Selection versus Incentives in Incentive Pay: Evidence from a Matching Model

Job Market Paper

Shuo Xia*

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ABSTRACT

Higher incentive pay is associated with better firm performance. I introduce a model of CEO-firm matching to disentangle the two confounding effects that drive this result. On one hand, higher incentive pay directly induces more effort; on the other hand, higher incentive pay indirectly attracts more talented CEOs. I find both effects are essential to explain the result, with the selection effect accounting for 12.7% of the total effect. The relative importance of the selection effect is the largest in industries with high talent mobility and in more recent years.

*Erasmus School of Economics, Erasmus University Rotterdam, and Tinbergen Institute, xia@ese.eur.nl.
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1 Introduction

What drives the positive correlation between CEO incentive pay and firm performance? John Thompson, the chairman of Microsoft, believes that incentive pay "attract[s] and motivate[s] a world-class CEO." Similarly, according to Apple Inc.'s 2016 proxy statement, its restricted stock grants, by far the largest component of incentive pay, are "the most effective way to attract and retain a talented executive team and to align executive interests with those of shareholders."[1] These examples highlight the dual role of incentive pay as both a selection and an incentive mechanism for maximizing performance as discussed in Lazear (2000).

The academic literature has long debated the relative importance of these two mechanisms. One strand of literature argues that differential manifestations of the agency problem between firms are the primary driver of cross-sectional differences in incentive pay (Gayle and Miller, 2009; Gayle et al., 2015). That is, the incentive effect is the dominant force. Another strand of literature argues that talent matching between CEOs and firms determines the variation in CEO pay (Gabaix and Landier, 2008; Tervio, 2008). That is, the selection effect is the dominant force. Despite these conflicting views, because of the endogenous nature of the problem, disentangling these two effects and assessing their relative importance remains an open issue.

The main contribution of this paper is its implementation of a matching model to shed light on both the incentive and selection effects of incentive pay on firm performance by empirically quantifying the relative importance of these effects. I first document that there exists a robust positive correlation between new CEOs incentive pay and firm performance. After controlling for the selection effect, the incentive effect indicates that a 1% increase in pay for performance leads to a 1.51% increase in firm performance, while the selection effect suggests that a 1% increase in pay for performance leads to a 0.21% increase in firm

[1] Many other firms also attest to the dual effects of incentive pay. For example, a similar statement is found in PayPal Holdings Inc.'s 2016 proxy statement, incentive pay *"attracts highly capable leaders in an extremely competitive talent market" and "compensates for the creation of longer-term value over time."*

performance. Hence, the incentive effect accounts for 87.3% of the total effect of incentive pay on firm performance and the selection effect accounts for 12.7% of the total effect.

The incentive effect is motivated by the existence of agency problems between managers and shareholders. Managers may seek to enjoy a quiet life (Bertrand and Mullainathan, 2003), or opt to pursue their own agenda by exploiting perks and individual prestige instead of maximizing shareholder value (Jensen and Meckling, 1976; Bebchuk and Fried, 2004). Hence, incentive pay is used to align managers' and shareholders' interests to generate better performance. The selection effect arises from the competitive equilibrium view that market forces can allocate human capital efficiently (Lucas, 1978; Rosen, 1981; Gabaix and Landier, 2008; Tervio, 2008). Therefore, incentive pay is part of the CEO-firm matching mechanism: better CEOs agree to work for firms with high incentive pay and their talents subsequently lead to better expected firm performance in the future. Therefore, even if CEOs' efforts have no effect on firm performance, high incentive pay still creates a positive assortative matching mechanism between firms and CEOs, generates higher matching value, and leads to better performance in the future.

Distinguishing between these two effect channels of incentive pay on performance raises several challenges. Incentive pay becomes an endogenous variable when more-talented managers work for firms offering higher incentive pay and talent cannot be correctly measured. Then, talent mismeasurement will result in unobserved talent factors correlating with the matching value and also firms' performance. Therefore, the directly estimated coefficients are biased. Unfortunately, the matching between CEOs and firms is a complex endogenous process involving a large number of observed and unobserved characteristics of both parties and other entities. This complexity makes finding valid instruments unlikely.

Instead, I use a structural model to overcome the endogeneity problem. The structural model combines two key ingredients: an assortative one-to-one matching model that controls for the selection effect explicitly in the CEO-firm matching equilibrium and an outcome equation that specifies the performance of the observed matches. The one-to-one matching

model implies that one firm can only match with one CEO and one CEO can only work for one firm at a time, thus the other agents participating in the same CEO labor market have an effect on the matching decision. In market contexts, agents' own characteristics determine the matching value, but it is the relative ranking that matters for matching decisions. Therefore, matching decisions not only depend on the characteristics of the two agents but also on other agents' characteristics in the market. As these other agents' characteristics are not likely to influence subsequent matched pair performance, the outcome equation only depends on the matched agents' characteristics. Exogenous variation in other agents' characteristics identifies the incentive and selection effect of incentive pay on performance.

The main assumption for identification is that agents are exogenously assigned across markets. That is, CEOs and firms cannot self-select to specific markets due to unobservable reasons. Specifically, I assume the CEO market is segregated by the calendar year; thus in each calendar year new CEO candidates and firms with job vacancies participate in the CEO labor market for exogenous reasons. Similar identification assumptions have been used in Sorensen (2007a); Park (2013); Chen (2014); Ni and Srinivasan (2015); Pan (2015); Akkus et al. (2016b).

This paper relates to four literature domains. The first domain focuses on the influence of the dual effect of incentive pay for executives and workers (Lazear, 2000, 2004; Oyer and Schaefer, 2005; Arya and Mittendorf, 2005). In this respect, I provide the first quantitative estimates of the incentive and selection effects of CEO incentive pay on firm performance.

Second, a growing body of literature uses matching models to correct for nonrandom sampling biases in different contexts such as venture capital markets (Sorensen, 2007a; Akkus et al., 2016a), M&A markets (Park, 2013; Akkus et al., 2016b), director labor markets (Matveyev, 2016), and executive labor markets (Pan, 2015), among others.

In methodological terms, this paper is also related to those finance studies that apply Markov Chain Monte Carlo (MCMC) methods. MCMC methods are particularly useful in

estimating models with many latent variables and hierarchical structures.[2]

This paper is also related to the extant literature investigating the effects of incentive pay on firm performance. Mehran (1995) shows incentive pay and firm performance are positively associated. Bandiera et al. (2009) carry out a field experiment and find that switching from fixed pay to incentive pay for managers increases firms' overall performance. Agarwal et al. (2009) show that hedge funds with higher incentive pay for fund managers are associated with superior fund performance. Lilienfeld-Toal and Ruenzi (2014) find that firms with higher CEO equity incentives outperform companies with lower CEO equity incentives by 4 to 10% annually.

This paper also sheds light on the regulation of CEO incentive pay. Regulating CEO incentive pay not only has an effect on CEOs motivation to perform well but also on the inefficient allocation of talent. In the absence of job mobility, local regulations on CEOs' incentive pay will have little effect on firms' performance. However, in a fully integrated market for CEOs, tough local regulations on CEOs' incentive pay will induce talented candidates to move. This distorts talent allocation, thus creating inefficiencies. When restricting CEO incentive pay, it is crucial that regulators consider the effect of talent mismatch on labor market dynamics and outcomes. [3] Therefore, a better understanding of these two effects could lead to smarter ways of regulating incentive pay.

The remainder of the paper is structured as follows. Section 2 presents the econometric framework. Section 3 outlines the data and discusses the estimation results. Section 4 explores the robustness of our results. Finally, Section 5 concludes.

[2]Other researchers have applied MCMC including: Li (1999) in the context of estimating the duration of Chapter 11 bankruptcy; Sorensen (2007a) to estimate matching between VCs and firms; Park (2013) to understand the incentive for mergers between mutual funds; Korteweg and Sorensen (2010, 2015) to accommodate dynamic selection; and finally Chen (2014) to explore loan markets. Korteweg (2013) provides an excellent review of MCMC methods and applications

[3]Recently, in the Netherlands, the Dutch parliament considered abolition of the 20 percent bonus cap in the financial industry. The proponents of this change contend that the Netherlands risks being uncompetitive relative to other European countries vis-á-vis attracting financial institutions that are considering moving from the UK to continental Europe before the conclusion of Brexit negotiations in March 2018. Importantly, other European Union countries limit financial industry bonuses to 100 percent of fixed pay.

