Essays on Markets for CEOs and Financial Analysts

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Essays on Markets for CEOs and Financial Analysts

Essays on markets voor CEO's en financiële analisten

Thesis

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Contents

Chapter I

Introduction

CEOs and financial analysts are key agents in the financial market and attract many attentions from different types of market participants. This dissertation contains three essays on empirical analysis of the market for CEOs and financial analysts. Analyzing the market for these two types of agents gives us the opportunity to understand how agents are matched, and the impact of the matching on agents' performances.

Chapter 2 of the thesis directly analyzes the market for CEOs itself. Previous researches on CEO succession mainly treat it as a one-time event. However, it is a cascade of events with different important announcements. This chapter focuses on two key events: The announcement of incumbent CEO step down news and the announcement of new CEO identity news. Previous researches treat both of the events happens at the same time. Based on hand-collected data on 1739 CEO turnovers, surprisingly, more than 30% of total CEO turnover in U.S. S&P 1500 firms experience a protracted succession that these two events do not happen at the same day. Also, contrary to the conventional view, a simple long-only strategy that buys stocks that experience protracted succession and sale when the information of new CEOs' identity is publicly available yields an annual four-factor alpha of 11%. This positive return is likely to be caused by two mechanisms: First, investors' under-reaction to lack of news about the successor during the period of protracted succession. Second, the internal tournament competition for CEO positions among different senior executives.

Chapter 3 and Chapter 4 of the thesis study the impact of two-sided matching in different markets for CEOs and financial analysts. The two-sided matching market contains two distinct group of agents, and they choose to match with each other based on their mutual choices. One critical feature of the two-sided matching market is that the matching decisions of two agents depend on their relative ranking on each side of the markets. That is, the matching decision not only depends on their own characteristics but also on other agents' characteristics as well. This feature creates difficulty in estimating the matching choices because when trying to evaluate one agent's choice, other agents choices need to take into account as well, especially when there are many unobserved characteristics. But on the other hand, creates sources to identify forces that are conventionally impossible to quantify.

Chapter 3 of the thesis study the match between new CEOs and firms in a one-to-one two-sided matching market, and try to quantify the relative importance of two co-founding effects that lead to new CEOs receive higher incentive pay performs better: incentivize CEOs to perform better (incentive effect) and select a better CEO (selection effect). These two effects work in the same direction and to disentangle them is difficult because the matching between new CEOs and firms is a complicated process involving observed and unobserved characteristics of both parties and other market agents. To overcome the problem, chapter 3 uses the feature of the two-sided matching market between new CEOs and firms that other agents' characteristics correlate with the matched pairs' decisions, but the outcomes do not. Therefore, if the agents' characteristics distribution exogenously varies across markets, these other agents' characteristics can serve as instruments to separate selection effect and incentive effect of incentive pay. The results show that the selection effect accounts for 12.7% of the total impact while the incentive effect accounts for 87.3% of the total impact. The selection effect becomes stronger in industries or period where the mobility of CEO talent is high.

Chapter 4 of the thesis analyzes the brokerage firm reputation effect on new analysts forecast accuracy. We find that new analysts work for better reputable brokerage firms on average issue more accurate forecasts. Two effects could explain this positive correlation: Better reputable brokerage firms provide better resources to help analysts forecast better; Talented analysts choose to work for better reputable brokerage firms. By using a Bayesian approach with Markov Chain Monte Carlo (MCMC) method to estimate a structure model that contains a one-to-many two-sided matching market, the result shows that the direct influence effect from brokerage firms accounts for 73% of the total impact and the indirect sorting effect that talented analysts sorts on brokerage firm reputation accounts for 27% of the total impact. The result highlights the benefit of working in the reputable firms for workers, also suggests possible incentives for firms to develop and maintain their reputation.

Declaration of Contribution

Chapter 2 is based on a co-authored paper by Gabarro, Gryglewicz, and Xia (2018), "Lame-Duck CEOs" (available at https://papers.ssrn.com/abstract=3193048). I actively participating in research design, writing, hand-collected all the data, and perform the empirical analysis.

Chapter 3 is based on a single paper by Xia (2018), "Selection versus Incentives in Incentive Pay: Evidence from a Matching Model" (available at https://papers.ssrn.com/abstract=3190685). I finished it by my own.

Chapter 4 is based on a co-authored paper by by Wang, and Xia (2018), "Standing on the shoulders of giants: The impact of broker reputation on analyst forecast". We each share 50% of the workload.

Chapter II

Lame-Duck CEOs

"You can tell that I'm a lame duck because nobody's following instructions."

- President Barak Obama's Farewell Address, 2017

"There is not one fiber in my body that feels like a lame duck. Nobody treats me differently, I am still the CEO, and I am incredibly busy."

- Joe Tucci, CEO of EMC, 2014

1 Introduction

The appropriate succession of key individuals is crucial to organizations' performance: both for presidents of countries and CEOs of firms. When a CEO departure is announced without a successor, the incumbent CEO becomes a "lame duck." Firms with lame duck CEOs are exposed to a potential lack of leadership that may result in stalling, high levels of uncertainty, and freezes in significant decisions. This generally negative view on protracted transitions has prompted the SEC and other regulatory bodies around the world to increase succession planning disclosure requirements.

