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The Determinants and Impact of Executive-Firm Matches

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Abstract. I estimate a model of executive-firm matching, in which both components of the executive labor market outcome—the assignment of managers to firms and the cross-sectional distribution of executive pay—are endogenously determined. Results in this paper reveal the importance of match specificity in productivity, driven by complementarities between firm and manager attributes. Therefore, one reason that larger, more diversified, research-intensive firms pay their executives more is because they are assortatively matched with managers that are talented, have more cross-industry experience, and are prone to innovation. More important, they outbid competing firms for these managers because they enjoy higher marginal productivity from given managerial skills. Announcement abnormal returns and executive tenure duration are both higher for matches with higher estimated productivity, suggesting mutual benefits for both the firms and the managers from assortative matching.

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Keywords: corporate finance • matching • executive compensation • executive labor market • structural estimation • complementarity

1. Introduction

It has long been argued that efficient matching of executives with different skill sets to firms with specific characteristics can create economic surplus (Rosen 1981, 1982). How to estimate the strength of such complementarities has been viewed by economists as important yet difficult. Milgrom and Roberts (1995, p. 205) highlight the importance of analyzing complementarities as providing "a promising way to give precision and analytical usefulness to the intuitive and often vague notions of *fit* and *synergies*." My paper empirically studies the sources of match-specific productivity using a multidimensional competitive assignment model of the executive labor market. As such, it departs from most of the corporate governance literature, which has concentrated on compensation design and incentives. However, hiring the right manager could be as important as providing incentives to the manager to take the right actions after being hired. Assessing the empirical relevance of match-specific productivity is a critical step in understanding the mechanism that governs the executive labor market.

The difficulty in assessing the value gains from matching firms with managers is twofold. First, market-wide job assignments and the cross-sectional distribution of managerial compensation are inherently related components of the executive labor market outcome; thus, both are endogenous. There are no obvious instruments in a two-sided matching market. Second, regressing managerial compensation on firm, manager attributes as well as their interactions could suffer from a multicollinearity problem because of the strong correlations between firm and manager attributes. Importantly, because of endogeneity, the coefficient on the interaction term in the regression is not the same as the match-specific productivity parameter that is the cross derivative of the production function.

Therefore, I estimate these parameters using a multidimensional matching model. The structure of the model provides identification via a plausible assumption: The same agent matched with different partners generates different levels of productivity, and the labor market is in a pairwise stable equilibrium. That is, an unmatched firm-manager pair cannot gain by forming a counterfactual match. Using a structural model allows for the identification of the match-specific productivity, captured by potential complementarities between managers and firms. The strength of these complementarities is derived from comparisons of actual versus counterfactual matches. They are the estimated productivity parameters that make the observed outcome best fit the equilibrium outcome in terms of both assignment and pay.

As Oyer and Schaefer (2011) point out, although the assumption of a complementarity between firm and employee attributes underlies the large literature on assortative matching in labor markets, most of this literature (e.g., Rosen 1982, Gabaix and Landier 2008) assumes a one-dimensional complementarity between, say, firm size and employee talent, and derives implications for equilibrium matching from that assumption. Although it serves the purpose of modeling abstraction, there is no reason to believe that matching is one-dimensional empirically. Estimating a multidimensional matching model helps to empirically establish and isolate match-specific productivity, including size/talent complementarity.

If there is no interaction between firm and manager attributes (e.g., firm and manager attributes are additive in the production function), in a competitive market, managers will simply earn their marginal productivity based on their own attributes. A manager with a given skill set should receive the same compensation regardless of her employer, or even start her own firm. As a result, there is no sorting on the executive labor market. However, casual empiricism or correlations between firm and manager attributes suggest sorting on multiple dimensions. One example is that CEOs of conglomerates often have previous work experience with similarly complex firms.[1] Another example is that most of the Silicon Valley firms are managed by CEOs with master's or PhD degrees in science. Therefore, managerial experience or innovative minds need to be combined with established product lines or patents of firms to generate high productivity.

However, assortative matching in multiple dimensions may not be satisfied in many cases. For example, suppose that a large firm is also research intensive, such as Advanced Micro Devices (AMD) Inc.[2] If there is complementarity in size/talent and in R&D/technical knowledge, AMD should be matched with a talented and innovative manager, if possible. But the most talented manager on the market may not have much technical expertise, and the manager with the most technical knowledge may not have a star-studded resume to prove her talent. Whether AMD goes for the talented manager or for the technical manager is an empirical question and depends on which complementarity contributes more to match-specific productivity. In the case of AMD, the company recently appointed Lisa Su, who has a PhD in electrical engineering from the Massachusetts Institute of Technology, as its CEO. In general, answering this question calls for a multidimensional matching model to consistently estimate the relative importance of multiple complementarities.

Using a sample of experienced senior executives at S&P 1,500 firms, productivity parameter estimates suggest that matching produces productivity gains from three central complementarities between firm and manager attributes. First, firm size is complementary to managerial talent, measured by managerial efficiency, indicating economies of scale. Second, the degree of diversification of the firm is complementary to the past experience of the manager in conglomerates, indicating economies of scope. Third, the R&D intensity of the firm is complementary to the technical expertise and innovativeness of the manager. Thus, there is technology/skill complementarity in addition to capital/skill complementarity. These complementarities can explain between 27% and 52% of the cross-sectional variation in observed executive assignments *and* pay under various empirical specifications. Turning off any of the three matching dimensions significantly reduces model fit. It is important to note that these complementarities lie behind the observed sorting between firms and managers, but do not simply stem from sorting that could arise for reasons other than productivity. The structural model requires both assignments and pay to match the equilibrium labor market outcomes. Therefore, the results in this paper suggest that high-type firms (larger, more diversified, research intensive) outbid low-type firms for high-type managers because high-type firms enjoy higher marginal productivity from given managerial skills.

The parsimonious structural model used in this paper allows players on both sides of the labor market to have arms-length bargaining power. The estimates of the firm-manager-specific sharing rule imply that in the matching game, companies on average obtain over 90% of the total match-specific productivity. However, when the productivity created by good matches is high, my estimates imply that managers get a higher fraction of the productivity, indicating a scarcity of managerial skills at the top of the labor pool.

Executive-firm matches are formed under the expectation of mutual gains. I provide evidence that higher estimated match-specific productivity based on my model is significantly associated with better outcomes for both firms and managers (besides higher compensation). Such productivity, measured as the weighted sum of the estimated complementarities, is positively and significantly associated with several measures of postmatching performance, for example, the abnormal returns around the new CEO appointment announcements. The results confirm that the three matching dimensions capture the initial match-specific productivity reasonably well, and executive-firm matching does have a real economic impact on both parties involved. Moreover, this analysis highlights the importance of the value of "hiring the right manager" separately from the value of a good manager. For example, market reacts negatively to a new executive's appointment announcement if there is evidence for underqualification of the new hire in terms of her talent, experience, or education.

This paper lies at the intersection of corporate finance, personnel economics, and industrial organization. The empirical estimation strategy builds upon the recent industrial organization literature (Fox 2010a, b), and does not require directly solving for equilibrium allocations and thus allows extension to multiple matching dimensions. Rather, it uses participation constraints on players from both sides of the market (Oyer 2004) as equilibrium conditions to back out match-specific productivity parameters that best satisfy these conditions.

The importance of match specificity revealed in this paper also implies the importance of considering interactions between firm and manager attributes when studying executive compensation. The empirical literature has largely ignored these interactions because of the challenges mentioned earlier. However, the results in this paper suggest that high-type firms pay their executives more not (just) because of some governance problems,[3] but because they are assortatively matched with high-type managers. Moreover, since the executive labor market is a matching market, it is incorrect to say that factors earn their marginal productivities in the usual sense—the increase in total productivity if a manager were to increase her type is proportional to the type of her current employer. In equilibrium, she could also move up in the ranking and be matched with a better company. Therefore, compensation is determined by interactions of all players in this market.