2 Econometric Framework

2.1 Identification strategy

In this section, I present a simple example to illustrate the identification method (see Table 1). Specifically, three CEO candidates (1, 2, and 3) and three different firms (A, B, and C) are in a market seeking for a match. X_i represents a vector containing each agent's characteristics. Panel A shows the matching of CEOs and firms in the market. The matches in the diagonal are observed matches, while the off-diagonal matches are counterfactual matches. The numbers in Panel A represent matching values of observed matches; these matching values are determined by the matched pairs' characteristics. To guarantee the observed matches are stable, the matching values of counterfactual matches need to satisfy the condition that no matched pair would want to deviate from the current match. Panel B illustrates possible matching value ranges for counterfactual matches to guarantee a stable match. Panel C shows the performance of matched CEO-firm pairs. For illustrative purposes, I explore one of the observed matches, CEO 2 and firm B, for an illustration. The matching value of CEO 2 and firm B is 20 in Panels B and C. This value is determined by the characteristics of CEO 2 and firm B and can be denoted as $V_{2B} \equiv f(X_2, X_B)$. For CEO 2 and firm B to be an observed match, this needs to satisfy the condition that neither CEO 2 nor firm B would like to deviate from the current match and to form a new match with the other agents that would also like to match with them. From the matching value range of counterfactual matches in Panel B, CEO 2 does not want to deviate to firm A because of $V_{2A} < V_{2B}$. CEO 2 might want to deviate and form a match with firm C if $V_{2C} > V_{2B}$, but firm C does not want to deviate because $V_{2C} < V_{3C}$. Firm B does not want to deviate to CEO 1 because $V_{2B} > V_{1B}$. Firm B might want to match with CEO 3 if $V_{3B} > V_{2B}$, but CEO 3 does not want to match with firm B because $V_{3C} > V_{3B}$. Because of these foregoing inequalities, the matching decision of CEO 2 and firm B not only depends on their characteristics but also on the characteristics of the other agents in the market. Thus, the

matching decision of CEO 2 and firm B can be denoted as $M_{2B} \equiv \mathbb{1}_{g(X_1,X_2,X_3,X_A,X_B,X_C)>0}$. However, the performance of the matched pair CEO 2 and firm B, Y_{2B} in Panel C, is unlikely to be influenced by other agents' characteristics. Then the outcome function can be denoted as $Y_{2B} \equiv y(X_2, X_B)$. The fact that the characteristics of other agents affect the matching decision but not the performance of the match can serve as the exogenous variation to control for selection from the incentive effect.

2.2 Two-sided matching model

This section presents a matching model to address the matching problem between firms and CEOs. The matching between CEOs and firms is a bilateral decision process that depends on agents' preferences on both sides. This feature is captured by a variation of the two-sided matching model for marriage market (Gale and Shapley, 1962; Roth and Sotomayor, 1992)[4]. Specifically, I present a generalized selection model where the first stage is a one-to-one matching model.

The labor market for CEOs contains two types and a finite number of agents on each side of the two-sided market. In market t, a set I_t contains all of the CEO candidates, and a set J_t contains all of the firms that need to hire a new CEO. Each CEO works for only one firm, and each firm attracts only one CEO. Then the number of CEO candidates and firms are equal. The set containing all possible matches between CEO candidates and firms in market t is denoted as M_t. Therefore $M_t = I_t \times J_t$. A matching contains observed matches in market t denoted as μ_t is a subset of M_t, where $\mu_t \subset M_t$. The matched firm for CEO i in market t is denoted as $\mu_t(i)$ and the matched CEO for firm j in market t is denoted as $\mu_t(j)$. If $ij \in \mu_t$, then $i = \mu_t(j)$ and $j = \mu_t(i)$.

Agents from each side of the market simultaneously choose their partners from the other side of the market to maximize the latent matching value. The matching process is frictionless and subject to complete information. I denote the matching value between CEO i and firm

[4]Other applications that use a similar model setting as matching market include Sorensen (2007a); Park (2013); Chen (2014); Ni and Srinivasan (2015); Akkus et al. (2016b)

j as V_{ij} regardless of whether ij is a matched pair or not. The matching values are assumed to be distinct to avoid the situation that agents can be indifferent between two matches.

To generate a feasible econometric model, the existence and uniqueness of the matching equilibrium needs to be established. According to Roth and Sotomayor (1992), the equilibrium for one-to-one matching always exists, but that equilibrium might not be unique. To guarantee the equilibrium is unique, I follow Niederle and Yariv (2009) and assume firms and CEOs in the market have aligned preferences; this condition is more restrictive than some of the identified sufficient conditions for uniqueness of an equilibrium match discussed in Eeckhout (2000); Clark (2006). In practice, a simple fixed sharing rule of the matching value between CEOs and firms can easily satisfy the aligned preferences requirement.[5]

The equilibrium concept used in the matching market is stability. A matching is stable if there is no matched pair of agents who would like to deviate from their current match. The unique equilibrium is characterized by a set of inequalities based on no blocking pairs for equilibrium matching.

Suppose CEO i and firm j are matched in market m, and let $\mu(i)$ denote the firm that matched with CEO i. In this case, it is firm j. Let $\mu(j)$ denote the CEO that matched with firm j. In this case, $i = \mu(j)$.

For ij to be a stable match, we require that no blocking pairs exist for ij, that is, the opportunity cost of CEO i remaining matched with firm j or the opportunity cost of firm j remaining matched with CEO i has to be smaller than V_{ij}, the matching value of ij.

The opportunity cost of CEO i, OC_i, is the maximum value that CEO i can get from the set of feasible deviations of CEO i instead of matching with firm j. The opportunity cost of firm j, OC_j, is the maximum value firm j can get from the set of feasible deviations of firm j instead of matching with CEO i. Because of the fixed sharing rule, finding the maximum value that agents can get is equivalent to finding the maximum matching value that agents

[5]This means a sub-standard CEO cannot match with a well performing firm by accepting a low stake or no stake in the firm. That is, the matching model framework used in this paper is a non-transferable utility model. See Fox (2009, 2017); Pan (2015) for estimating matching models with transfers.

can make. That is,

$$V_{ij} > max[OC_i, OC_j],$$

where

$$OC_i = max(V_{ij'}), \forall j' \in J \cap (V_{ij'} > V_{\mu(j')j'}),$$
$$OC_j = max(V_{i'j}), \forall i' \in I \cap (V_{i'j} > V_{i'\mu(i')}).$$

In another circumstance that executive i and firm j are not matched in market m, then ij cannot be the blocking pair for their own current matches. Then the matching value of ij has to be smaller than the matching value of the current match of executive i and the matching value of the current match of firm j. That is:

$$V_{ij} < max[V_{i\mu(i)}, V_{\mu(j)j}].$$

We denote $\overline{V}_{ij} \equiv max[OC_i, OC_j]$ and $\underline{V}_{ij} \equiv max[V_{i\mu(i)}, V_{\mu(j)j}]$. More formally, for μ to be a stable matching, the following conditions need to hold:

$$V_{ij} < \overline{V}_{ij}, \forall ij \notin \mu, \tag{1}$$
$$V_{ij} > \underline{V}_{ij}, \forall ij \in \mu. \tag{2}$$

2.3 Empirical method

The first part of the empirical model is a matching function determining the matching value of the possible match between two agents. The matching value is unobserved and modeled as a latent variable in the model. Without loss of generality, the matching function for CEO i and firm j can be written as:

$$V_{ij} = \alpha W_{ij} + \eta_{ij}, \forall ij \in M_t, \tag{3}$$

where W_{ij} contains observed characteristics of CEO i and firm j. η_{ij} contains characteristics of CEO i and firm j that are unobservable to econometricians and $\eta_{ij} \sim N(0,1)$. The scale of the parameters is normalized by the assumption that the variance of η_{ij} is one.

The second part of the empirical model is the outcome equation; this determines the outcome of all of the possible matches and the outcome variable Y_{ij} is only observed when ij is one of the observed matches. The outcome equation of ij can be written as:

$$Y_{ij} = \beta X_{ij} + \varepsilon_{ij}, \forall ij \in M_t, \tag{4}$$

where X_{ij} contains observed characteristics of CEO i and firm j. ε_{ij} contains characteristics of CEO i and firm j that are unobservable to econometricians, and $\varepsilon_{ij} \sim N(0, \sigma_\varepsilon)$.

Direct estimation of equation (4) leads to biased results as the matching decision between firm i and manager j is not random but correlated with the error term in the equation (4) under dimensions that cannot be observed by econometricians. This problem arises when ε_{ij} and η_{ij} are correlated. To address this issue, it is convenient to assume $\varepsilon_{ij} = \delta\eta_{ij} + \xi_{ij}$, where $\xi_{ij} \sim N(0, \sigma_\xi)$. Then $\sigma_\varepsilon^2 = \delta^2 + \sigma_\xi^2$. If there is no correlation between ε_{ij} and η_{ij} then $\delta = 0$.