In contrast to this view, this paper shows that firms with protracted CEO successions experience positive abnormal returns. We document an annual four-factor alpha of 11% during the reign of lame duck CEOs. We then examine the returns around important dates to better understand the mechanisms that explain this positive alpha. First, the market under-reacts to the lack of news during "lame duck" CEO reigns-that is, to the time-varying probability that a new CEO is announced. Second, the market under-estimates the positive effects of the tournament among CEO candidates.

Our empirical analysis is based on CEO turnovers in S&P 1500 firms from 2005 to 2014. During this period, there were 1,739 CEO turnover events, of which 537 (31%) are protracted CEO successions. Specifically, for each CEO succession, we identify the first news about the CEO departure (departure announcement), the first news about the successor (successor announcement), and the date that the incumbent CEO leaves office and the new CEO takes over (departure date).

If the successor announcement takes place after the departure announcement, we define this CEO succession as protracted; otherwise, we define it as prompt. We then form monthly portfolios as follows. We include a firm in the protracted succession portfolio at the beginning of the following month after the departure announcement until the beginning of the next month after the successor announcement. We obtain the monthly four-factor alpha by calculating the protracted firm portfolio returns after controlling for the market, size, growth, and momentum factors. Overall, the portfolio of firms with a lame duck CEO, or protracted successions, outperforms others by an annual four-factor alpha of 11%. This positive alpha cannot be explained by industry, observed characteristics, or stock return volatility change associated with the turnover event.

We offer two possible explanations for the mechanisms behind the surprising positive performance of lame duck CEOs. The first one focuses on the stock market positive abnormal returns. We document that investors under-react to the lack of news about a successor during the period between the incumbent CEO's departure announcement and the successor announcement. As in Giglio and Shue (2014), no news contains information on the probability that the firm will finish the CEO search and appoint a successor, and investors should interpret the passage of time as information and incorporate it into stock prices. We start by estimating a hazard model and non-parametrically estimate the successor announcement hazard rate for the amount of time following the incumbent CEO's departure announcement. Then, we show that the weekly stock returns are positively associated with the empirical hazard rate: for each 1% increase in hazard rate, the weekly stock return will increase by 1.27%. Finally, we construct calendar-time portfolios based on firms' hazard rates across calendar time. We find that the portfolio containing firms with high hazard rates exhibit a monthly alpha of 1.4%, much higher than the portfolio of firms with a low hazard rate, which has a monthly alpha of 0.5%. The results indicate that investors' under-reaction to no news is part of the explanation of the positive excess return during lame duck CEO periods.

The second explanation focuses on the economic mechanism driving the lame duck firm's performance. Following the incumbent CEO's departure announcement, firms undergo a tournament to select a successor from potential internal candidates. This internal tournament competition can be thought of as one type of intangible assets that benefits firm value but is slowly incorporated into stock price (Edmans, 2011). We start by creating calendar-time portfolios based on firms' ex-ante tournament competition among executives below the CEO level. According to the tournament model Rosen (1981); Main et al. (1993), competition intensity increases when the potential candidates share a similar probability of winning. We use inverse standard deviation among senior executives to measure tournament competition levels and sort firms into a high tournament portfolio and a low tournament portfolio. The portfolio associated with high tournament competition results in the significant positive monthly alpha of 1.5%. We also test the internal tournament competition hypothesis by sorting the portfolios based on whether the ultimate successor is internal or external. The portfolio with internal successors is associated with more than 2% monthly excess return. The abnormal return around earnings announcement is highest for firms with high tournament competition and internal CEO successors.

We also explore other possible mechanisms that might explain the positive excess return during the lame duck CEO period. We examine alphas of calendar-time portfolio returns sorts on different turnover and on firm characteristics. We conclude that alternative explanations, such as different motives for the incumbent CEO's departure, and having a capable interim CEO or a well-functioning board, are likely to explain the abnormal returns of firms with lame-duck CEOs.

Our findings contribute to the empirical literature on CEO succession planning that followed the latest regulatory changes. Cvijanovic et al. (2017) study the effects of a formal succession plan (based on firms' disclosure), while Naveen (2006) and Mobbs and Raheja (2012) study the effects of planned "relay" successions, in which a firm grooms a president or a chief operating officer as the new CEO. We contribute to this literature by documenting abnormal returns during protracted CEO successions.

