG&A) costs should be regarded as intangible investments rather than expenses, we repeat our main analysis using an alternate price-cost margin measure in which operating costs include only the costs of goods sold.Tables H32 and H33 in online Appendix H show the results. Because the price-cost margin is the key moment that identifies the product substitutability, σ, the estimates of σ differ significantly from the corresponding baseline estimates in Table 5. Nevertheless, the CEO impact estimates are still over a hundred times higher than the GL impact estimate.

Our results are robust when we repeat our analysis using the Hoberg and Phillips (2010) 10-K Text-based Fixed Industry Classifications (seeTables H34 and H35 in online Appendix H). The CEO impact is still significant (1.05%–5.28%) and varies across industries primarily driven by the product substitutability, rather than variation in the CEO talent dispersion.

7. Conclusions

We develop a structural industry equilibrium model that incorporates competitive CEO-firm matching and the product market environment. In sharp contrast with the findings of previous structural frameworks, but consistent with the evidence from reduced-form approaches, we show that CEOs have quantitatively important impacts on firms. Our CEO impact estimates vary significantly across industries with most of the variation stemming from variation in product market characteristics, rather than variation in the CEO talent distribution. We also derive the effects of product market characteristics on CEO pay and firm size. Our quantitative analysis suggests that changes in product markets significantly influence CEO pay and firm size distributions as well as CEO impact, but more direct evidence necessitates further empirical analysis.

To directly compare with previous structural models, we abstract away from other factors such as corporate governance and CEO turnover. In our model, a firm of given quality is matched to a CEO of the same talent so that there is no turnover in equilibrium. It would be interesting to extend our framework to more explicitly incorporate CEO and firm turnover as well as imperfect information about CEO talent (e.g., Taylor (2010, 2013); Eisfeldt and Kuhnen (2013)).

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