This paper is closely related to Allgood and Farrell (2003), who demonstrate the usefulness of the job match concept in explaining higher CEO turnovers in the earlier years of tenure. Gabaix and Landier (2008) and Terviö (2008) calibrate a competitive assignment model based on the complementarity between firm size and managerial talent. The prior literature in this area thus focuses on one-dimensional matching between managerial talent and firm size, with two recent exceptions. Edmans and Gabaix (2011) add risk aversion to the matching model. Eisfeldt and Kuhnen (2013) develop a model in which managers (but not firms) differ along multiple dimensions to explain CEO turnovers. My work stands apart from these studies by using an empirical, multidimensional matching model of both job assignments and executive compensation to estimate the *sources* of match-specific productivity. Finally, Graham et al. (2012) suggest using fixed effects to control for matching based on time-invariant characteristics. My work builds on Graham et al. (2012) by using a model to offer substantially more details about match characteristics.

2. The Competitive Assignment Model

Roth and Sotomayor (1990) describe the general difference between commodity market and two-sided matching markets as follows. In commodity markets, the identity of the agents does not matter—the product is a commodity. In matching markets, agents on both sides of the market care about who they trade with. The senior executive labor market is a clear example of a matching market. First, the managerial population exhibits large heterogeneity (e.g., Bertrand and Schoar 2003), which likely spans over multiple dimensions: innate talent, experience, education, etc. Second, the expertise of a manager is not a commodity—her marginal productivity depends on where she works, and therefore varies at different firms.

I characterize the two-sided executive labor market using two finite and disjointed sets of agents: firms $C=\{c_1, c_2, \ldots, c_k\}$ and managers $M=\{m_1, m_2, \ldots, m_l\}$.[4] Both types of agents simultaneously maximize their expected utilities by selecting their partners. Utility is expressed in monetary terms and is transferable between firms and managers.

The search for a match is costless in the model.[5] Players observe the lists of potential employers and employees and have frictionless access to potential partners. Each firm $c_n \in C$ may hire at most q_n managers, but each manager works only for one firm.

Suppose company c_n hires manager m_u to be one of its top executives. Let $F(c_n, m_u)$ denote the matching production function, which transforms the firm's endowment and the manager's skills into some joint output shared between c_n and m_u. The hiring firm c_n retains a positive payoff $V(c_n, m_u)$ and pays $p(c_n, m_u)$ as compensation to manager m_u.[6] Therefore, if c_n and m_u are matched,[7]

$$F(c_n, m_u) = V(c_n, m_u) + p(c_n, m_u). \tag{1}$$

An assignment A is a $k\times l$ matrix with elements $a_{nu} \in \{0,1\}$, defined for all possible pairs $(c_n, m_u) \in C\times M$, where $a_{nu}=1$ if c_n and m_u are matched and $a_{nu}=0$ if c_n and m_u are unmatched. The set of all employed executives by company c_n under A is denoted as H_{c_n}, that is, $H_{c_n}=\{m_u \in M \text{ s.t. } a_{nu}=1\}$. H_{m_u} is similarly defined for manager m_u. An outcome $(\vec{V}, \vec{p}, A)$ for this market is determined by specifying an assignment and the way in which the total value generated by each match is split between the two partners.

If the payoffs for each player across different partners are additively separable, the many-to-one matching in the executive labor market becomes isomorphic to one-to-one matching.[8] In this case, the total payoff for c_n under the outcome $(\vec{V}, \vec{p}, A)$ is $V_{c_n} = \Sigma_{m_u \in H_{c_n}} V(c_n, m_u)$. The assumption that all workers are gross substitutes from the standpoint of each firm in Kelso and Crawford (1982), for example, satisfies the additive separability in payoffs across matches.[9]

A pair of counterfactual partners can block an assignment if they are currently unmatched, but both would be better off if they got matched. I adopt one of the most common equilibrium notions in the matching literature and define a matching outcome $(\vec{V}, \vec{p}, A)$ to be pairwise stable if it is not blocked by any individual player or any pair of players. Two necessary conditions for the pairwise stable equilibrium arise from the equilibrium definition:

Definition 1. If $(\vec{V}, \vec{p}, A)$ is pairwise stable, then for each $c_i \in C$ and $c_j \in C$ $(c_i \neq c_j)$, the following two inequalities must be satisfied, $\forall\, m_i \in (H_{c_i})$ and $m_j \in (H_{c_j})$:

$$[F(c_i, m_i) - p(c_i, m_i)] \geq [F(c_i, m_j) - p(c_j, m_j)] \quad (2)$$

and

$$[F(c_j, m_j) - p(c_j, m_j)] \geq [F(c_j, m_i) - p(c_i, m_i)]. \quad (3)$$

To see this, consider a subset of the actually matched pairs: $\{(c_i, m_i); (c_j, m_j)\}$. Suppose c_i wants to form a blocking pair with m_j. The payoff it can get is at most $[F(c_i, m_j) - p(c_j, m_j)]$ because it has to pay m_j at least $p(c_j, m_j)$ to attract her away from her current employer c_j. In a stable equilibrium, c_i would not do that because this counterfactual payoff is not greater than the actual payoff when matched with the current partner m_i, which is $[F(c_i, m_i) - p(c_i, m_i)]$. By the same logic, the blocking pair (c_j, m_i) fails if condition (3) holds.

The pairwise individual rationality (I.R.) conditions above illustrate the fact that in a matching market, the decision of two players to team up depends on their effective choice sets, which are constrained by the decisions of other players in the market. Therefore, compensation is endogenous in the matching model and is determined not only by the attributes of the manager and her employer, but also by the interactions of other players in this market. These two inequalities underlie the maximum score estimation introduced in the next section.

3. Maximum Score Estimation

3.1. Hypotheses on the Sources of Match-Specific Productivity

One of the primitives that govern a two-sided matching game is the concept of complementarity versus substitution. Value creation from matching depends directly on the combination of both parties' capabilities: some could be strength building on strength; others could be strength of one party substituting for what the other party lacks. Becker (1973) shows that assortative matching comes from the complementarity of certain characteristics of players on different sides of the market. If players' characteristics are substitutes, there will be antiassortative matching in equilibrium.

Previous studies on executive-firm matching primarily focus on the capital/skill complementarity between firm size and managerial talent, based on economies of scale. The argument is that the larger the firm, the larger the stock of resources that can be affected by managerial decisions. Studies of managerial characteristics show that management skills spread across many dimensions; thus, executive-firm matching is likely to be multidimensional, too. In this paper, I explore whether the economies of scope contribute to match-specific productivity in addition to economies of scale, and whether there is technology/skill complementarity in addition to capital/skill complementarity.

Rose and Shepard (1997) and Berry et al. (2006) suggest that executives in diversified firms have different skills from executives in focused firms. Maksimovic and Phillips (2002) show that more diversified conglomerates have a higher level of general managerial (or organizational) ability than less diversified conglomerates. What kind of general managerial ability is most valuable in diversified firms? Based on economies of scope, a manager's past work experience in conglomerates is complementary to the degree of diversification of a company. Because of the complex nature of conglomerate operations, an executive without experience in managing multidivisional organizations will find the tasks in diversified firms more challenging. Hypothesis 1A is thus the following:

Hypothesis 1A. *A manager's conglomerate work experience is complementary to the degree of diversification of a company.*

If most of the turnovers are driven by directional changes in a firm's business scope, for example, if conglomerates need new managers when they want to refocus, and single-segment firms need new managers when they want to diversify their business, the cross-industry skills of the new managers could be substitutive to the firms' degree of diversification. The alternative Hypothesis 1B is the following:

Hypothesis 1B. *A manager's conglomerate work experience is substitutable to the degree of diversification of a company.*

In addition to capital, technology developed in house provides a competitive advantage in generating output. Research-intensive firms require higher levels of technological know-how and expect top executives to be able to quickly process new ideas. A marker of this skill is advanced education, especially in science. Furthermore, education could serve as an indicator of a person's value and cognitive preferences. Therefore, an executive's exposure to advanced education, especially in science, is complementary to the research and development (R&D) intensity of the firm. Hypothesis 2A is thus as follows:

Hypothesis 2A. *A manager's technical expertise is complementary to the R&D intensity of a firm.*

In the sense that innovative managers bring in advanced technical concepts or stimulate innovation that the firm lacks, the alternative Hypothesis 2B is as follows:

Hypothesis 2B. *A manager's technical expertise is substitutive to the R&D intensity of a firm.*

3.2. Specification of the Production Function

Prior and contemporaneous studies have applied two-sided matching models to the marriage market (Becker 1973), the venture capital market (Sørensen 2007), the loan markets (Chen and Song 2013), mergers and acquisitions (Park 2013, Akkus et al. 2016), the IPO market (Fernando et al. 2005, Akkus et al. 2014), and the director labor market (Matveyev 2012). Following Fox (2010a), the setting in this paper allows utilities to be transferable so that the division of match output is determined endogenously at the time the match occurs and is different across matches. It is worthwhile noting that the research focus of this paper is not to derive the primitive preferences of the individual players, because the preferences here are purely monetary, but to infer the productivity parameters in the production function F.