To identify the parameters in the outcome equation, ideally an instrument should be exploited that correlates with the matching decision of firms and CEOs but is independent from the outcome of the match. According to Edmans et al. (2017), matching between CEOs and firms is a complex and endogenous process involving various types of agents and third parties, rendering an instrumental variable strategy infeasible. However, the matching nature of the problem suggests that other agents participating in the same CEO labor market have an effect on the matching decision. In a market, agents' own characteristics are determinants of the matching value, but it is the relative ranking that matters for the matching decision. Thus, a top-notch CEO can easily match with a top-notch firm in a market where other agents' abilities are normally distributed. However, he might not be able to match with

a top-notch firm if the ability distribution of other CEO candidates participating in this market is left-skewed. These other agents characteristics are unlikely to have an effect on the performance of the matching. Under the key identification assumption that the distribution of the agents in a particular market is exogenously given, we can use the variation of other agents' characteristics to identify the outcome equation and the incentive effect.[6]

To estimate relevant parameters, we configure the likelihood function of the conditional probability of observing the matching value and the matched pair performance given the available data and observed matching market structure. Based on the valuation and outcome equation system, according to the error term structure, and denoting $\theta \equiv \{\alpha, \beta, \delta, \sigma_\xi\}$, the likelihood function is given by:

$$\begin{aligned}
L(V_{ij}, Y_{ij}|\theta, X, W) &= L(Y_{ij}|\theta, X, W) \times L(V_{ij}|\theta, X, W) \\
&= L(Y_{ij}|\theta, X, W) \times L(V_{ij}|\theta, X, W, ij \in \mu) \times L(V_{ij}|\theta, X, W, ij \notin \mu) \\
&= C \times \prod_{ij \in \mu} exp(-\frac{Y_{ij} - \beta X - \delta(V_{ij} - \alpha W_{ij})}{2\sigma_\xi})^2 \\
&\times \prod_{ij \in \mu} exp(\frac{V_{ij} - \alpha X_{ij}}{2})^2 \times \prod_{ij \notin \mu} exp(\frac{V_{ij} - \alpha X_{ij}}{2})^2
\end{aligned}$$

There are two different ways to estimate the coefficients. The first method assumes matching value information for observed matches, but not for unobserved matches. We can recover the valuation bound for unobserved matches from the equilibrium matching condition. The second approach is to use a Markov Chain Monte Carlo method to simulate parameters block by block conditional on all other information to recover the joint posterior distribution. I will principally defer to the first method and discuss the second method in the robustness section that follows.

Assuming we have matching value information for observed matches, from the equilibrium matching condition in Equation 1, the matching value for unobserved matches ij is upper bounded by $\overline{V_{ij}}$, which is the larger value between the observed matches $V_{i\mu(i)}$ and $V_{\mu(j)j}$.

[6] A more formal discussion about this identification strategy is provided in Sorensen (2007b).

Following Akkus et al. (2016a), the likelihood function becomes:

$$L(V_{ij}, Y_{ij}|\theta, X, W) = C \times \prod_{ij\in\mu} exp(-\frac{Y_{ij} - \beta X - \delta(V_{ij} - \alpha W_{ij})}{2\sigma_\xi})^2$$
$$\times \prod_{ij\in\mu} exp(\frac{V_{ij} - \alpha X_{ij}}{2})^2 \times \prod_{ij\notin\mu} exp(\frac{\overline{V_{ij}} - \alpha X_{ij}}{2})^2,$$

leading to an estimation procedure similar to a two-stage Heckman estimation as follows.

First, from the proxied matching value and the market equilibrium conditions, we obtain the matching value upper bounds for all of the counterfactual matches. Because the counterfactual matches cannot be blocking pairs, their matching values are upper bounded by the maximum of the opportunity cost of the agents in the counterfactual matches.

Then, in the first stage estimation, we estimate the matching equation by carrying out a censored regression for all possible matches in the market where the matching values for counterfactual matches are truncated from above at $\overline{V}_{ij}$ and the observed matches' matching value is a given value. We extract the residuals from the censored regression for use in the second stage regression.

In the second stage, we include these residuals as an additional regressor to control for unobserved characteristics, in the spirit of the Heckman selection model's second stage.

This method does not require a perfect measure for the matching value (Akkus et al., 2016b), as that value purely represents a ranking of agents' preferences. Therefore, a monotonic transformation of the matching value would not change the preference order of the agents. Therefore, a perfect measure of matching value is not needed provided the order of the matching value is reasonable.

The second advantage is that estimation complexity decreases compared with directly estimating coefficients using maximum likelihood and Markov Chain Monte Carlo methods, which makes estimating the matching model more flexible.

The main drawbacks of the generalized selection method are that the estimator is less efficient and the standard errors in the second stage are inconsistent. Therefore, we need to

obtain consistent standard errors from bootstrapping. A Monte Carlo exercise demonstrating the efficacy of the method is discussed in Appendix A.

3 Data and estimation results

3.1 Data

This paper focuses on the CEO labor market for US S&P 1500 firms. I collect CEO-firm match information when there is a succession event. I eliminate cases that involve turnover interim/acting CEOs, CEO turnover associated with mergers and full acquisitions, spin-offs, CEO turnovers involving co-CEOs, wrongly identified CEOs, new CEO tenure less than 12 months, non-listed firms and firms for which stock price information is unavailable via CRSP data. Then I use both Execucomp and Boardex datasets to identify the career path of these new CEOs and their age at the contracting year. The full sample contains 1645 S&P 1500 CEO firms matches from 1995 to 2011 as I require 5-year rest matching performance.

I divide the matches in the sample into different markets according to the calendar year that a firm hires a new CEO and assume the CEO labor market is segmented every calendar year and independent from each other as in Pan (2015). There are 17 markets with 1645 executive-firm matches. Firm standard characteristics data are taken from Compustat, and the incentive pay measures mainly derive from the method developed by Core and Guay (2002); Naveen et al. (2006). Salaries and total compensation data are from Execucomp. Table 2 presents summary statistics of model variables. Following Bennedsen et al. (2007), I use the difference between firms three-year average return on assets after the initial contracting year and firms three-year average return on assets before the initial contracting year as the main performance measure. The three-year average change in market-to-book ratio is used as the second performance measure. As many external factors might influence firm performance, for the sake of robustness I also measure the performance of the match in terms of whether the length of CEO tenure has passed a particular time, three or four

years.[7] Hence, this measure is a good alternative and complements the previous accounting and market measures of firm performance.

According to Edmans et al. (2017), there are three different measures of incentive pay that suit different assumptions about the form of the production and cost functions. As the primary performance measure is a ratio metric (return on assets or market-to-book ratio) I assume the CEO has a multiplicative effect on firm value. Also, by assuming the CEO's cost function is additive, then the best incentive pay measure is the *efficient dollar ownership*. This is measured by the change in the CEO's wealth if the firm's stock increases by 1%. Table 2 Panel B presents the natural logarithm of the new CEO's initial year incentive pay. *Salary* and *Vega* are the natural logarithms of initial year amounts. *Vega* measures new CEOs' initial risk-taking incentives as the natural logarithm of executive wealth change if the firm's annualized standard deviation of stock returns increases by 1%. *Total Pay* is the natural logarithm of the new CEO's initial year total compensation. There are three variables that capture CEOs' characteristics. *Age* measures the CEO's age at initial contracting, *male* indicates the gender of the CEO and *MBA* measures whether the CEO has an MBA degree. *Leverage* and *market-to-book* ratio both pertain to one year before the CEO-firm match year and calculated following Leary and Roberts (2014).

3.2 Naive OLS results

One could argue that other executives and external factors also influence firm performance. Therefore, in columns 5 and 6, I present results on measures with a pure CEO focus: the CEO staying in the job more than three or four years. The linear probability models show that for a 1% increase in CEOs' initial incentive pay, CEO tenures are on average 2.9% more likely to pass the three-year threshold and 4.7% more likely to pass the four-year threshold.

These results show that across different proxies for firm performance, new CEOs initial

[7] This measure is based on arguments from Allgood and Farrell (2003) and Jenter and Kanaan (2015); the CEO turnover rate drops substantially after an initial three to four year period.

incentive pay has a positive effect on firm performance. The results are significant both statistically and economically. Overall, the results provide empirical support for the positive association between new CEOs initial incentive pay and firm performance.

Unfortunately, this methodology does not allow us to distinguish between the incentive and selection effects. The incentive pay that firms provide to their CEOs also attracts better CEOs based on CEO attributes (Graham et al., 2013) and these CEO attributes are very likely to be related to firm performance. Therefore, if other dimensions of CEO attributes exist that cannot be captured and these dimensions are correlated with the choice of CEO-firm match, the estimated coefficients will be biased. Also, because of the endogenous nature of the problem, a valid instrument is hard to find. To overcome the endogeneity problem, I now turn to estimated results from the matching model and the generalized selection method.