More broadly, our findings are related to the extensive literature on causes and consequences of CEO turnover (Coughlan and Schmidt, 1985; Warner et al., 1988; Weisbach, 1988; Denis and Denis, 1995; Parrino, 1997; Huson et al., 2001; Zhang and Rajagopalan, 2004; Huson et al., 2004; Eisfeldt and Kuhnen, 2013; Taylor, 2010; Jenter and Kanaan, 2015). However, unlike our analysis, most papers in this field consider CEO turnover as a single-date event. Notable exceptions are Vancil (1987); Shen and Cannella (2002); Naveen (2006) and Intintoli (2013), who also explore the multi-event process of "relay" and "marathon" CEO successions, respectively. We contribute to their findings by exploring the market reactions to these events and shedding light on the mechanisms driving them. Because we document tournament incentives as a crucial mechanism underlying the positive abnormal returns of lame duck CEOs, our paper also relates to the extensive literature on tournament incentives, such as (Kale et al., 2009; Kini and Williams, 2012).[1]

Our study has some implications for the regulation of succession planning. In their staff legal bulletin in 2009, the SEC advocated for firms to be aware of the potential risk of a vacancy in

[1]See Connelly et al. (2014) for a detailed review of the tournament theory and corresponding empirical studies.

leadership associated with poor succession planning (SEC, 2009). Since then, the regulatory discussion on planned succession has overwhelmingly taken a one-sided view that prompt successions are superior to protracted ones. They therefore advocate that firms be mandated or incentivized to formally prepare for smooth CEO successions under various contingencies, increasing corporate governance scrutiny on succession planning. Our results indicate that firms that opt for protracted successions perform better than expected, insofar as the market underestimates some benefits of such successions. Hence, our results do not support increased regulatory attention to CEO succession planning that guarantees prompt CEO turnovers.

The remainder of this paper is organized as follows. Section 2 discusses the practice of protracted CEO successions and presents our data and empirical methodology. Section 3 contains our main results and robustness tests. Section 4 explores possible explanations for the positive alpha. Section 5 discusses alternative explanations and long-run performance. Section 5 concludes the paper.

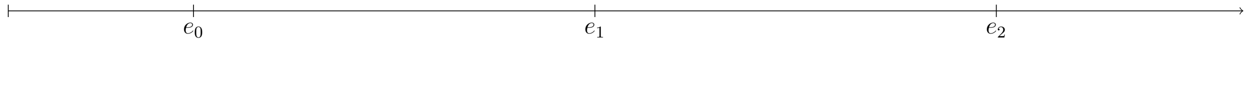
2 Background, Data, and Empirical Methodology

2.1 Lame-Duck CEOs Background

CEO turnover is arguably one of the most significant events for any firm and can become a key determinant of firms' success. The multi-period, lengthy process of CEO turnover has many events and key dates, and includes firm-specific idiosyncrasies. However, a stylized CEO succession process involves, at the very least, three crucial, publicly known events. First, a firm announces that the incumbent CEO is stepping down (departure announcement). Second, the firm announces the successor's identity (successor announcement). Third, the incumbent CEO formally steps down, and the new CEO officially takes over the firm's operations (departure date). Figure (1) plots these events.

Figure 1. CEO Turnover Timeline

This timeline plots a stylized CEO turnover event. *Departure announcement* is the announcement that the incumbent CEO is stepping down. *Successor announcement* is the announcement of the successor's identity. *Departure date* is the date when the outgoing CEO formally steps down and the new CEO officially takes over the firm's operations.



To understand the lame duck CEO phenomenon, we focus on the period between the incumbent CEO's departure announcement (e_0) and the announcement of a successor (e_1). This is the period with the highest potential for risk, in terms of lack of leadership and stagnation, and has been referred to publicly as a "long goodbye" (see, for example, Lublin (2004) and Lublin (2014)). Alternatively, the lame duck period may last until e_2; that is, until the new CEO takes office. We do not include the period between the successor announcement (e_1) and the point at which a new CEO takes office (e_2) in our main specification for a couple of reasons.[2] First, how the period between the successor announcement and the incumbent's departure is defined changes depending on whether the successor is externally appointed or internally promoted, thereby potentially clouding our results. Second, the situation changes dramatically after a new CEO is nominated: the tournament incentives to become the next CEO disappear and the incumbent CEO focuses on helping the new CEO to understand the firm's operations and financial conditions. Finally, there is no lack of leadership after e_1: the new CEO may not be in office, but everyone knows who he/she is. In short, the appointment of a new CEO affects any decision made between e_1 and e_2, even if the formality of taking office has not yet taken place. After e_1, any firm's performance change is likely to be impacted by the new CEO.

2.2 Data

We analyze CEO turnover for S&P 1500 firms during the period 2005-2014. Our sample starts in 2005, following the SEC announcement effective August 23rd, 2004, requiring firms to disclose any relevant information about the departure or appointment of principal executive officers within four business days and to file the corresponding 8-K form under Section 5.02. Importantly for our study, the SEC clarifies that this disclosure requirement is triggered by information regarding the CEO's employment termination, not only by actual job termination. Hence, from 2005 onwards, we can identify "lame duck" CEOs more precisely. We only include CEO turnover data through 2014 to ensure that all of our observations are completed CEO successions. We eliminate all CEO turnover events involving interim or acting CEOs, mergers and acquisitions, spin-offs, co-CEOs, CEOs appointed for a term shorter than twelve months, and firms that do not have stock price information listed in CRSP.