The production function F describes how the capabilities of a manager (e.g., talent, experience, knowledge) and the capabilities of a firm (e.g., scale, scope, growth) can be combined to generate match-specific productivity. I first specify the production function up to the productivity parameter vector ω. Let the parameter space be $\Omega = R^{\chi}$, where χ is the number of productivity parameters to be estimated. Let $F_{\omega}^{D}(c_i, m_i)$ be the deterministic part of the match output generated by the pair (c_i, m_i), given parameter value ω.

To examine the three interactions between firm and manager attributes, I specify the following baseline match production function:

$$F_{\omega}(c_i, m_i) = \omega_1 C_{1i} M_{1i} + \omega_2 C_{2i} M_{2i} + \omega_3 C_{3i} M_{3i} + \xi covariates_{c_i, m_i} + \varepsilon_{c_i, m_i}, \quad (4)$$

where $c_i = (C_{1i}, C_{2i}, C_{3i})$ and $m_i = (M_{1i}, M_{2i}, M_{3i})$ are vectors of company and manager characteristics, respectively. The variable C_{1i} is the size of firm i; M_{1i} is the talent of manager i; C_{2i} is the degree of diversification of the company; M_{2i} is the past work experience of the manager in conglomerates; C_{3i} is the research intensity of the firm; M_{3i} is the innovation propensity of the manager. All of the variables are in cumulative distribution functions (CDFs) every year and thus reflect the ranks of players on the same side of a market. In addition, to capture the importance of industry-specific skills, I control for a covariate that is an indicator function of whether the manager had experience along her career path in the same industry as the matched company.

The matching concept lends itself to a multiplicative separable form of the production function.[10] The interaction terms capture the match specificity in productivity studied in this paper. They are identified by comparisons between actual and counterfactual matches in I.R. conditions (2) and (3). Noninteractive terms (such as firm size) could contribute to productivity, but difference out in equilibrium because both the actual and counterfactual partners value them in the same way. The matching model is thus robust to, for example, firm fixed effects.

The cross-partial derivatives reflect the observed matching pattern on the executive labor market. Complementarity implies that the cross derivatives are positive. Substitution, in contrast, implies negative cross-partial derivatives and antiassortative matching.

On the quantitative side, the relative magnitude of the cross-partial derivatives represents the relative importance of each matching dimension. That is, if $\partial^2 F_{\omega}(c, m)/\partial C_1 \partial M_1 > \partial^2 F_{\omega}(c, m)/\partial C_2 \partial M_2$, or equivalently, $\omega_1 > \omega_2$, then the interaction between C_1 and M_1 contributes relatively more to productivity than does the interaction between C_2 and M_2. The dimension with a larger cross partial must be satisfied first in equilibrium if simultaneous matching in both dimensions is prohibited (see Fox 2010a for a formal proof). In sum, ω describes the observed matching pattern in the executive labor market and thus reveals the primitives that govern this market, such as the degrees of complementarities or substitutabilities in company and manager attributes.

3.3. Structural Identification

The parameter vector ω is structurally identified in the main analysis. That is, the identification comes from the assumption that the observed outcome is the equilibrium outcome in terms of the I.R. conditions (2) and (3). This is analogous to other common approaches taken in structural estimation, like matching moments or maximizing likelihood. To estimate F, I apply a semiparametric approach—the maximum score estimation (see the Internet appendix for its details)—that borrows insights from semiparametric identification of single-agent, discrete choice problems in Manski (1975). More recently, Fox (2010a) provides proofs of set identification and consistency for maximum score estimators in a two-sided matching game. Fox (2010b) demonstrates how to perform a semiparametric estimation of match production functions in two-sided matching games with transferable utility.

The objective function is the number of satisfied I.R. conditions:

$$\begin{aligned}\max_{\omega} Q(\omega) &= \sum_{y=1}^{Y} \sum_{i=1}^{M_y - 1} \sum_{j=i+1}^{M_y} \mathbf{1}\{[F_{\omega}^{D}(c_i, m_i) - F_{\omega}^{D}(c_i, m_j)] \\ &\geq [p(c_i, m_i) - p(c_j, m_j)] \cap [F_{\omega}^{D}(c_j, m_j) - F_{\omega}^{D}(c_j, m_i)] \\ &\geq [p(c_j, m_j) - p(c_i, m_i)]\}, \quad (5)\end{aligned}$$

where c_i denotes the vector of firm i's attributes, and m_i denotes the vector of manager i's attributes. The variable M_y is the number of matches observed in market y. I assume there is one national senior executive labor market every year and markets in different years are independent of each other.

The econometric model in this paper uses information on both observed job assignments and the transfer data (executive compensation), instead of just the former as in Fox (2010a). Therefore, it has richer identification power. The differentials in compensation on the right-hand side of the inequalities in (9) provide units for the estimation of F, the total output of each match. The level of match-specific productivity is identified and is thus used as the measure of matching quality.

4. Findings

4.1. Key Data Features and Alternative Approaches

In this section, I present exploratory analysis of the matching pattern in the data, highlighting key data features that give rise to the identification of structural parameters. In addition, 4.1.1 explains why one cannot draw inferences on matching based only on simple correlations. 4.1.2 illustrates that equilibrium matching is a bliss point and thus hard to be identified by regressions. 4.1.3 compares the structural matching model with selection models that use probit/logit in the first stage.

4.1.1. Correlations Between Firm, Manager Attributes, Their Interactions, and Managerial Compensation. Executive-firm-year observations are included in the sample when there is a succession event (i.e., a job match) in terms of either promoting internal candidates or hiring external candidates for the top five executive positions of a company. I use both ExecuComp data and company press releases to identify the date and succession origin of turnover events. I collect information on the company and the manager before the appointment to construct a sample of job matches for executives with tractable previous career paths, from 1993 to 2006. Table 1, panel A lists the number of executive-firm matches by year, for a total of 2,335 job matches before any other data restrictions. Summary statistics of executive compensation, as well as firm and manager attributes, are provided in Table 1, panel B. Detailed variable definitions are reported in Internet Appendix A.

Table 2 presents correlations between total compensation, firm and manager attributes, and their interactions. From now on, both compensation and firm or manager attributes are in their annual CDFs. A few patterns in this table are worth noting. First, based on the correlations in bold in the upper-left corner of the table, all three interactions of firm-manager attributes are positively and significantly correlated with the manager's total compensation. Second, based on the correlations in bold in the lower-right corner, all three pairs of company and manager characteristics are positively and significantly correlated. The correlations between the degree of diversification and cross-industry experience, and between R&D and education are larger than the correlation between firm size and managerial talent. Therefore, although sorting is stronger on these first two dimensions, their correlations with compensation are not as strong as the size/talent dimension. But, this could be due to the fact that firm size has the strongest correlation with compensation. In sum, which complementarity contributes most to the match-specific productivity is inconclusive from the two sets of highlighted correlations.