3.3 Generalized selection method results

3.3.1 Main results

According to the estimation method discussed in Section 2, we need to have a valid proxy for the matching value of CEOs and firms. The matching value needs to represent agents' preferences over different matches. In Gabaix and Landier (2008)'s assignment model, CEOs and firms are matching on firm size. The best CEO matches with the largest firm, whilst the second best CEO matches with the second largest firm. The main measure of firm size is the firm's total market capitalization. Similarly, I use the natural logarithm of the firm's total market capitalization at the first fiscal year end after the new CEO takes the job as the proxy for the matching value. I present the estimated results of the matching equation in Table 4. Unfortunately, we cannot directly interpret the coefficients as the matching equation purely estimates the preferences of agents. However, we can still interpret the relative importance of different independent variables. In explaining matching value variation, firm size and market to book ratio are the two largest factors. Results show that incentive pay is estimated to be the third largest effect factor on matching value

variation, well above other compensation factors: compensation *Vega*, *Base salary* and *Total pay* during the first year. Hence, these results provide strong evidence for the importance of incentive pay on CEO-firm matching value. In column (2) and column (3), I split the market into two periods. During both periods, the incentive is positive, significant, and of similar magnitude. This indicates agents' incentive preferences do not change much over time. Comparing the matching equation estimation in the two periods, another interesting finding is that the coefficient associated with CEO compensation *Vega* is still significant during the first half of the sample period 1995 to 2004. However, during the second half of the sample period, *Vega* not only decreases in magnitude but also becomes insignificant. This finding indicates incentive pay is important and stable through time, but compensation *Vega* is less so.

After estimating the censored regression, I extract the residuals and add them into the outcome equation to control for selection. Table 5 shows the coefficients estimated from the outcome equation. These estimated coefficients control for the endogenous matching between firms and CEOs with the matching equation from Table 4 Column (1). In all cases, the coefficient associated with *Incentive pay* is positive and significant but smaller than the corresponding OLS estimated coefficients in Table 3 from column (1)-(3). The difference is controlled by including the matching residual in the regression. In all cases, coefficients associated with *Matching residual* are positive and significant. This indicates that unobserved agents' characteristics have an effect on matching values and also on matching outcomes. This highlights the key point of the paper: controlling for matching is crucial given its large quantitative effect. Lastly, comparing model R^2 between the OLS regression and the outcome equation after controlling for matching, we can observe that R^2 in Table 5 column (1)-(3) increases by 150%, 19%, and 11.5% respectively. These results show that the pattern of matching is particularly informative about the variation in firm performance.

In Panel B, I test for coefficient differences between the naive OLS regression and the matching corrected outcome equation. In all cases, the effect of CEO incentives on firm

performance decreases by more than 10% in economic magnitude and the difference is statistically significant. The total effect of a 1% increase in CEO incentive pay is a 1.72% increase in firm performance (Table 3 column (3)), divided between an incentive effect of 1.51% and a selection effect of 0.21%. Therefore, the selection effect accounts for 12.7% of the total effect, whilst the incentive effect dominates with 87.3%.

3.3.2 Outcome equation time trend estimation

In Table 4, I show that agents' matching value preferences change over time. Therefore, the influence of these characteristics on firm performance could also evolve. In Table 6, I estimate the OLS regression and the outcome equation with matching residuals over two different periods. In columns (1) and (2) I estimate the model during the first half of the total sample period from 1995 to 2004. In columns (3) and (4) I estimate the model during the second half of the total sample period from 2005 to 2011. During the first half the sample period, the coefficient associated with matching residuals is insignificant, thus the difference between the incentive pay coefficients is trivial. Therefore, in the early years, the estimated selection effect is very weak. During the second half of the sample period, the coefficient associated with matching residuals is positive and significant. The difference between the incentive pay coefficients in the naive OLS and matching corrected outcome equation is 18% of the total effect estimated in the naive OLS regression. This result highlights that, over time, the selection effect becomes more pronounced. The total effect of the incentive on firm performance increases by 57%, although the relative magnitude of the selection effect more than triples, increasing from 5.47% to 18% of the total effect. The absolute effect increases 5-fold.

There are two potential and plausible explanations for this increase in the selection effect over time. The first explanation relates to increased monitoring by boards of directors following the passage of the SarbanesOxley Act, as well as the 2004 NYSE and NASDAQ listing rules strengthening board and committee independence. After 2004, the listing rules

changed. US public traded firms need to have a majority of independent directors and full independence in nomination, compensation, and auditing committees. Because independent directors are on average more likely to serve as monitors of executives, the post-rule change period is associated with an increase in board monitoring (Knyazeva et al., 2013; Guo and Masulis, 2015). This increase in monitoring substitutes away the need for the incentive effect. Therefore, the relative importance of the selection effect increases. The second explanation relates to the competition for talent hypothesis. Murphy and Zabojnik (2004); Custódio et al. (2013) show that the increasing importance of general ability leads to an increase in market competition for talent. Because general ability increases the talent mobility between firms, the demand for top talent increases because more and more firms are competing for the same talent. More importantly, because of the multiplicative effect of CEOs' talent, especially CEOs' general ability, increasing numbers of large firms are involved in competing for talent. Larger firms are also more likely to provide high incentive pay; therefore, CEOs with the same level of talent are more likely to match with higher incentive pay in more recent years compared to earlier times. This also leads to an increase in the relative importance of the selection effect.

3.3.3 Industry competition

The foregoing results suggest that the selection effect of incentive pay is not trivial in influencing firm performance. We expect this effect to be stronger in industries that exhibit a higher degree of talent competition. In Panel A of Table 7, I show the degree of CEO talent competition in different Fama-French 5 industries. Similar to Cremers and Grinstein (2014), I measure CEO talent competition as the percentage of new CEOs that an industry hired from outside the firm from 1995 to 2011. During the sample period, 36% of the new CEOs hired in *HiTec* industry are from outside of the firm. Other industries' external CEO hire rates are all below 30%, much lower than the *HiTec* industry. Therefore, I would expect the selection effect is stronger in *HiTec* than in other industries. In Panel B, I estimate naive

OLS regressions and corresponding matching corrected outcome equations for *Non-HiTec* and *HiTec* industries respectively. From the estimated results, the selection effects on firm performance in *Non-HiTec* industries are small both in terms of economic magnitude and statistical significance. The selection effect accounts for almost 20% of the total effect in *HiTec* industry.

Overall, the estimation results show that both the incentive effect and the selection effect of CEO's initial incentive pay on firm performance are important. The incentive effect accounts for 87% of the total effect and the selection effect accounts for 13% of the total effect. Increased monitoring and more intense talent competition both increase the importance of the selection effect.

4 Robustness

4.1 Alternative matching value proxies

According to Gabaix and Landier (2008), the firm's market capitalization is a good proxy for CEO-firm matching value. However, the findings could still be sensitive to the choice of value measure on CEO-firm matching. In this section, I use the market-to-book ratio as a new proxy for matching value to investigate the sensitivity of matching value choices on outcome equation estimates.

The firm market-to-book ratio offers a good alternative when it is valid to argue that firms and CEOs have a long horizon and all prefer high growth potential to current large size. Therefore, future benefits are more important. In Table 8, I use firms' fiscal year-end market-to-book ratio after the match with their new CEOs. Compared with column (1) in Table 5 and Table 8, overall, results remain similar but with some minor changes in the magnitude of coefficients associated with matching residuals and the corresponding R^2s; both values become larger. These findings indicate that using the market to book ratio as a proxy for matching value might offer more matching specific information that influences

firm performance.

4.2 Alternative performance measures

In the above analysis, the main measure of firm performance is the change in industry-adjusted return on assets during CEO succession. If CEOs can manipulate accounting numbers, return on assets might not accurately reflect firm performance; therefore, here I use firm value as a performance measure.

I estimate a matching corrected outcome equation that uses three years change in market-to-book ratio as the performance measure in Table 9 column (1). The first stage matching equation is the same as in Table 4 column (1). The coefficient associated with matching residuals is also positive and significant. The difference in incentive effect is 0.05, which accounts for 9% of the total effect of incentives on firm value.

Next, we focus on an internal measure of CEO performance: CEO tenure. I use a dummy variable to capture whether the CEO's tenure passes three years or four years, given that a typical CEO employment agreement's term is three years with automatic extension for one more year if mutually agreed between the CEO and the firm. I examine the effect of incentive pay on CEO tenure in Table 9 Column (2) and (3). The coefficients of matching residuals are both positive and significant with slightly less importance attributable to the selection effect. In all cases, using a matching model to correct for selection is necessary.