We then hand-collect from the Factiva database the date of the first publicly known announcement that the incumbent CEO i is stepping down (e_0^i). Similarly, we hand-collect from Factiva the date when the firm announces his/her successor's identity (e_1^i) and the date when the incumbent

[2] As a robustness test, in Table 5, we repeat our main analysis by defining protracted successions as lasting until e_2, and we obtain very similar results in terms of both economic and statistical significance.

CEO i relinquishes his/her CEO position (e_2^i). Then, we define a CEO's i succession as *Protracted* if e_0^i takes place before e_1^i. Our sample includes 1,739 CEO turnovers, with 537 protracted CEO successions. We refer to the incumbent CEO in protracted successions as a "lame duck" CEO in the period between e_1^i and e_2^i. Table 1 Panel A tabulates all CEO successions and protracted successions by year. Panel B shows the summary statistics on protracted period length. Table 1 shows that the percentage of protracted successions is relatively stable across years and that the average (median) lame duck CEO presides for 173 (142) days.

Table 1. Summary Statistics CEO turnovers

This table provides summary statistics for CEO turnovers. Panel A focuses on succession types, presenting data for All CEO, Prompt Successions, and Protracted Successions. Prompt Successions are defined as CEO turnover cases in which the announcement of the incumbent CEO's resignation (e_0) takes place at the same time that the firms reveals the identity of the successor CEO (e_1); otherwise, they are defined as Protracted Successions. Panel B presents detailed summary statistics for the duration of protracted successions, the difference between e_0 and e_1, in days.

Panel A: Succession types

Year	All	Prompt successions		Protracted successions	
	Number	Number	Percent(%)	Number	Percent(%)
2005	195	138	70.8	57	29.2
2006	181	124	68.5	57	31.5
2007	188	131	69.7	57	30.3
2008	198	140	70.7	58	29.3
2009	155	115	74.2	40	25.8
2010	149	107	71.8	42	28.2
2011	186	129	69.4	57	30.6
2012	175	109	62.3	66	37.7
2013	161	107	66.5	54	33.5
2014	151	102	67.5	49	32.5
Total	1739	1202	69.1	537	30.9

Panel B: Protracted succession duration

Year	Number	mean	5p	25p	50p	75p	95p
2005	57	152.3	13	131	174	174	413
2006	57	195.5	22	105	158	211	639
2007	57	144.9	4	75	118	180	360
2008	58	182.9	1	64	134	221	672
2009	40	167.4	2	83	125	172	609
2010	42	156.7	16	87	158	210	330
2011	57	202.5	29	94	141	222	695
2012	66	168.3	40	118	155	201	293
2013	54	154.7	35	101	133	200	306
2014	49	181.1	36	110	154	201	377
Total	537	173.2	19	92	142	203	440

Table 2 presents summary statistics for the variables in our analysis for all CEO successions, prompt successions, and protracted successions, separately. Most notably, the industry-adjusted return on asset is higher in prompt succession firms, with a mean value of 0.069 in prompt succession firms and 0.050 in protracted succession firms; the difference is significant at the 5% level. Firms that experience prompt successions also enjoy higher valuation than firms with protracted succession, with a market-to-book difference of 0.19, significant at the 5% level. Firms with prompt successions are 11.6% more likely to pay dividends than firms with protracted successions. This difference is statistically significant at the 1% level. Interestingly, on average, firms with protracted successions have higher tournament incentives than firms with prompt successions; the mean value is almost one time higher. This difference is statistically significant at the 1% level. Appendix A includes a definition of all of our variables.

Table 2. Summary Statistics

This table provides summary statistics for all of our variables. All variables are defined in appendix A. Column (1) shows the average value for all successions. Columns (2) and (3) show averages for prompt and protracted CEO turnovers, respectively. Column (4) shows the two-sided t-test results for the difference in mean. In column (4) t-statistics are in parentheses. In columns (1) through (3), standard errors are in square brackets. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. Our sample includes firms in the S&P 1500 from 2005 to 2014.

Variable	All (1)	Prompt (2)	Protracted (3)	Difference: Prompt - Protracted (4)
Total asset($bn)	19.237	18.271	21.693	-3.422
	[100.909]	[89.901]	[124.697]	(-0.951)
Ind-adj ROA	0.064	0.069	0.050	0.019**
	[0.159]	[0.168]	[0.131]	(2.249)
Leverage	0.218	0.223	0.204	0.018
	[0.235]	[0.248]	[0.196]	(1.156)
Market-to-book	1.537	1.591	1.401	0.190**
	[1.532]	[1.692]	[1.021]	(2.133)
Dividend Payer	0.560	0.593	0.476	0.116***
	[0.497]	[0.492]	[0.500]	(3.687)
CEO focus score	0.106	0.104	0.111	-0.006
	[0.077]	[0.078]	[0.073]	(-1.417)
Tournament incentive	0.024	0.019	0.037	-0.018***
	[0.113]	[0.022]	[0.212]	(-2.678)

Overall, Table 2 suggests that protracted successions are likely to occur in less profitable and less valued firms. Protracted succession firms are also less likely to pay dividends and have higher tournament incentives than prompt succession firms. As such, we need to control explicitly for these characteristics in our empirical methodology. To do so, we use the Carhart (1997) four factors obtained from the Kenneth R. French Data library.