Third, the correlations in bold in the middle part suggest that the firm-manager interactions are strongly collinear with the corresponding noninteractive firm- or manager-specific characteristics. This is not surprising given the positive and significant correlations between firm and manager attributes. For example,

Table 1. Descriptive Statistics

Panel A: Number of matches by year

Turnover year	Number of firm-executive matches
1992	25
1993	45
1994	85
1995	136
1996	160
1997	223
1998	185
1999	209
2000	191
2001	222
2002	204
2003	182
2004	145
2005	182
2006	141

Panel B: Summary statistics

Variable	Observations	Mean	Std. dev.	Min	Max
Assets	2,039	7.76	1.97	0.27	13.84
$Talent_{dea}$	2,025	0.62	0.58	0.00	5.06
Div_{sale}	2,039	0.36	0.46	0.00	2.03
Exp_{sale}	2,122	0.44	0.46	0.00	1.95
RD	2,126	0.10	0.94	0.00	35.17
Edu_{tech}	2,126	1.83	1.04	1.00	5.00
Tcomp	2,123	7.63	1.37	−6.91	12.47

Notes. Panel A reports the number of firm-executive matches by year, prior to restrictions from data availability of firm characteristics. Panel B reports summary statistics for the raw data of firm and manager variables used in the regressions and maximum score estimation. *Assets* is in a natural logarithm of millions of dollars. *Tcomp* is in a natural logarithm of thousands of dollars. See Internet Appendix A for detailed explanations of variable construction.

Table 2. Correlation Table

	$Tcomp$	$Assets \times Talent_{dea}$	$Div_{sale} \times Exp_{sale}$	$RD \times Edu_{tech}$	$Assets$	Div_{sale}	RD	$Talent_{dea}$	Exp_{sale}
$Assets \times Talent_{dea}$	**0.39*** **								
$Div_{sale} \times Exp_{sale}$	**0.08*** **	0.22***							
$RD \times Edu_{tech}$	**0.14*** **	−0.13***	−0.13***						
$Assets$	0.48***	**0.71*** **	0.23***	−0.05**					
Div_{sale}	0.03	0.17***	**0.70*** **	−0.14***	0.17***				
RD	0.11***	−0.19***	−0.20***	**0.74*** **	−0.14***	−0.19***			
$Talent_{dea}$	0.10***	**0.69*** **	0.11***	−0.19***	**0.13*** **	0.08***	−0.23***		
Exp_{sale}	0.07**	0.17***	**0.76*** **	−0.09***	0.17***	**0.20*** **	−0.17***	0.10***	
Edu_{tech}	0.12***	−0.02	0.01	**0.79*** **	0.05**	−0.03	**0.21*** **	0.08***	0.04

Notes. This table reports the correlations between total compensation, the main firm and manager characteristics, as well as their interactions, used in the regressions and maximum score estimation. $Assets$, Div_{sale}, RD, $Talent_{dea}$, Exp_{sale}, and Edu_{tech} are firm and manager characteristics in their annual CDFs. $Tcomp$ is the annual CDF of total compensation.

*** and ** indicate that the correlations are significant at the 1% and 5% levels, respectively.

$Assets \times Talent_{dea}$ is correlated with $Assets$ at 0.71 and with $Talent_{dea}$ at 0.69. However, such colinearity provides the first indication that regressing compensation on firm, manager attributes and their interactions will not provide consistent estimates of match-specific productivity.[11] Finally, correlations in the lower-left corner show that noninteractive firm or manager attributes are also positively correlated with total compensation in general.

Although these simple correlations suggest sorting based on the three dimensions proposed in this paper, one cannot tell whether an assignment model describes the underlying data-generating process in the executive labor market. In experiments (1.1) and (1.3) in Table A1 in Internet Appendix B.2, the correlations between the firm and manager attributes are the same. However, the pay distribution in (1.1) sustains pairwise equilibrium, whereas the pay distribution in (1.3) does not. Furthermore, the correlations between firm and manager attributes are the same in experiments (2.1) and (2.2), but the pairwise stable equilibrium is not sustained in (2.2) because of the stronger sorting in the dimension with lower complementarity. A positive and significant correlation between firm and manager attributes is thus a necessary, but not sufficient, condition for the pairwise equilibrium. The complementarity between firm and manager attributes does not simply stem from assortative pairing that could arise for reasons other than productivity.[12] Therefore, a structural model is needed to estimate the underlying competitive assignment game.

4.1.2. Using Interactions of Firm and Manager Attributes in Regressions. Next, I relate actual job assignments to the other component of the labor market outcome: compensation. Table 3, panel A reports the estimation results for the following specification:

$$Compensation_{c_i,m_i} = \beta_1 Size_{c_i} + \beta_2 Talent_{m_i} + \varepsilon_{c_i,m_i}. \quad (6)$$

Column (1) confirms that both firm and manager attributes are each positively correlated with managerial compensation. The interaction between size and talent is added in column (2) and is positively and significantly correlated with compensation. At the same time, the coefficient on talent changes to negative and becomes insignificant, due to the multicollinearity problem documented in Table 2. One advantage of the maximum score estimation over regressions is that it does not suffer from the multicollinearity problem. In experiment (2.1) in Table A1 in Internet Appendix B.2 where assortative matching is the true data-generating process, even though C_1M_1 and C_1M_2 are strongly positively correlated, the maximum score estimation consistently recovers the productivity parameters associated with them. The specifications in columns (3) and (4) are similar to (1) and (2), except that firm fixed effects are added. Controlling for fixed effects, only firm size remains a significant determinant of managerial compensation. Neither managerial talent nor its interaction with firm size is significantly correlated with compensation anymore. The results in this table suggest that it is firm fixed effects, not measurement errors, that render the interaction between firm size and managerial talent insignificant in the compensation regressions.

I add other firm and manager attributes and their interaction terms in panel B. In general, the coefficients on the interaction terms are positive. However, controlling for firm fixed effects, only $RD \times Edu_{tech}$ is significantly correlated with compensation. The pay effect of noninteractive firm and manager attributes is mostly absorbed by these interaction terms, except for firm size. However, firm size alone is not the source of match-specific productivity and will drop out in equilibrium when comparing actual versus counterfactual matches. The importance of firm size is consistent with Gabaix and Landier (2008) who show that the increase in executive compensation is attributable to the increase in firm size. Graham et al. (2012) suggest

Table 3. Initial Analysis

Panel A: Firm size and managerial talent

	Tcomp			
	(1)	(2)	(3)	(4)
Assets	0.47***	0.37***	0.46***	0.44***
	(0.02)	(0.04)	(0.13)	(0.15)
$Talent_{dea}$	0.05**	−0.06	0.13***	0.10
	(0.02)	(0.04)	(0.04)	(0.09)
$Assets \times Talent_{dea}$		0.21***		0.04
		(0.07)		(0.13)
Constant	0.24***	0.29***	0.21***	0.22***
	(0.02)	(0.02)	(0.07)	(0.08)
Firm fixed effects			x	x
Observations	2,025	2,025	2,025	2,025
Adjusted R^2	0.232	0.235	0.351	0.350

Panel B: Multiple dimensions

	Tcomp	
	(1)	(2)
Assets	0.45***	0.41***
	(0.13)	(0.15)
Div_{sale}	0.03	0.01
	(0.06)	(0.10)
RD	0.12	−0.43
	(0.15)	(0.27)
$Talent_{dea}$	0.13***	0.09
	(0.04)	(0.09)
Div_{sale}	0.01	−0.01
	(0.04)	(0.09)
Edu_{tech}	0.17***	−0.10
	(0.05)	(0.17)
$Assets \times Talent_{dea}$		0.06
		(0.13)
$Div_{sale} \times Exp_{sale}$		0.14
		(0.14)
$RD \times Edu_{tech}$		0.45**
		(0.27)
Firm fixed effects	x	x
Observations	2,025	2,025
Adjusted R^2	0.366	0.368

Notes. Both panels in this table report the results of regressing total compensation on firm and manager attributes, various firm-manager interactions, and firm fixed effects. *Assets*, Div_{sale}, *RD*, $Talent_{dea}$, Exp_{sale}, and Edu_{tech} are firm and manager characteristics in their annual CDFs. *Tcomp* is the annual CDF of total compensation. Robust standard errors are reported in parentheses.

*** and ** indicate significance at the 1% and 5% levels, respectively.

that once manager fixed effects are included, the elasticity of CEO pay to firm size is significantly smaller. None of them aims to confirm economies of scale by directly estimating which talent measure is complementary to firm size.