4.3 Markov Chain Monte Carlo

One drawback of this generalized selection method is that if the measurement errors associated with matching value increase, the coefficient associated with the matching residuals in the second stage will suffer from attenuation bias. Therefore, the coefficient is less reliable and should be interpreted with caution.

In this section, I explore robustness to an alternative estimation method that does not involve finding proxies for matching value. Assuming the matching value for observed matches

cannot be observed and the joint distribution of $(\varepsilon_{ij}, \eta_{ij})$ is independent for different matches and follows the bivariate normal distribution:

$$\begin{pmatrix} \varepsilon_{ij} \\ \eta_{ij} \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\varepsilon^2 & \delta \\ \delta & 1 \end{pmatrix} \right],$$

We can use a full information estimator to estimate the coefficients. There are two ways to estimate this full information estimator: maximum likelihood and Markov Chain Monte Carlo (MCMC). The maximum likelihood method is computationally intensive because of the matching nature of the problem. For illustrative purposes, I compare MCMC to the Heckman selection model.

Recall that the selection function for a Heckman selection model is a simple probit model and error terms are independent of each other. Assuming a Heckman selection model with a similar form to the matching model:

$$V_i = \alpha W_i + \eta_i,$$
$$Y_i = \beta X_i + \varepsilon_i,$$

and agent i will be selected if $V_i > 0$ and Y_i can only be observed when $V_i > 0$. Error terms are jointly normally distributed with zero mean and correlation of δ. Then the probability of agent i being selected is:

$$\begin{aligned} Pr(V_i > 0|W_i) &= Pr(\eta_i > -\alpha W_i|W_i) \\ &= \int 1[\eta_i > -\alpha W_i] dF(\eta_i), \end{aligned}$$

thus the likelihood function of the selection equation can be written as:

$$L = \prod_{i=1}^{N_0} \int 1[\eta_i \leq -\alpha W_i] dF(\eta_i) \prod_{i=N_0+1}^{N} \int 1[\eta_i > -\alpha W_i] dF(\eta_i),$$

where we assume N total observations and N_0 observations cannot be observed. The likelihood function can factor into a product over the likelihood of each observation's selection choice because one agents decision is independent of others' decisions. However, in the matching model, the probability that a pair ij is matched:

$$\begin{aligned} Pr(V_{ij} > \underline{V_{ij}}|W_{ij}) &= Pr(\eta_{ij} > \underline{V_{ij}} - \alpha W_{ij}|W_{ij}) \\ &= \int 1[\eta_{ij} > \underline{V_{ij}} - \alpha W_{ij}]dF(\eta_{ij}), \end{aligned}$$

where, from the equilibrium characterization $\underline{V}_{ij}$ also depends on other agents' characteristics in the market, as $\underline{V}_{ij}$ depends on other agents' characteristics in the market and error terms are correlated with each other. Therefore, this simple probability becomes high dimensional:

$$Pr(V_{ij} > \underline{V_{ij}}|W_{ij}) = \int\int ... \int 1[\eta_{ij} > \underline{V_{ij}} - \alpha W_{ij}]dF(\eta_{ij})dF(\eta_{ij+1})dF(\eta_{i+1j})...,$$

this makes the likelihood function high dimensional integration and it cannot be factored out compared with the situation in the Heckman selection model. Solving the integration directly is not computationally feasible. To circumvent this complexity, I defer to a Bayesian method. Based on a Gibbs sampling algorithm and data augmentation (Tanner and Wong, 1987; Albert and Chib, 1993), the method simulates parameters block by block conditional on all other information to recover the joint posterior distribution. This transforms an integration problem into a simulation problem and reduces the computational complexity substantially. The detailed estimation procedure is discussed in the Appendix B.

The matching equation estimation results under MCMC are presented in Table 10 Column (2). The coefficient associated with Incentive is positive and significant, thus firms providing higher incentives have higher matching value and are on average more attractive to CEOs. Firms providing high incentives could be firms with better sources or larger capacities; working for these types of firms could make it easier for CEOs to transfer their abilities to real productivity. Table 10 Column (1) shows the coefficients estimated from

the outcome equation. These estimated coefficients are controlled for endogenous matching between firms and CEOs. The coefficients associated with Incentive are positive and significant and of a similar magnitude as in Table 9 Column (1). δ is the correlation between unobservables between the outcome and valuation equations. This positive and significant result also indicates the necessity to control for endogenous matching.

Overall, the findings in the main analysis are robust to alternative matching value proxies, alternative CEO labor market definitions, different performance measures and alternative estimation methods.

5 Conclusion

This paper finds that higher initial CEO incentive pay is associated with better performance. To disentangle the incentive and selection effects from incentive pay, I estimate a matching model to control for the selection effect. In that model, matching decisions not only depend on matched agents characteristics but also on other agents characteristics in the market. This method circumvents the need to identify instrumental variables in studying CEO-firm matching. These other agents characteristics have an effect on matching decisions but not on the final output of the matching; this feature provides exogenous variation in identifying the outcome equation.

In the sample of 1645 CEO-firm matches from 1995 to 2011, both the incentive effect and selection effect have significantly influence firm performance. The incentive and selection effects account, respectively, for 87.3% and 12.7% of the total incentive pay effect on performance. The selection effect becomes more pronounced after 2004, when governance monitoring and talent mobility both started to increase. The selection effect is also stronger in the *HiTec* industry where CEO talent competition is severe.

The results in this paper have important policy implications in terms of how best to regulate CEO incentive pay. For instance, in regulating CEO incentives, regulators should

not only examine the incentive effect but also be aware of the existence of the selection effect. A simple incentive cap might have unintended consequences that serve to decrease the supply of top talents.

Table 1. Demonstration example

This example is configured in terms of a matching market consisting of three CEOs (1, 2, 3) and three firms (A, B, C) to visualize the estimation method for separating the selection effect from the incentive effect. Panel A shows the stable matching values between firms and CEOs for all possible matches. The three matches in the diagonal are observed matches and the off-diagonal matches are counterfactual matches. The matching values are determined by the characteristics of the agents forming the matches. Panel C shows the final outcomes of the observed matches. These final outcomes are also dependent on matching agents' characteristics.

Panel A: Observed matches

		Firms		
		A	B	C
	1	10	NA	NA
CEOs	2	NA	20	NA
	3	NA	NA	30

Panel B: All matches

		Firms		
		A	B	C
	1	10	(-inf, 20)	(-inf, 30)
CEOs	2	(-inf, 20)	20	(-inf, 30)
	3	(-inf, 30)	(-inf, 30)	30

Panel C: Performance

		Firms		
		A	B	C
	1	2	NA	NA
CEOs	2	NA	5	NA
	3	NA	NA	8

Table 2. Summary Statistics

This table presents summary statistics for US S&P 1500 firm-CEO matches from 1995 to 2011. Panel A reports the number of firm-CEO matches in each calendar year. Panel B reports summary statistics for firms' and CEOs' characteristics. Age measures the age of CEOs when they are initially matched with firms. Male indicates whether the CEO's gender is male. MBA captures whether the CEO has an MBA degree. Incentive pay is the natural logarithm of the CEOs wealth increase when the firm's stock price increases by 1% during the first fiscal year following the match. Vega is the natural logarithm of the CEOs wealth increase when the firm's stock volatility increases by 1% during the first fiscal year following the match; it measures the CEO's risk taking incentive. Salary is the natural logarithm of the CEOs base salary in the first fiscal year following the match. Total Pay is the natural logarithm of the CEO's total compensation in the first fiscal year. Firm size is the natural logarithm of total assets one fiscal year before the match. Leverage and market-to-book ratio are calculated following Leary and Roberts (2014).