2.3 Empirical Methodology

We construct equally weighted portfolios with monthly rebalancing based on the publicly available information for CEO succession announcements, as follows. The *Protracted Succession* portfolio includes all firms currently experiencing a lame duck CEO reign: the incumbent departure has been announced, but the new CEO identity is unknown. Specifically, we add a firm in the *Protracted Succession* portfolio at the beginning of the following month after the incumbent CEO announces his/her departure, that is, e_1. The firm remains in the *Protracted Succession* portfolio until the end of the month when the new CEO identity is revealed, that is, e_2. To ensure performance is not the result of differences in risk, we control for the Carhart (1997) four-factor model described as follows:

$$R_t = \alpha + \beta_{mkt} * mktrf_t + \beta_{smb} * smb_t + \beta_{hml} * hml_t + \beta_{umd} * mom_t + \varepsilon_{i,t} \tag{1}$$

The dependent variable R_t is the return of the *Protracted Succession* portfolio in month t in excess of a benchmark. α measures the abnormal risk-adjusted return of the *Protracted Succession* portfolio. $mktrf_t$, smb_t, hml_t and umd_t are the returns on the market, size, value, and momentum factors. As in Edmans (2011), we calculate the returns R_t over three different benchmarks. First, we use the risk-free rate. Second, we use the 49 Fama-French average industry returns, which ensures that our results are not driven by some industry-specific risk that is not captured by the Carhart (1997) four-factor model. Third, we use the characteristics-adjusted benchmark by Daniel et al. (1997), which matches each stock to a portfolio of similar firms in terms of size, value, and momentum. This ensures that our results are not driven by the explanatory power of the Carhart (1997) four factors. We correct the standard errors for heteroscedasticity and serial correlation using Newey and West (1987), with the optimal lag-selection method in Newey and West (1994).

We also run short-period event studies around earnings announcements during the CEO succession process. As is standard in finance literature (Brown and Warner (1985)), we use the market model with an estimation period between -255 days to -46 days before the event. Given the short event period window (up to a couple of days), the results are robust to alternative specifications of expected returns.

Overall, our empirical methodology relies on market-based estimates of firm performance. We do so to ensure that our results are not clouded by some (unobserved) factors, such as firms' or CEOs' characteristics, which could otherwise bias our results. We expect market participants to efficiently incorporate into prices any cross-sectional differences in firm characteristics that could otherwise bias our results.

3 Lame-Duck CEO Performance

3.1 Stock Returns

In this section, we study the performance of lame duck CEOs at firms undergoing protracted successions. First, Figure 2 shows the cumulative abnormal returns of the *Protracted Succession* portfolio, that is, it accumulates the monthly α from equation (1). We plot the results for the cumulative abnormal returns using three different benchmarks: the risk-free rate, the 49 Fama-French average industry returns, and the characteristics-adjusted benchmark. Second, we show the regression equivalent in Table 3 Panel A. Columns (1), (2), and (3) show the results using the risk-free rate, the 49 Fama-French average industry returns, and the characteristics-adjusted benchmark, respectively.[3] The relative over-performance of firms with lame duck CEOs remains constant and statistically significant across specifications, with the *Protracted Succession* portfolio annualized α around 10%.

We then document that lame duck CEOs indeed drive our results, not any potential confounding effects arising from CEO turnover. In Table 3 Panel B, we show that our results are similar when we use a "long and short" portfolio (instead of the "long only" in Panel A) that shorts for non-lame duck CEO successions. We call this portfolio "Prompt Succession" and we construct it as follows. Akin to the "Protracted Succession" portfolio, we include a firm in the portfolio at the end of the month that news of the incumbent CEO's departure is made public. There is no obvious holding period for firms with prompt succession to remain in the "Prompt Succession" portfolio: as per the prompt succession definition, the new CEO is announced jointly with the incumbent CEO departure. We choose six months, as this is the average (and median) holding period for protracted turnover firms. The "long and short" portfolio obtains an annualized α around 8.5%, similar to Table 3 Panel A, both in terms of economic and statistical significance.[4]

3.2 Earnings Announcements

The stock return results show that there is information contained within the lame duck CEO period, and that this information is beneficial to firm value but not incorporated into stock returns immediately. The slow-moving information affects stock returns gradually until outsiders update their information set. One particularly important event for outsiders' information updating is an

[3] The characteristics-adjusted benchmark data ends in 2012, so we have fewer (monthly) observations.

[4] In untabulated tests, we repeated our analysis for holding periods of 3 and nine months, and our results are similar both in economic magnitude and statistical significance.

Figure 2. Cumulative Abnormal Returns for Lame Duck CEOs

This Figure plots the cumulative abnormal return of the equally weighted long-only portfolio based on firms with protracted successions in our main sample. Firms are added to the protracted portfolio at the end of the month that the incumbent CEO's resignation is announced (e_0). The holding period concludes at the end of the month that firms reveal the identity of the successor CEO (e_1). The abnormal returns are based on Carhart (1997) four-factor model. The Figure plots the monthly cumulative abnormal return of the protracted portfolio from Jan 2005 to Dec 2014 in excess of the risk free rate and the industry average return.