However, one cannot draw strong inferences from this reduced-form analysis. Experiment (2.2) in Table A1 in Internet Appendix B.2 suggests that even with a nonrandom distribution of managerial compensation, if sorting does not occur in the dimension with higher complementarity, a stable equilibrium may not be sustained. Also, one cannot conclude that there is no complementarity between firm size and managerial talent although the regression coefficient for their interaction term is insignificant. Besides the multicollinearity problem, as pointed out by Eeckhout and Kircher (2011), this approach does not identify match-specific productivity. In a competitive assignment framework, the optimal allocation is a bliss point. For a manager who is matched with a lower ranked firm, her compensation increases when the rank of the employer increases because the executive-firm "fit" improves. In contrast, when the firm is ranked higher than the manager, compensation falls by matching with an even better firm. The numerical example below illustrates this point.

C_i	M_i	$F(c_i, m_i)$	$p(c_i, m_i)$	$V(c_i, m_i)$
1	1	1	0.5	0.5
2	2	4	2	2
3	3	9	4.5	4.5
4	4	16	8	8

There are four companies on the matching market, with C_i (say, size) from 1 to 4. Let c_i denote the ith company ranked on size. There are four managers on the matching market, with M_i (say, talent) from 1 to 4. Let m_i denote the ith manager ranked on talent. I specify the match production function to be $F(c_i, m_i) = C_i M_i$. Suppose c_i is matched with m_i. In this setting, a (50%–50%) sharing rule between the firm and the manager would sustain a pairwise stable equilibrium. I calculate actual compensation for the manager $p(c_i, m_i)$ and actual net profit for the company $V(c_i, m_i)$ in the last two columns of the table above.

In a counterfactual experiment, suppose m_2 is matched with c_1. The total match-specific productivity for this counterfactual pair would be 2. However, c_1 would agree to hire m_2 only if its profit after paying her compensation is at least 0.5. Therefore, the maximal compensation m_2 receives is 1.5. By pairing with c_2, her compensation increases to 2. In a second counterfactual, suppose m_2 is matched with c_3. The total match output for this counterfactual pair would be 6. However, c_3 would agree to hire m_2 if its profit after paying her compensation is at least 4.5. Therefore, the maximal compensation m_2 receives is only 1.5. If m_2 wants to match with an even better employer c_4, her compensation falls to 0. This is because m_2 has to sacrifice more to compensation c_4 for giving up a much more talented manager m_4.

This example illustrates that in a matching market, taking into consideration all players in the market, compensation does not necessarily change in a monotone way with respect to company characteristics, even if manager characteristics are held fixed. In a matching market, it is incorrect to say that factors earn their marginal productivities in the usual sense: the increase in F if a manager were to increase her ability M_i is proportional to C_i. This is because in equilibrium, she could also move up in the ranking and be matched with a better company. All else equal, some managers working for other companies could move down and experience a decrease in productivity. Therefore, compensation is endogenous in the model and is determined not only by the attributes of the manager and her employer, but also by interactions of other players in this market. The coefficients on the interaction terms in the regressions are not the same as the match-specific productivity parameters that are cross derivatives of the production function.

A classical approach for dealing with endogeneity is to use instrumental variables, which are difficult to find in this context. Instruments have to be independent of compensation but related to the characteristics determining who matches with whom. However, there are no natural exclusion restrictions in the matching market (Sørensen 2007): any characteristics that matter for the matching will be intrinsically related to the other component—compensation. The mutually selective nature of the executive labor market therefore calls for a structural investigation that identifies the matching synergy through comparisons between actual and counterfactual matches.

4.1.3. Discrete Choice Models. The structural matching model has a few advantages over discrete choice models. First, there is no price in the discrete choice model. In the matching model, executive compensation is the endogenously determined matching price, taking into consideration all participation constraints in the market. Second, one of the main properties of multinomial logit is the independence of irrelevant alternatives (IIA), which could give rise to, for example, the red bus/blue bus paradox. Random-coefficients logit models (e.g., Berry 1994, Berry et al. 1995) solve the IIA problem. However, a conceptual issue with the single-agent discrete choice models is that they are unable to capture the sorting. In a typical selection model, a player (say, a consumer) faces a unilateral decision: he selects a product based on various product attributes. But this does not prohibit other consumers from selecting the same product. Probit and logit models typically assume that agents on both sides of the market make their partner choices separately. In the one-to-one (or many-to-one) matching framework, a firm can only hire one CEO (or up to a certain quota of managers), and a manager can only work for one firm. The numerical example in §4.1.2 illustrates that the two-sided matching model addresses the interdependence in agents' choices. Sørensen (2007) on VC-company matching and Park (2013) on mutual fund mergers provide a detailed explanation why the empirical matching model is better than discrete choice models to control for endogeneity from sorting.

Fox (2010a) shows that maximum score estimation allows for the logit errors but does not impose them. Using a Monte Carlo experiment, Akkus et al. (2016) show that the maximum score estimation performs better than the standard multinomial logit for one-to-one matchings.

Finally, it is worthwhile noting that the total matching output F in Equation (5) is not observable, because it depends on the quality of both the current and the future management (Terviö 2008). Therefore, Equation (5) cannot be directly estimated using a regression approach in the second stage.

4.2. Maximum Score Estimates

In a multidimensional matching framework, one important question is which dimension is dominant in equilibrium, as simultaneous (anti-)assortative matching in multiple dimensions is prohibited in many cases. Evaluating the relative strength in each complementarity using maximum score estimation is important. For example, Table 3 shows a negative correlation between *Assets* and *RD* but a positive correlation between $Talent_{dea}$ and Edu_{tech}. If the technology/skill complementarity is more important than the capital/skill complementarity in generating output, then in equilibrium, a small, growth firm would be able to pay high compensation for a manager with high technical education (and a proven track record), who is highly desirable but scarce on the labor market. If, however, highly talented and technically competent managers get matched to large, value firms, we can infer that the capital/skill complementarity contributes more to match-specific productivity.

The maximum score estimation presents a unified empirical model to examine the three matching dimensions simultaneously. It quantifies the extent to which the corresponding firm and manager attributes complement or substitute each other. It also addresses the correlations among the match-specific terms, just as multivariate regressions address correlations among the explanatory variables. Last but not least, the maximum score estimation aims to jointly explain the interrelated components of the executive labor market outcome—marketwide job assignments and the cross-sectional distribution of pay levels.

Table 4, panel A reports summary statistics of the three interaction terms, capturing the three matching dimensions: size and talent, degree of diversification and cross-industry experience, R&D intensity and education. Panel B reports maximum score estimates for the baseline production function (4), along with their

Table 4. Maximum Score Estimation

Panel A: Summary statistics

Interaction terms	Sample statistics of firm attribute × Manager attribute: Mean	Std. dev.
$(Assets \times Talent_{dea})$	0.27	0.24
$(Div_{sale} \times Exp_{sale})$	0.39	0.19
$(RD \times Edu_{tech})$	0.45	0.18

Panel B: Maximum score estimates in specification (5)

	Production function estimates							
	(1)		(2)		(3)		(4), until 2012	
Interaction	PointEst	95% CI	PointEst	95% CI	PointEst	95% CI	PointEst	95% CI
$Assets \times Talent_{dea}$	3.2	(1.8, 3.8)	0.7	(−0.2, 1.0)	0.3	(0.1, 0.9)	1.8	(0.7, 2.9)
$Div_{sale} \times Exp_{sale}$			3.4	(2.7, 4.1)	4.8	(3.0, 5.9)	5.4	(0.4, 5.9)
$RD \times Edu_{tech}$			2.1	(0.9, 2.8)	2.8	(1.2, 3.9)	3.9	(1.0, 5.0)
1[*same ind*]					78.0	(68, 89)	65.8	(42, 110)
No. of I.R.	343,528		343,528		343,528		407,388	
% satisfied	12.7		38.7		52.0		56.1%	

Notes. Panel A reports the summary statistics for the three interaction terms between firm and manager attributes. Panel B reports the results for the baseline production function (4), estimated with empirical strategy (5), including the point estimates and the confidence intervals. Columns (1)–(3) report the results using the main sample until 2006. Column (4) reports the results using a longer sample until 2012; 1[*same ind*] is an indicator variable that equals one if the executive had managerial experience at firms in the same (two-digit SIC) industry as the current firm before becoming its top executive. $Assets$, Div_{sale}, RD, $Talent_{dea}$, Exp_{sale}, and Edu_{tech} are firm and manager characteristics in their annual CDFs. The percentage of inequalities satisfied with the estimates serves as a measure of the statistical fit.

confidence intervals. $\hat{\omega}_1$, $\hat{\omega}_2$, and $\hat{\omega}_3$ are the parameters that maximize the number of satisfied I.R. conditions in the objective function (5).