Panel A: Number of matches per year	
Turnover year	Number of matches
1995	67
1996	62
1997	69
1998	75
1999	102
2000	128
2001	127
2002	93
2003	92
2004	99
2005	117
2006	98
2007	127
2008	128
2009	102
2010	85
2011	74

Panel B: Summary statistics					
Variable	Observation	Mean	Std. dev.	Min.	Max.
Age	1645	52.37	6.732	32	80
Male	1645	0.970	0.172	0	1
MBA	1645	0.388	0.487	0	1
Incentive pay	1645	4.498	1.514	0	10.692
Vega	1645	3.448	1.616	0	7.890
Salary	1645	6.234	0.783	0	7.664
Total Pay	1645	7.938	1.261	6.428	11.410
Firm size	1645	7.314	1.649	0	12.905
Leverage	1645	0.234	0.225	0	3.466
Market to book	1645	1.573	1.528	0.039	28.567

Table 3. Performance as a function of incentive pay in naive OLS regression

This table presents naive OLS coefficient estimates showing that new CEOs initial incentive pay is positively associated with different performance measures. The dependent variables are different measures of firm performance. In columns (1)-(3), firm performance is defined as industry-adjusted ROA. In column (4), firm performance is defined as industry-adjusted Market-to-book ratio. In columns (5)-(6), firm performance is defined as an indicator variable equal to one if the new CEO passes a minimum tenure. Changes in profitability and firm value are computed as differences between average three-year post-succession performance minus the three-year pre-succession average. The year of succession is omitted. ROA and market-to-book ratio are defined following Leary and Roberts (2014). Incentive pay is the new CEO's first year incentive pay, measured as the natural logarithm of the CEO's wealth increase if firm value increases by 1%. Other control variables are defined in Table 2. Robust T-statistics are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Dependent variable: firm performance					
	Δ ROA			Δ MtB	CEO minimum tenure	
					3 years	4 years
	(1)	(2)	(3)	(4)	(5)	(6)
Incentive pay	0.006***	0.010***	0.010***	0.055***	0.029***	0.047***
	(3.728)	(3.097)	(3.306)	(2.604)	(3.418)	(4.714)
Age		-0.001	-0.001	-0.007	-0.006***	-0.011***
		(-1.512)	(-1.644)	(-0.932)	(-4.264)	(-6.448)
Male		0.007	0.008	-0.096	0.059	0.073
		(0.569)	(0.636)	(-0.884)	(1.116)	(1.211)
MBA		0.006	0.002	0.062	-0.003	0.025
		(1.181)	(0.468)	(1.029)	(-0.204)	(1.225)
Total Pay		-0.001	-0.002	0.002	0.006	-0.002
		(-0.420)	(-0.547)	(0.053)	(0.487)	(-0.124)
Salary		0.000	-0.000	0.041	0.033*	0.057***
		(0.110)	(-0.130)	(0.999)	(1.867)	(3.424)
Vega		-0.006***	-0.004*	-0.068***	-0.015**	-0.016*
		(-2.972)	(-1.750)	(-2.588)	(-1.979)	(-1.690)
Firm size		0.001	-0.000	0.028	-0.001	-0.010
		(0.345)	(-0.064)	(0.646)	(-0.130)	(-1.078)
Book leverage		0.088*	0.082	0.551	0.034	0.055
		(1.755)	(1.547)	(0.923)	(0.906)	(1.332)
Market-to-book		0.004	0.004	-0.040	-0.014**	-0.011
		(0.832)	(0.746)	(-0.468)	(-1.967)	(-1.465)
Industry FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
Location FE	No	No	Yes	Yes	Yes	Yes
Observations	1,599	1,599	1,599	1,441	1,645	1,645
R-squared	0.008	0.058	0.104	0.077	0.063	0.091

Table 4. Matching equation estimation

This table presents censored regression coefficient estimates of the matching equation. Matching values of observed matches are measured by the natural logarithm of firm-level market capitalization at the first fiscal year end after the new CEO has been hired. The censored regression includes all observed CEO-firm matches and all counterfactual CEO-firm matches. Coefficient estimates in columns (1)-(3) pertain to censored regressions under the full 1995-2011 sample, the 1995-2004 sub-sample, and the 2005-2011 sub-sample, respectively. Incentive pay is the new CEO's first year incentive pay, measured as the natural logarithm of the CEO's wealth increase if the firms value increases by 1%. Other control variables are defined in Table 2. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Dependent variable: Market cap		
	1995-2011	1995-2004	2005-2011
	(1)	(2)	(3)
Incentive pay	0.249***	0.255***	0.238***
	(18.713)	(14.930)	(11.048)
Age	0.004*	0.003	0.004
	(1.926)	(1.339)	(1.491)
Male	0.107	0.146	0.078
	(1.366)	(1.194)	(0.778)
MBA	0.014	0.013	0.014
	(0.503)	(0.340)	(0.362)
Salary	0.049**	0.036	0.063
	(2.181)	(1.414)	(1.386)
Vega	0.045***	0.063***	0.018
	(3.569)	(3.251)	(1.031)
Total Pay	0.051***	0.040*	0.063**
	(3.061)	(1.793)	(2.350)
Firm size	0.548***	0.535***	0.576***
	(41.705)	(31.444)	(27.393)
Book leverage	-0.526***	-0.287***	-0.745***
	(-8.630)	(-2.811)	(-8.050)
Market-to-book	0.177***	0.182***	0.204***
	(22.462)	(16.228)	(15.492)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes
Observations	167,461	88,550	78,911

Table 5. Main results

Panel A presents outcome equation estimation results on firm performance adding the matching residuals in the regression. The dependent variable is defined as post-succession industry-adjusted ROA minus the three-year pre-succession average. The year of succession is omitted. The three different specifications are comparable with columns (1)-(3) in Table 3. The matching residuals are computed from Table 4 column (1). Panel B provides Hausman test results concerning differences in incentive pay coefficients and the relative change in magnitude after adding the matching residuals. Incentive pay is the new CEO's first year incentive pay, measured as the natural logarithm of the CEO's wealth increase if firm value increases by 1%. Matching residuals are extracted from the first stage censored regression. Other control variables are defined in Table 2. Bootstrapped Z-statistics are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Outcome equation estimation			
	Dependent variable: Δ ROA		
	(1)	(2)	(3)
Incentive pay	0.004**	0.008***	0.009***
	(2.169)	(2.760)	(3.282)
Age		-0.001	-0.001
		(-1.085)	(-1.391)
Male		0.006	0.007
		(0.444)	(0.475)
MBA		0.007	0.003
		(1.467)	(0.670)
Total Pay		-0.002	-0.002
		(-0.586)	(-0.586)
Salary		0.001	-0.000
		(0.133)	(-0.120)
Vega		-0.006***	-0.004
		(-2.578)	(-1.520)
Firm size		-0.001	-0.003
		(-0.191)	(-0.727)
Book leverage		0.089	0.084*
		(1.453)	(1.720)
Market-to-book		0.003	0.003
		(0.557)	(0.460)
Matching residual	0.016***	0.016***	0.017***
	(3.408)	(2.655)	(3.499)
Industry FE	No	No	Yes
Year FE	No	No	Yes
Location FE	No	No	Yes
Observations	1,599	1,599	1,599
R-squared	0.020	0.069	0.116

Panel B: Changes in Incentive pay's coefficients			
Difference	0.0025***	0.0011**	0.0013**
Relative change	40.9%	11.8%	12.7%

Table 6. Outcome equation estimation time trend

This table shows the results of estimating the outcome equation including matching residuals over time. Columns (1) and (3) contain OLS regression coefficient estimates. Columns (2) and (4) pertain to second stage regressions after estimating sub-period censored regressions in Table 4 columns (2) and (3), respectively. The dependent variable is defined as post-succession industry-adjusted ROA minus the three-year pre-succession average. The year of succession is omitted. Incentive pay is the new CEO's first year incentive pay, measured as the natural logarithm of the CEO's wealth increase if firm value increases by 1%. Matching residual is the residual extracted from the first stage censored regression of estimating the matching equation. Other control variables are defined in Table 2. Bootstrapped Z-statistics are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Dependent variable: Δ ROA			
	1995-2004		2005-2011	
	Naive OLS	Outcome equation	Naive OLS	Outcome equation
	(1)	(2)	(3)	(4)
Incentive pay	0.009**	0.008**	0.014**	0.011**
	(2.287)	(2.264)	(2.562)	(2.008)
Age	-0.001**	-0.001**	-0.000	0.000
	(-2.094)	(-2.448)	(-0.116)	(0.239)
Male	-0.007	-0.007	0.014	0.010
	(-0.372)	(-0.349)	(0.761)	(0.512)
MBA	0.009	0.010	-0.007	-0.007
	(1.291)	(1.297)	(-0.928)	(-0.927)
Total Pay	-0.004	-0.004	0.001	-0.000
	(-0.693)	(-0.642)	(0.141)	(-0.071)
Salary	-0.001	-0.001	0.001	0.001
	(-0.145)	(-0.172)	(0.097)	(0.078)
Vega	-0.004	-0.004	-0.005*	-0.005
	(-1.224)	(-0.853)	(-1.860)	(-1.541)
Firm size	0.004	0.003	-0.006	-0.011*
	(0.903)	(0.741)	(-1.194)	(-1.885)
Book leverage	0.058*	0.060**	0.089	0.087
	(1.871)	(2.434)	(1.027)	(1.115)
Market-to-book	0.002	0.002	0.004	0.002
	(0.580)	(0.636)	(0.273)	(0.165)
Matching residual		0.007		0.030***
		(1.095)		(2.707)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Observations	883	883	716	716
R-squared	0.129	0.131	0.105	0.139