Table 3. Main results: Lame Duck CEOs Performance

This table shows the relative over-performance of firms undergoing a lame duck CEO period. The dependent variable is the return for the Protracted Succession portfolio (that is, firms with a lame duck CEO) less either the risk-free rate, the industry-matched portfolio return, or the characteristics-matched portfolio return in columns (1), (2) and (3), respectively. The table shows monthly regressions for the equally weighted portfolio on the Carhart (1997) four factors, MKT, SMB, HML, and MOM. Panel A shows the long-only portfolio of protracted firms. Panel B shows the long-short portfolio: long the protracted succession firms and short the prompt succession firms. α is the excess risk-adjusted return. Standard errors are corrected for heteroscedasticity and serial correlation. T-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Long-only portfolio				Panel B: Long-short portfolio			
	Excess returns over				Excess returns over		
	Risk-free	Industry	Charact.		Risk-free	Industry	Charact.
	(1)	(2)	(3)		(1)	(2)	(3)
α	**0.009****	**0.007***	**0.010****	α	**0.007****	**0.006***	**0.013*****
	(2.203)	(1.956)	(2.017)		(2.037)	(1.797)	(2.740)
β_{MKT}	1.147***	0.129	0.443**	β_{MKT}	0.155*	0.185**	0.175*
	(13.976)	(1.394)	(2.392)		(1.848)	(2.054)	(1.663)
β_{SMB}	0.737***	0.660***	0.346	β_{SMB}	-0.005	0.113	-0.129
	(5.905)	(5.094)	(1.083)		(-0.031)	(0.671)	(-0.533)
β_{HML}	-0.072	0.046	-0.176	β_{HML}	-0.330**	-0.235	-0.362**
	(-0.531)	(0.266)	(-1.023)		(-2.336)	(-1.487)	(-2.384)
β_{MOM}	-0.479***	-0.422***	-0.538***	β_{MOM}	-0.198***	-0.187**	-0.216
	(-5.784)	(-4.640)	(-5.281)		(-3.289)	(-2.529)	(-1.308)
Observations	120	120	84	Observations	120	120	84
Adj. R-squared	0.789	0.396	0.320	Adj. R-squared	0.100	0.112	0.081

earnings announcement. At earnings announcements, firms release material information and answer questions from analysts. We therefore expect significant stock price movements during those events, especially in information intense periods, such as the reign of "lame ducks".

Table 4 Columns (1) and (2) examine the stock return around earnings announcements for firms in the lame duck CEO period. We calculate a three-day window abnormal return around all earnings announcements from January 2005 to January 2015 from the I/B/E/S dataset.[5] We find that abnormal returns around earnings announcements are on average 1% higher during the lame duck CEO period than any other period. This finding is robust when controlling for firm characteristics similar to Pan et al. (2015). Interestingly, in column (3) and column (4), we do not observe the mean earnings surprise is different for firms in protracted succession period. Also, in column (5) and (6), we do not observe the median earnings surprise is different for firms in protracted succession period. The results in Table IV seems to indicate that the information disclosed during earnings announcements do not directly lead to (short-term) earnings increase. However, the positive stock market reaction suggests that this disclosed information relates to firms' performance in the long-run.

[5]We estimate the abnormal returns using the market model with a -255 to -46 days estimation window. Given the short event window, our results are robust to many alternative abnormal returns models.

Table 4. Main result: earnings announcement

This table shows abnormal returns around earnings announcements and analysts' forecasts for earnings from 2005 to 2015. The dependent variable is the three-day window cumulative abnormal returns around the earning announcements in columns (1) and (2). Abnormal returns are calculated above a market model with a -255 to -46 day estimation window. Protracted is a dummy variable indicating protracted successions: it has a value of 1 if the length in days between the announcement of an incumbent CEO's resignation (e_0) and the announcement of a successor CEO (e_1) is greater than zero, and 0 otherwise. The dependent variable in columns (3) and (4) is the firm's quarterly earnings per share surprise when compared with the mean level of analysts' forecasts. The dependent variable in columns (5) and (6) is the firm's quarterly earnings per share surprise when compared with the median level of analysts' forecasts. All earnings surprises are scaled by the firm's stock price. We exclude all financial firms and utility firms. T-statistics are reported in parentheses. Standard errors are clustered at the firm and time levels. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	CAR[-1,+1]		Mean earning surprise		Median earning surprise	
	(1)	(2)	(3)	(4)	(5)	(6)
Protracted	0.010**	0.012**	0.001	0.001	0.001	0.001
	(2.335)	(2.465)	(0.747)	(0.861)	(0.734)	(0.890)
Ln asset		-0.006***		-0.001***		-0.001***
		(-4.181)		(-2.856)		(-2.728)
Market-to-book		0.004***		-0.000*		-0.000
		(6.006)		(-1.704)		(-1.459)
Leverage		-0.012***		0.002		0.002
		(-2.740)		(1.437)		(1.524)
Ind-adj ROA		0.016***		0.011*		0.011*
		(10.240)		(1.881)		(1.778)
Dividend payer		-0.009***		-0.003***		-0.003***
		(-4.200)		(-2.963)		(-2.924)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74,259	61,184	57,895	47,370	57,895	47,370
R-squared	0.042	0.048	0.088	0.092	0.089	0.095

3.3 Robustness and Risk Explanation

Our main results already show that firms' outperformance during lame duck CEO periods is not due to their industry affiliation or matched characteristics, nor to some generic events around all CEO turnovers. We now expand our robustness: first, we show that our results are robust to different methodologies and holding periods; second, we show that volatility does not drive our results.