I focus on the signs and relative magnitude of the estimates when interpreting the results. Results show that all the productivity estimates, which are the cross-partial derivatives of the production function, are positive. Therefore, executive-firm matching is driven by complementarities in manager and firm attributes rather than substitution. High-type firms hire high-type managers and pay high compensation; assortative matching arises in equilibrium in the executive market. Both Hypothesis 1A and 2A are thus supported by the data: a more diversified firm makes an attractive and productive option for a manager with more heterogenous industry experience, in line with economies of scope. There is cross-fertilization between a firm's R&D effort and a manager's technical knowledge, in line with technology/skill complementarity.

The productivity parameters correspond to the strength of complementarities in firm-manager attribute pairs. The relative magnitude of these cross-partial derivatives reflects whether matching in one pair of characteristics dominates another pair. The first specification in Table 4, panel B shows that the complementarity between *Assets* and $Talent_{dea}$ is important. The point estimate is positive and significant, and this single dimension explains 13% of the variation in job assignments and pay observed in the data. Moreover, the relative magnitude of the estimates in the second specification reveals that the complementarities between *RD* and *Education* as well as between Div_{Sales} and Exp_{Sales} contribute twice or even three times as much to match-specific productivity. These three matching dimensions jointly explain 39% of the observed equilibrium assignments and pay. As a benchmark, by randomly assigning firms to the managers in the sample, but keeping the pay distribution associated with the managers, the three interaction terms satisfy less than 10% of the equilibrium conditions in (5).

Firm attributes and fixed effects will drop out in equilibrium. Manager fixed effects will drop out too. Productivity parameters on observable manager characteristics could be identified in the model using transfer data but turn out to be insignificant in the empirical estimation. Therefore, the interactions between firm and manager attributes contribute more to value creation rather than managerial attributes alone.

The coefficient on the indicator variable reflecting whether the manager had work experience in the same industry as the firm suggests that industry-specific managerial skill also plays an important role in executive-firm matching, consistent with Cremers and Grinstein (2011). The magnitude of the estimate is not directly comparable to the strength of the three complementarities, as this covariate is on a different scale. However, adding the industry-specific matching dimension increases the explanatory power of the model to 52%.

There was a change in the variable *tdc1* in ExecuComp after 2006. Still, as a robustness check, column (4) in Table 4 reports maximum score estimators using this longer sample period, which are qualitatively similar to the results in column (3).

4.3. Predicting Assignments and Pay

Results from the structural estimation in Table 4, panel B suggest that firms and managers are matched based on multiple dimensions. However, the reduced-form analysis in Table 3, panel B suggests that the only important matching dimension is $RD \times Edu_{tech}$. Next, I compare the predicted assignments and pay distribution from one-dimensional and multidimensional matching to the actual data pattern, to gauge the importance of using structural estimation to learn about the determinants of executive-firm matches.

In the upper panel in Table 5, I focus on the main sample (1992–2006) and use the point estimates from multidimensional match (Table 4, panel B) to compute the match-specific productivity for each possible pair, which determines each player's rankings of its possible partners. I then compute the stable matching from applying the Gale-Shapley algorithm (1962) to the rankings. In column (1), I report the percentage of the actual firm-manager matches as predicted by equilibrium matches, and the percentage of the actual managerial compensation as predicted by the equilibrium pay (interval). In column (2), I report the results using the $RD \times Edu_{tech}$ dimension only. Multidimensional matching outperforms one-dimensional matching a lot, in terms of explaining the observed labor market outcome using an assignment model. In the lower panel of Table 5, I repeat this exercise, but apply the in- sample estimates on the out-of-sample data (2007–2012). Estimates from the multidimensional, structural matching model predict the out-of-sample matching pattern much better than a one-dimensional matching model according to the reduced-form approach.

To measure the welfare loss if the firm-manager matching pattern was different, I compute the average and median estimated productivity ($\hat{\beta}_1 Assets \times Talent_{dea} + \hat{\beta}_2 Div_{sale} \times Exp_{sale} + \hat{\beta}_3 RD \times Edu_{tech}$) using point estimates from Table 4, panel B, but firm-manager pairing based on multidimensional matching, one-dimensional matching, and random assignments. The average productivity increased by 25% from random assignments to multidimensional matching.

4.4. Matching Quality and Announcement Abnormal Return

Executive-firm matches are formed under the expectation of mutual gains. Next, I relate estimated match-specific productivity to postmatching outcome variables for both the firm and the new manager.

Unlike the actual players in the senior executive labor market, investors in the financial market have limited information about the list of active players from both sides of the labor market. Thus, I examine whether the information on match-specific productivity conveyed through announcements of executive appointments is capitalized in the stock market. Results on the impact of matching quality on long-run firm performances are reported in Internet Appendix D.

Research on abnormal returns surrounding CEO turnover announcements generally shows positive market reactions for short windows around these events (Weisbach 1988, Denis and Denis 1995). Following this literature, I use the news search in Factiva and

Table 5. Assignments and Pay Predicted by Structural vs. Reduced-Form Analysis

	(1) Structural	(2) Reduced form	(3) Random
In sample			
% correctly predicted match	70.60	19.20	
% correctly predicted pay (interval)	50.10	23.00	
Average match-specific productivity	2.22	2.03	1.77
Median match-specific productivity	2.02	1.88	1.68
Out of sample			
% correctly predicted match	63.20	21.40	
% correctly predicted pay (interval)	51.80	23.20	
Average match-specific productivity	2.20	2.01	1.83
Median match-specific productivity	2.02	1.82	1.69

Notes. This table reports the percentage of *predicted* firm-executive matches and executive compensation (interval) that are the same as the *actual* matches and pay. The predictions in column (1) are based on the multidimensional matching (as suggested by structural estimation in Table 4, panel B) and the predictions in column (2) are based on one-dimensional matching (as suggested by reduced-form analysis in Table 3, panel B). It also reports the average and median match-specific productivity using point estimates from Table 4, panel B, but firm-manager pairing based on multidimensional matching, one-dimensional matching, as well as random assignments (column (3)). The upper panel contains results using the in sample data (1992–2006). The upper panel contains results using the out of sample data (2007–2012).

read the appointment announcement for each event. I identify whether the appointee is an internal or external successor, or just serving as an interim executive, and whether the appointment is the result of a merger. For most of the external successions, I can find the exact announcement date. However, I cannot determine exactly when the executives rose to the top of their companies in some of the internal successions.[13] Numbers of different succession types are listed in Table 6, panel A.

Next, I form portfolios of companies based on each individual matching dimension, as well as the combined matching quality, and investigate the market reaction to executive succession announcements for various subgroups. The three-day $(-1,1)$ CARs are calculated using the value-weighted market index and the Carhart (1997) four-factor model. Results in Table 6, panel B suggest that on the $Assets \times Talent_{dea}$ dimension, good matches (top decile) lead to positive whereas bad matches (bottom decile) lead to negative announcement CAR, although none of them is significant. One reason that the market is not surprised could be that the managerial pool studied in this paper consists of mostly "talented" managers with proven track records—all of them had prior managerial experience at public firms before joining the sample firm. Another reason could be that the market anticipates the lesser importance of this dimension in generating match-specific productivity compared to other matching dimensions.

On the $Div_{sale} \times Exp_{sale}$ dimension, good matches, that is, conglomerates matches to managers with great cross-industry experience, lead to the highest average announcement abnormal return (1.22%). But there is no negative market reaction to a low matching quality on this dimension, again potentially because of the fact that most (more than 80%) of the managers in the sample have had some conglomerate experience prior to joining the sample firm (although the degree of diversification of the prior employers still varies).