Table 7. Talent competition

This table presents split sample estimation results based on CEO talent competition at the Fama-French 5 industry level. Panel A shows the rate at which new CEOs are hired from outside the firm in a specific Fama-French 5 industry. Columns (1) and (3) in Panel B are OLS regression coefficient estimates. Columns (2) and (4) pertain to second stage regressions after estimating sub-sample censored regressions in different industries. The dependent variable is post-succession industry-adjusted ROA minus the three-year pre-succession average. The year of succession is omitted. Incentive pay is the new CEO's first year incentive pay, measured as the natural logarithm of the CEO's wealth increase if firm value increases by 1%. Matching residual is the residual extracted from the first stage censored regression of the estimating matching equation. Other control variables are defined in Table 2. Bootstrapped Z-statistics are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Panel A: Talent competition within industries	
	External hire rate	Fama-French 5 industry
Highest	36%	HiTec
	29%	Cnsmr
	26%	Manuf
	25%	Hlth
Lowest	24%	Other

	Panel B: Regressions on different industries			
	Dependent variable: Δ ROA			
	Non-HiTec industies		HiTec industy	
	Naive OLS	Outcome equation	Naive OLS	Outcome equation
	(1)	(2)	(3)	(4)
Incentive pay	0.006**	0.005**	0.028**	0.023**
	(2.084)	(2.104)	(2.243)	(1.968)
Matching residual		0.006		0.047***
		(1.370)		(2.702)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Observations	1,280	1,280	319	319
R-squared	0.066	0.070	0.333	0.371

Table 8. Robustness: alternative matching value proxy

This table presents the estimation results for both matching and outcome equations using the fiscal year end market-to-book ratio after succession as a proxy for matching value. Column (1) estimates a censored regression for all potential matches in markets. Columns (2)-(4) estimate the outcome equation together with the Matching residual to control for endogenous matching. The dependent variable is defined as post-succession industry-adjusted ROA minus the three-year pre-succession average. The year of succession is omitted. Incentive pay is the new CEO's first year incentive pay, measured as the natural logarithm of the CEO's wealth increase if firm value increases by 1%. Matching residual is the residual extracted from the first stage censored regression. Other control variables are defined in Table 2. Bootstrapped Z-statistics are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Matching equation	Outcome equation estimation		
		Δ ROA		
	(1)	(2)	(3)	(4)
Incentive pay	0.125***	0.003*	0.007**	0.008**
	(8.634)	(1.682)	(2.190)	(2.563)
Age	-0.006***		-0.001**	-0.001**
	(-2.638)		(-1.961)	(-2.570)
Male	0.007		0.007	0.007
	(0.076)		(0.452)	(0.518)
MBA	-0.003		0.003	-0.000
	(-0.083)		(0.645)	(-0.020)
Salary	-0.009		0.001	-0.000
	(-0.365)		(0.269)	(-0.089)
Vega	-0.030**		-0.006***	-0.003
	(-2.168)		(-3.550)	(-1.373)
Total Pay	-0.013		-0.003	-0.003
	(-0.834)		(-0.705)	(-0.825)
Firm size	-0.041***		0.004	0.003
	(-3.071)		(1.155)	(0.957)
Book leverage	0.458***		0.081**	0.075*
	(5.800)		(2.158)	(1.747)
Market-to-book	0.380***		-0.008	-0.009
	(33.449)		(-1.176)	(-1.281)
Matching residual		0.025*	0.032**	0.034**
		(1.802)	(2.516)	(2.082)
Industry FE	Yes	No	No	Yes
Year FE	Yes	No	No	Yes
Location FE	Yes	No	No	Yes
Observations	164,330	1,570	1,570	1,570
R-squared		0.061	0.113	0.160

Table 9. Robustness: alternative outcome variables

This table presents the estimation results for the outcome equation under different performance measures using fiscal year-end total market capitalization after succession as a proxy for matching value. The dependent variable in column (1) is defined as post-succession industry-adjusted market-to-book ratio minus the three-year pre-succession average. The year of succession is omitted. The dependent variable in columns (2) and (3) captures whether the new CEOs tenure lasts for at least 3 years, or 4 years, respectively. The year of succession is omitted. Incentive pay is the new CEO's first year incentive pay, measured as the natural logarithm of the CEO's wealth increase if firm value increases by 1%. Matching residual is the residual extracted from the first stage censored regression. Other control variables are defined in Table 2. Bootstrapped Z-statistics are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Δ MTB	CEO minimum tenure	
		3 years	4 years
	(1)	(2)	(3)
Incentive pay	0.050***	0.026**	0.044***
	(2.559)	(2.507)	(5.174)
Age	-0.007	-0.006***	-0.010***
	(-1.127)	(-4.552)	(-5.555)
Male	-0.091	0.057	0.071
	(-0.961)	(1.253)	(1.506)
MBA	0.057	-0.001	0.026
	(1.162)	(-0.069)	(1.218)
Total Pay	0.004	0.005	-0.003
	(0.076)	(0.393)	(-0.235)
Salary	0.042	0.034*	0.057***
	(1.058)	(1.775)	(3.460)
Vega	-0.049***	-0.014*	-0.015
	(-2.728)	(-1.756)	(-1.475)
Firm size	0.039	-0.007	-0.015*
	(0.809)	(-0.887)	(-1.650)
Book leverage	0.544	0.036	0.057
	(0.917)	(0.838)	(1.425)
Market-to-book	-0.035	-0.016*	-0.013
	(-0.348)	(-1.808)	(-1.616)
Matching residual	0.075***	0.041***	0.032**
	(2.863)	(2.761)	(2.448)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes
Observations	1,441	1,645	1,645
R-squared	0.079	0.070	0.094

Table 10. MCMC estimation results

The table presents Bayesian parameter estimates for the two equations in the structural model. The dependent variable in the outcome equation is the average market-to-book ratio change three years after CEO succession to three years before CEO succession. The dependent variable in the matching equation is the latent valuation variable. Coefficient magnitudes in the matching equation are not interpretable in economic terms because they represent preferences. Estimations are based on 200,000 simulations of the posterior distribution. The initial 100,000 simulations are discarded for burn-in. T-statistics are in parentheses.

	Dependent variable: Δ ROA	
	Outcome equation	Matching equation
	(1)	(2)
Incentive pay	0.007**	0.447***
	(2.532)	(3.501)
Age	-0.007	0.004***
	(-1.127)	(4.762)
Male	-0.091	0.009
	(-0.961)	(0.597)
MBA	0.057	0.003
	(1.162)	(0.629)
Total Pay	0.004	0.735***
	(0.076)	(2.776)
Salary	0.042	-0.263***
	(1.058)	(-2.607)
Vega	-0.049***	-0.302***
	(-2.728)	(-3.889)
Firm size	0.039	0.232***
	(0.809)	(3.264)
Book leverage	0.544	-0.549
	(0.917)	(-1.110)
Market-to-book	-0.035	0.540***
	(-0.348)	(3.764)
δ	0.054***	
	(3.352)	
Industry yummy	Yes	Yes
Location dummy	Yes	Yes

A Monte Carlo Exercise

This section presents a Monte Carlo exercise to demonstrate the effectiveness of the two-step estimation method. The simulated dataset contains one single market where 500 CEOs and 500 firms are the participants. Each agent exhibits only one observed characteristic. Matching values and all possible outcomes of matched pairs are generated from the equation system that:

$$V_{ij} = \beta_c XC_i + \beta_f XF_j + \eta_{ij},$$
$$Y_{ij} = \alpha_c XC_i + \alpha_f XF_j + \varepsilon_{ij},$$

where $\varepsilon_{ij} = \delta\eta_{ij} + \xi_{ij}$. In the equation system, all agents' characteristics: XC_i, XF_j, η_{ij} and ε_{ij} are drawn from a normal distribution that $N(0, 4)$. The true coefficients in the equation system are set as follows: $\beta_c = 2$, $\beta_f = 4$, $\alpha_c = 2$, $\alpha_f = 1$ and $\delta = 0.5$. The simulated dataset contains the matching values and outcomes of all possible matches. To determine a stable match, I adapt the following top-down elimination algorithm.

In the first step, I find the maximum matching value in the market and the corresponding CEO and firm ID. In the market there are no blocking pairs that can block this match, thus the match pair that generates the maximum matching value much be stable.

In the second step, assuming CEO i and firm j generate the maximum matching value, I eliminate all matches containing CEO i or firm j.