First, we undertake a portfolio analysis similar to our main results, but extend the holding period of protracted succession until the new CEO officially takes over the office. Table 5 shows that the alphas for the portfolio with extended holding periods are similar to the results found in table 3.

Table 5. Robustness: alternative holding period

This table shows a portfolio test on the different holding periods of the protracted firm portfolio. The dependent variable is the return for the Protracted Succession portfolio (that is, firms with a lame duck CEO) less either the risk-free rate, the industry-matched portfolio return, or the characteristics-matched portfolio return, in columns (1), (2) and (3), respectively. The table shows monthly regressions of the equally-weighted portfolio on the Carhart (1997) four factors, MKT, SMB, HML, and MOM. We use our alternative definition of protracted succession, in which the holding period is redefined as extending until the new CEO takes office. We exclude all financial firms and utility firms. Standard errors are corrected for heteroscedasticity and serial correlation. T-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Panel A: Long-only portfolio			
	Excess returns over		
	Risk-free	Industry	Charact.
	(1)	(2)	(3)
α	**0.008****	**0.006****	**0.008***
	(2.372)	(2.123)	(1.890)
β_{MKT}	1.101***	0.087	0.389**
	(13.619)	(0.946)	(2.120)
β_{SMB}	0.761***	0.669***	0.413
	(6.572)	(5.517)	(1.421)
β_{HML}	-0.023	0.091	-0.139
	(-0.151)	(0.491)	(-0.789)
β_{MOM}	-0.453***	-0.398***	-0.522***
	(-5.556)	(-4.500)	(-5.267)
Observations	120	120	84
Adj. R-squared	0.799	0.401	0.317

Panel B: Long-short portfolio			
	Excess returns over		
	Risk-free	Industry	Charact.
	(1)	(2)	(3)
α	**0.006****	**0.006***	**0.009*****
	(2.065)	(1.797)	(3.398)
β_{MKT}	0.109	0.143	0.133
	(1.316)	(1.542)	(1.336)
β_{SMB}	0.019	0.122	-0.046
	(0.127)	(0.825)	(-0.277)
β_{HML}	-0.281*	-0.190	-0.344**
	(-1.904)	(-1.181)	(-2.168)
β_{MOM}	-0.172***	-0.163**	-0.139***
	(-3.221)	(-2.410)	(-3.311)
Observations	120	120	84
Adj. R-squared	0.100	0.112	0.081

We then control for several individual firm characteristics that might drive returns but are not captured by the four-factor models. Following Edmans (2011), we perform characteristics regressions: raw, industry-adjusted, and characteristics-adjusted monthly returns on different firm characteristics by using two different methods. First, we conduct Fama and MacBeth (1973) regressions. Second, we use a panel regression approach and cluster standard errors along firm and time dimensions. Table 6 presents the results. For all three methodologies, firms undergoing a lame duck CEO period are associated with an additional return of 70 to 120 basis points. These results suggest that the relative outperformance of firms during lame duck CEO periods does not stem from any variation in the controlled individual firm's characteristics.

Table 6. Robustness: characteristics regressions

This table presents the results of characteristics regressions to calculate firms' abnormal returns during lame duck CEO period. From columns (1) to (3), we present Fama-Macbeth monthly regressions for individual stock returns on the dummy variable Protracted and on controls. From columns (4) to (6), we present panel regressions with two-way clustered standard errors along firm and month dimensions. We exclude all financial firms and utility firms. T-statistics are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Fama-Macbeth regression			Panel regression		
	Raw	Industry	Charact.	Raw	Industry	Charact.
	(1)	(2)	(3)	(4)	(5)	(6)
Protracted	0.008***	0.008**	0.012**	0.008**	0.007**	0.011**
	(2.621)	(2.218)	(2.610)	(2.319)	(1.995)	(2.332)
Size	-0.000	-0.000	-0.000	-0.000	-0.001	0.000
	(-0.266)	(-0.353)	(-0.035)	(-0.645)	(-0.806)	(0.306)
Market-to-book	0.000	0.001	0.001	-0.000	-0.000	0.006**
	(0.150)	(1.121)	(0.340)	(-0.855)	(-0.142)	(2.200)
Yield	-0.000	0.000	-0.000	0.000	0.000	0.000
	(-0.373)	(0.046)	(-0.008)	(0.061)	(0.412)	(0.076)
Ret2-3	0.002	0.003	0.002	-0.000	0.002	-0.001
	(0.508)	(0.625)	(0.329)	(-0.054)	(0.366)	(-0.164)
Ret4-6	-0.001	-0.001	-0.002	-0.006	-0.005	-0.007
	(-0.169)	(-0.142)	(-0.333)	(-0.833)	(-0.813)	(-0.893)
Ret7-12	0.001	-0.001	-0.002	-0.001	-0.002	-0.000
	(0.205)	(-0.213)	(-0.852)	(-0.160)	(-0.624)	(-0.121)
L2.Volume	0.000	0.000	0.000	0.000	0.000	0.000
	(0.750)	(0.478)	(0.464)	(0.416)	(0.568)	(0.088)
L2.Price	0.000	0.000	0.000	0.000*	0.000*	0.000
	(0.661)	(0.703)	(0.502)	(1.673)	(1.948)	(1.331)
Two-way cluster	No	No	No	Yes	Yes	Yes
Month fixed effect	No	No	No	Yes	Yes	Yes
Observations	420,560	416,279	271,780	420,560	416,279	271,780
Adj. R-squared	0.023	0.020	0.029	0.126	0.018	0.107
Number of groups	120	120	90			