On the $RD \times Edu_{tech}$ dimension, good matches lead to positive, whereas bad matches lead to negative announcement abnormal returns on average. Only 35% of the managers in the sample have graduate degrees, and only less than 20% of the managers have a degree in science. Given the lack of advanced, technical education in the general managerial population, market reaction to new hires is more polarized depending on whether the firm was able to secure a new manager with technical expertise.

Then I form portfolios based on the total match-specific productivity, $M_{quality}$, and investigate market reactions to the announcements in the top and bottom decile portfolios. The average announcement CAR to low-quality matches is negative, although not significant. However, firms with high matching quality

Table 6. Market Reaction to Executive Appointment Announcements

Panel A: Succession origin		
Succession	Frequency	Percent
External	1,456	62.36
Internal	556	23.81
M&A	173	7.41
Spin-off	62	2.66
Founder/family	30	1.28
Interim	30	1.28
Rejoin	28	1.20
Total	2,335	100
Panel B: Initial announcement CAR		
	CAR $(-1,1)$ (%)	t-stat.
External	0.95	$(4.53)^{***}$
Internal	0.88	$(2.16)^{**}$
High ($Assets \times Talent_{dea}$)	0.73	(1.16)
Low ($Assets \times Talent_{dea}$)	−0.31	(0.94)
High ($Div_{sale} \times Exp_{sale}$)	1.22	$(2.31)^{**}$
Low ($Div_{sale} \times Exp_{sale}$)	0.05	(0.52)
High ($RD \times Edu_{tech}$)	1.03	$(2.06)^{**}$
Low ($RD \times Edu_{tech}$)	−0.47	$(1.86)^{*}$
High $M_{quality}$	1.09	$(2.61)^{**}$
Low $M_{quality}$	−0.04	(0.04)
High $M_{quality}$ CEO	4.80	$(2.13)^{**}$
Low $M_{quality}$ CEO	0.43	(1.04)

Panel C: Managerial underqualification and announcement CAR	
	CAR $(-1,1)$
Dummy ($Assets > Talent_{dea}$)	-0.005^{*}
	(0.003)
Dummy ($Div_{sale} > Expe_{sale}$)	-0.016^{**}
	(0.008)
Dummy ($RD > Edu_{tech}$)	-0.011^{*}
	(0.006)
Year fixed effects	x
Observations	2,025
Adjusted R^2	0.027

Notes. Panel A summarizes succession origins in the sample. The "External" subsample includes turnovers with managers hired from outside of the company. The "Internal" subsample includes turnovers with managers promoted within the company. The "M&A" and "Spin-off" subsamples include turnovers related to mergers and acquisitions, or spin-offs, respectively. The "Founder/family" subsample includes turnovers with successors being the founder or from the owner family. The "Interim" subsample includes executives holding interim positions. The "Rejoin" subsample includes managers that rejoin the company. Panel B reports the average cumulative abnormal return (CAR) around the announcements of the executive appointments for external versus internal successions, high-quality versus low-quality matches, high-quality versus low-quality executive-firm matches and high-quality versus low-quality CEO-firm matches with a clear gap between the departure and arrival announcements. $M_{quality}$ is measured by $\sum_{n=1,2,3} \hat{\omega}_n C_n M_n$ with $\hat{\omega}_n$ estimated in Table 4, panel B, column (3). Panel C reports how management underqualification affects CAR. Portfolio times-series (CDA) t-statistics are reported in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, using a two-tailed test.

have a positive and significant announcement CAR of 1.09%, corresponding to about $25.6 million in market value for an average-sized firm in the sample. Both the t-statistics and Z-statistics show that the difference between the two group means are significant at the 5% level. Untabulated results show that the difference in announcement abnormal returns for matches with high versus low quality also holds in the external succession subsample. These results suggest that the financial market understands the positive economic implication of high match-specific productivity.

The time between the announcements of firing and hiring decisions could be close. To check whether the market reactions are just picking up the effect of the firing decisions, I next examine a subsample of CEO turnovers with a gap of more than one day between these two events. The average $(-1, 1)$ CAR for CEO-firm matches with $M_{quality}$ in the bottom decile is only 0.43%, and not significant. By comparison, the average CAR return around announcements of CEO appointments in the top matching quality decile is 4.8%. The effect of high matching quality is even stronger than in the whole sample with all executive-firm matches, which suggests that the arrival of a well-matched CEO is one of the most important and positive events for a firm.

Better assessment of the "surprise" to the market requires directly measuring market's ex ante expectation of the new manager. One reasonable assumption is that market expects the firm to hire a new manager with attributes ranked in the supply pool similarly to the rank of firm attributes in the demand pool. This expectation cannot necessarily be met ex post, leading to a surprise. As an extreme example, suppose that a firm ranks high in firm size, diversification, and R&D, but there is no manager that ranks high in talent, conglomerate experience, and technical education. The firm will have to end up hiring a manager that underqualifies in at least one dimension. Results from the structural estimation with multidimensional matching suggests that the firm hires a manager with the most conglomerate experience. Panel C of Table 6 further investigates market's reaction when there is managerial underqualification, using three dummy variables capturing underqualification of the new hires (i.e., the rank of the managerial attribute is lower than the rank of the firm attribute) in each dimension. Market reaction is more negative to managerial underqualification in terms of conglomerate experience and technical expertise, consistent with the importance of these two dimensions.

4.5. Matching Quality and Tenure Length

The I.R. conditions in (5) are more easily satisfied for more compatible partners. Thus, one would expect a better matched executive-firm pair to be more stable and last longer (Allgood and Farrell 2003). To test this prediction, I regress the executive's total tenure length on her match-specific productivity, controlling for noninteractive firm and manager characteristics, firm performance (average ROA over the tenure), and industry or firm fixed effects.

Results in Table 7 suggest that managers with higher technical education tend to stay longer with the firm. Smaller firms and firms with lower R&D intensity tend to have less executive turnover. The better the firm performance, the longer the manager will be retained. More important, tenure length is positively and significantly related to match-specific productivity. It contributes more than the individual firm and manager characteristics to the stability of job matches. A one-standard-deviation change in matching quality is associated with a change in executive's tenure length by 1.6 years, about one-third of the median tenure duration. Thus, it is not the firm or manager characteristics alone that affect the tenure duration, but also the firm-manager complementarities studied in this paper.

Taken together, results in Tables 6 and 7 confirm mutual benefits for both the managers and the firms from assortative matching, as well as the important underlying assumption of the matching market—a manager's marginal productivity depends on where

Table 7. Matching Quality and Tenure Duration

	Tenure duration	
$M_{quality}$	6.53***	6.29**
	(2.56)	(2.98)
$Talent_{dea}$	0.003	−0.048
	(0.02)	(0.07)
Exp_{sale}	2.96	−1.14
	(2.23)	(1.71)
Education	1.77**	1.93
	(0.74)	(2.62)
Assets	−2.55***	−2.92**
	(0.58)	(1.40)
Div_{sale}	−2.74	0.57
	(1.97)	2.14
RD	−1.21***	−4.36
	(0.19)	(5.51)
Avg ROA over tenure	0.04**	0.02
	(0.02)	(0.04)
Industry fixed effects	x	
Firm fixed effects		x
Observations	2,025	2,025
Adjusted R^2	0.07	0.465

Notes. This table reports the results of regressing the total tenure length of the executives on the quality of executive-firm matches, noninteractive manager and firm characteristics, firm performance (average ROA over the entire tenure), and industry or firm fixed effects. $M_{quality}$ is measured by $\sum_{n=1,2,3}\hat{\omega}_n C_n M_n$ with $\hat{\omega}_n$ estimated in Table 4, panel B, column (3). Robust standard errors are reported in the parentheses.

*** and ** indicate significance at the 1% and 5% level, respectively.

she works, thus highlighting the value of "hiring the right manager" separately from the value of a good manager.