Then, for the remaining matches in the market I repeat the algorithm from the first step until there is only one match existing in the market. Finally, I collect all of the matches selected from these iterations and form the stable match.

Table A1. Single market Monte Carlo exercises

This table presents biased OLS regression and matching corrected regression coefficient estimates based on a simulated dataset containing 500 CEOs and 500 firms in one single market. Simulated stable matching is generated from the top-down elimination algorithm. Column 1 shows the true values for each coefficient. Column 2 shows the biased OLS coefficient estimates ignoring matching correction. Column 3 represents the matching corrected estimation results with bootstrapped standard errors. Z-values are presented in parentheses.

	True value	Biased OLS	Matching corrected result
	(1)	(2)	(3)
α_c	2	1.732***	2.041***
		(11.15)	(11.82)
α_f	1	1.331***	1.003***
		(8.98)	(5.87)
β_c	2	1.322***	1.925***
		(-1.521)	(31.25)
β_f	4	4.702***	4.061***
		(44.20)	(66.88)
δ	0.5		0.512***
			(6.79)

B MCMC Estimation

To simplify notation, assuming there are four equations in the econometric model:

$$V_{ij} = W'_{ij}\alpha + \eta_{ij},$$

$$Y_{ij} = X'_{ij}\beta + \varepsilon_{ij},$$

$$\varepsilon_{ij} = \eta_{ij}\delta + \xi_{ij},$$

What we observe: W_{ij}, X_{ij}, μ_{ij}; Y_{ij} if $ij \in \mu$

Latent variables: V_{ij}, Y_{ij} if $ij \notin \mu$;

Coefficients: α, β, δ.

Let's assume θ contains all the parameters in the model, $\theta \equiv (\alpha, \beta, \delta)$.

I assume that the prior distribution that $\alpha_0 \sim N(0, 10I)$, $\beta_0 \sim N(0, 10I)$ and $\delta_0 \sim N(0, 10)$.

B.1 Conditional posterior distribution

The joint density of the latent variables conditional on the exogenous variables and the parameters is as follows:

$$\begin{aligned} p(V_m, Y_m|\theta, X_m, W_m) &= p(V_m|\theta, X_m, W_m) \times p(Y_m|V_m, \theta, X_m, W_m) \\ &= C \times \prod_{ij \in M_m} exp(-\frac{(V_{ij} - W'_{ij}\alpha)^2}{2}) \\ &\times \prod_{ij \in \mu_m} exp(-\frac{(Y_{ij} - X'_{ij}\beta - (V_{ij} - W'_{ij}\alpha)\delta)^2}{2}) \end{aligned} \tag{5}$$

If the markets are independent, then the product of $p(V_m, Y_m|\theta, X_m, W_m)$ for m =1,2,...M gives the joint density $p(V, Y|\theta, X, W)$ for all markets. The augmented posterior density is:

$$\begin{aligned} p(V, Y, \theta|S, \mu, X, W) = C \times p(\theta) \times 1[\delta \geq 0] \times \prod_{m=1}^{M} (1[Y_m \in \Gamma_{S_m}] \\ \times 1[V_m \in \Gamma_{\mu_m}] \times p(V_m, Y_m|\theta, X_m, W_m)). \end{aligned} \tag{6}$$

B.1.1 Conditional posterior distribution of Outcome variables

The following equations are conditional augmented posterior density functions for each latent variable.

$$\pi(Y_{ij}|V, Y_{-ij}, \theta, S, \mu, W, X|) = C \times exp(-\frac{(Y_{ij} - X'_{ij}\beta - (V_{ij} - W'_{ij}\alpha)\delta)^2}{2}) \tag{7}$$

The above density function represents a normal distribution $N(X'_{ij}\beta + (V_{ij} - W'_{ij}\alpha)\delta, 1)$

B.2 Conditional posterior distribution of Valuation variables

When executive j and firm i are not matched, the conditional augmented posterior density function of V_{ij} is:

$$\pi(V_{ij}|V_{-ij}, Y, \theta, S, \mu, W, X|) = C \times 1[V_{ij} \leq \bar{V_{ij}}] \times exp(-\frac{(V_{ij} - W'_{ij}\alpha)^2}{2}) \tag{8}$$

Then $V_{ij} \sim N(W'_{ij}\alpha, 1)$ and truncated above at $\overline{V}_{ij}$.

When executive j and firm i are matched, then we need to consider the correlation between the error terms. According to the bivariate normal distribution of $(\varepsilon_{ij}, \eta_{ij})$, we have:

$$\begin{aligned}\pi(V_{ij}|V_{-ij}, Y, \theta, S, \mu, W, X|) = C \times 1[V_{ij} \geq \underline{V}_{ij}] \\ \times exp(-\frac{(V_{ij} - W'_{ij}\alpha - \frac{(Y_{ij} - X'_{ij}\beta)\delta}{1+\delta^2})^2}{2 \times \frac{1}{1+\delta^2}})\end{aligned} \tag{9}$$

Then $V_{ij} \sim N(W'_{ij}\alpha + \frac{(Y_{ij} - X'_{ij}\beta)\delta}{1+\delta^2}, \frac{1}{1+\delta^2})$ and truncated below at $\underline{V}_{ij}$.

B.3 Conditional distribution of Parameters

According to Bayes' rule, we have:

$$
\begin{aligned}
p(\alpha|V,Y,\beta,\delta,S,\mu,X,W) &\propto p_0(\alpha)\times p(V,Y|\alpha,\beta,\delta,S,\mu,X,W)\\
&= C\times p_0(\alpha)\times\prod_{m=1}^{N}(\prod_{ij\in M_m} exp(-\frac{(V_{ij}-W'_{ij}\alpha)}{2})\\
&\times\prod_{ij\in\mu_m} exp(-\frac{(Y_{ij}-X'_{ij}\beta-(V_{ij}-W'_{ij}\alpha)\delta)^2}{2}))\\
&= C\times exp[-\frac{\frac{1}{\sum_\alpha}(\alpha-\bar{\alpha})^2}{2}-\sum_{m=1}^{n}\sum_{ij\in M_m}\frac{W'_{ij}W_{ij}}{2}(\alpha-W_{ij}^{-1}V_{ij})\\
&-\sum_{m=1}^{n}\sum_{ij\in\mu_m}\frac{\delta^2W'_{ij}W_{ij}}{2}(\alpha-((W'_{ij}\delta)^{-1}X'_{ij}\beta+(W'_{ij})^{-1}V_{ij}-(W'_{ij}\delta)^{-1}Y_{ij})^2]
\end{aligned}
$$

Then we know that

$$p(\alpha|V,Y,\beta,\delta,S,\mu,X,W)\sim N(\frac{M_\alpha}{N_\alpha},\frac{1}{N_\alpha}) \tag{10}$$

where

$$M_\alpha=\frac{\bar{\alpha}}{\sum_\alpha}+\sum_{m=1}^{N}[\sum_{ij\in M_m}W'_{ij}V_{ij}+\sum_{ij\in\mu_m}\delta W_{ij}(\beta X_{ij}+\delta V_{ij}-Y_{ij})] \tag{11}$$

$$N_\alpha=\frac{1}{\sum_\alpha}+\sum_{m=1}^{N}(\sum_{ij\in M_m}W'_{ij}W_{ij}+\sum_{ij\in\mu_m}\delta^2W'_{ij}W_{ij}) \tag{12}$$

Similarly, we have

$$p(\beta|V,Y,\alpha,\delta,S,\mu,X,W)\sim N(\frac{M_\beta}{N_\beta},\frac{1}{N_\beta}) \tag{13}$$

where

$$M_\beta=\frac{\bar{\beta}}{\sum_\beta}+\sum_{m=1}^{N}\sum_{ij\in\mu_m}X_{ij}(Y_{ij}-V_{ij}\delta+W'_{ij}\alpha\delta) \tag{14}$$

$$N_\beta=\frac{1}{\sum_\beta}+\sum_{m=1}^{N}\sum_{ij\in\mu_m}X'_{ij}X_{ij} \tag{15}$$

and

$$p(\delta|V, Y, \alpha, \beta, S, \mu, X, W) \sim N(\frac{M_\delta}{N_\delta}, \frac{1}{N_\delta}) \tag{16}$$

truncated from below at zero, where

$$M_\delta = \frac{\bar{\delta}}{\sum_\delta} + \sum_{m=1}^{N} \sum_{ij \in \mu_m} (V_{ij} - W_{ij}\alpha)(Y_{ij} - X_{ij}\beta) \tag{17}$$

$$N_\delta = \frac{1}{\sum_\delta} + \sum_{m=1}^{N} \sum_{ij \in \mu_m} (V_{ij} - W_{ij}\alpha)^2 \tag{18}$$

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