4.6. Synergy and Surplus Sharing

After the deterministic part of the match-specific productivity is estimated and validated, the last step is to examine how it is divided between the firm and the manager. An important characterization of the matching game is that firms and managers play cooperatively and are able to negotiate their individual payoffs. The pairwise stability conditions imply that a contract between a firm and a manager will not be signed unless both parties are sure that more favorable terms cannot be achieved elsewhere. The manager's share is her compensation divided by match-specific productivity:

$$\theta_i = p(c_i, m_i)/\hat{F}(c_i, m_i). \tag{7}$$

Table 8, panel A lists the summary statistics of $1-\theta_i$, the firm's share from total matching output. At the median, managers obtain 12.8% of the total synergy generated by their job matches. The surplus generated by a better match, say (c_i, m_i), based on the match-specific productivity, compared to a worse match, (c_j, m_j), is shared between c_i and m_i. Denote η_{ij} as the portion of this surplus obtained by manager m_i:

$$\eta_{ij} = [p(c_i, m_i) - p(c_j, m_j)]/[\hat{F}(c_i, m_i) - \hat{F}(c_j, m_j)], \tag{8}$$

where η_{ij} is determined by the shape of the matching graph,[14] which is in turn governed by the empirical joint distribution of firm and manger attributes. Thus, it can be interpreted as the bargaining power of manager m_i based on her market position.

To examine the impact of each of the three complementarities on managerial bargaining power, I estimate the following regression:

$$\begin{aligned}\eta_{ij} = {} & \alpha_0 + \beta_1 \triangle_{m_i m_j} Exp_{sale} + \beta_2 \triangle_{c_i c_j} Div_{sale} + \beta_3 \triangle_{m_i m_j} Exp_{sale} \\ & \times \triangle_{c_i c_j} Div_{sale} + \lambda_1 \triangle_{m_i m_j} Edu_{tech} + \lambda_2 \triangle_{c_i c_j} RD \\ & + \lambda_3 \triangle_{m_i m_j} Edu_{tech} \times \triangle_{c_i c_j} RD + \gamma_1 \triangle_{m_i m_j} Talent_{dea} \\ & + \gamma_2 \triangle_{c_i c_j} Assets + \gamma_3 \triangle_{m_i m_j} Talent_{dea} \\ & \times \triangle_{c_i c_j} Assets + \epsilon_{ij},\end{aligned} \tag{9}$$

where η_{ij} is the bargaining power of manager m_i. The $\triangle$s are the differences in company or manager characteristics of the two pairs. For example, $\triangle_{c_i c_j} Assets = Assets_{c_i} - Assets_{c_j}$. Table 8, panel B reports the estimation results. Every observation now contains information for two matched pairs (c_i, m_i) and (c_j, m_j). The coefficients on the interaction terms β_3, γ_3, and λ_3 reflect the effect of a better match on the managerial bargaining power. The estimated coefficients are all positive and significant. Thus, the marginal effect of the gap in manager characteristics on managerial bargaining power increases when the gap in the corresponding firm characteristics is larger. For a certain degree of diversification discrepancy between two companies (e.g., if c_i is a diversified firm and c_j is a focused firm), the more heterogeneous industry experience manager m_i has relative to m_j, the larger is the proportion of the surplus she can obtain. The same interpretation

Table 8. Bargaining Power and Relative Ranking

Panel A: Split of total match-specific productivity

Percentiles (%)	Firm's share of total matching output
1	0.578
5	0.701
10	0.746
25	0.806
50	0.872
75	0.935
90	0.972
95	0.985
99	0.996
Mean	0.862
Std. dev.	0.092

Panel B: The effect of firm-manager relative ranking on the split

	Manager's bargaining power
$\triangle_{m_i m_j} Talent_{dea} \times \triangle_{c_i c_j} Assets$	0.06**
	(0.02)
$\triangle_{m_i m_j} Exp_{sale} \times \triangle_{c_i c_j} Div_{sale}$	0.71***
	(0.03)
$\triangle_{m_i m_j} Education \times \triangle_{c_i c_j} RD$	0.87***
	(0.05)
$\triangle_{m_i m_j} Talent_{dea}$	−0.01
	(0.01)
$\triangle_{m_i m_j} Exp_{sale}$	0.10***
	(0.01)
$\triangle_{m_i m_j} Education$	0.10***
	(0.01)
$\triangle_{c_i c_j} Assets$	0.002
	(0.01)
$\triangle_{c_i c_j} Div_{sale}$	0.04**
	(0.01)
$\triangle_{c_i c_j} R\&D$	0.06***
	(0.02)
Year fixed effects	x
Observations	171,764
Adjusted R^2	0.03

Notes. Panel A reports the summary statistics of firm's share $(1-\theta)$ of the estimated total match-specific productivity; see Equation (7). Results from specification (9) are reported in panel B. The dependent variable is the surplus share (bargaining power) for the manager, η_{ij} in Equation (8). The $\triangle$ variables measure the discrepancies in firm or manager characteristics of each pair of observed job matches i and j. For example, $\triangle_{m_i m_j} Talent_{dea}$ is the difference in managerial talent between manager i and manager j. Robust standard errors are included in the parentheses.

*** and ** indicate significance at the 1% and 5% level, respectively.

applies to the other two dimensions as well. For example, a manager with talent ranked 10% higher than her counterpart in a firm ranked 10% smaller would have a bargaining power gain of 0.06%.

5. Conclusion

Using a competitive assignment model, this paper empirically studies and isolates the gains from executive-firm matches. Examining the matching determinants is important. If the necessary managerial skills are not there to begin with, changing the contract or the oversight will not increase productivity. The results suggest that instead of superior information, network, or luck, the importance of firm-manager complementarities highlight the importance of heterogeneity in desirable firm attributes across competing firms in explaining their different abilities to match with desirable managers. Attributes of the active firms and mangers determine their positions on the demand and supply sides of the executive labor market and, therefore, affect both their bargaining power and payoff. The stock market also applauds the announcement of high-quality matches, measured by firm-manager complementarities.

This paper focuses on the matching outcome instead of the matching process. The empirical analysis focuses on a subsample of experienced managers and discounts search costs, potential initial uncertainty about the match value due to imperfect information (see Pan et al. 2015), and other types of market frictions, which should be taken into account for a more comprehensive study of the matching process. The econometric literature is ahead of the empirical literature in identifying the distribution of unobserved complementarities in matching games (Fox and Yang 2012). Together with the recent developments in industrial organization, this paper opens up several potential new directions of empirical research in the executive-firm matching area.

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Endnotes

[1] For example, James McNerney worked for Procter and Gamble and General Motors, before becoming the CEO of 3M.

[2] Both AMD's total assets and R&D intensity consistently rank in the top 10% of the Compustat universe.

[3] For example, "abnormal" compensation, which is the residual of regressing compensation on firm attributes and manager attributes, is usually used as a measure for governance problems.

[4] Firm and manager attributes are exogenous, as in most of the matching models. See Baranchuk et al. (2011) for endogenizing firm size.

[5] Imposing search costs that are symmetric across actual and counterfactual partners does not change the results.

[6] Following the standard job matching model (Jovanovic 1979a, b; McLaughlin 1991), I assume that managers write spot contracts with the company and that managerial compensation is flexible and negotiated each period.

[7] For simplicity, I assume if c_n and m_u are both left unmatched, then $V(c_n, m_u) = 0$ and $p(c_n, m_u) = 0$. Because all matches generate positive incremental surplus, no agent will prefer to deviate and be left unmatched.

[8] The equilibrium is unique because the preferences of the company are aligned with the preferences of the manager (Gale and Shapley 1962).

[9] Econometrically, these auxiliary assumptions restrict the specification of the production function (see §4). Section B.5 in Internet Appendix B (available as supplemental material at https://doi.org/10.1287/mnsc.2015.2278) provides a model of many-to-one matching without the restriction of additive separability as a robustness check.

[10] Prior theoretical studies in this area also commonly use the Cobb-Douglas type of production functions (see Terviö 2008, Gabaix and Landier 2008, Edmans et al. 2009). See the Internet appendix for an alternative specification.

[11] A reduced-form analysis could still be useful in identifying noninteractive firm or manager attributes or fixed effects as determinants of managerial compensation.

[12] For example, Grinstein and Hribar (2004) find that CEOs who have more power to influence board decisions receive significantly larger bonuses after completing M&A deals that increase the firm size.

[13] Confounding events and interim successions are dropped.

[14] Matching graph is a function describing who matches with whom.

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