Second, we show that the positive alpha is not associated with a change in risk during firms' lame duck CEO periods. Our main analysis already controls for systematic risk using the Carhart (1997) four-factor model. However, there may be some temporary changes in risk during the reign of lame duck CEOs that may not be well captured by these factors. If the market prices such temporary changes in risk, the protracted succession portfolio's abnormal returns may be compensated for the additional risk. As is standard in the literature, our measure of risk is equity return volatility (e.g. Ang et al. (2006, 2009)). Hence, we explicitly study changes in volatility around the onset of a lame duck CEO.

Table 7 shows that there are no economically (nor statistically) meaningful changes in volatility around protracted CEO successions. In Panel A, we focus on changes in the realized stock return volatility, while in Panel B, we focus on changes in idiosyncratic volatility. In columns (1) and (2), we show changes in volatility for the 90 days after the CEO departure announcement compared to the 90 days before. We repeat the analysis with changes around 120 and 255 days in columns (3) and (4), and columns (5) and (6), respectively. In the even-numbered columns, we control for firm-specific characteristics measured one year prior to news of the incumbent CEO's departure. Our results are robust to all specifications.

Table 7. Robustness: Volatility change

This table presents the results for changes in volatility around the announcement of the incumbent CEO's resignation. The dependent variables in columns (1) and (2) are the average stock return volatility for the 90 days after the announcement less the average stock return volatility for the 90 days before the announcement. The dependent variables in columns (3) and (4) are the average stock return volatility 120 days after the announcement less the average stock return volatility 120 days before the announcement. The dependent variables in column (5) to (6) are the average stock return volatility 225 days after the announcement less the average stock return volatility 225 days before the announcement. *Protracted* is a dummy variable that takes a value of 1 if the succession is protracted, and 0 otherwise. All variables are defined in appendix A. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Panel A: Realized return volatility					
	Δ Vol 90 days		Δ Vol 120 days		Δ Vol 225 days	
	(1)	(2)	(3)	(4)	(5)	(6)
Protracted	-0.002	-0.002	-0.007	-0.007	-0.017*	-0.015
	(-0.373)	(-0.307)	(-0.933)	(-0.825)	(-1.678)	(-1.360)
Ln asset		-0.002		-0.003		-0.004
		(-0.812)		(-1.074)		(-1.022)
Ind-adj ROA		0.053**		0.027		-0.011
		(2.251)		(0.999)		(-0.315)
Leverage		0.015		0.018		0.027
		(0.967)		(1.112)		(1.298)
Market-to-book		-0.003*		-0.005**		-0.005**
		(-1.656)		(-2.342)		(-1.992)
Dividend payer		0.008		0.011		0.022**
		(1.201)		(1.353)		(2.387)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,391	1,204	1,388	1,201	1,380	1,196
R-squared	0.210	0.215	0.311	0.299	0.477	0.461

	Panel B: Idiosyncratic return volatility					
	Δ Vol 90 days		Δ Vol 120 days		Δ Vol 225 days	
	(1)	(2)	(3)	(4)	(5)	(6)
Protracted	0.005	0.004	0.003	0.002	0.001	-0.002
	(0.707)	(0.503)	(0.444)	(0.287)	(0.138)	(-0.152)
Ln asset		-0.004**		-0.004		-0.005
		(-2.039)		(-1.556)		(-1.466)
Ind-adj ROA		0.056**		0.049*		-0.012
		(2.202)		(1.817)		(-0.351)
Leverage		-0.001		0.003		0.024
		(-0.044)		(0.182)		(1.105)
Market-to-book		-0.002		-0.003		-0.005**
		(-0.904)		(-1.498)		(-1.987)
Dividend payer		0.007		0.009		0.011
		(1.293)		(1.401)		(1.262)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,391	1,204	1,388	1,201	1,380	1,196
R-squared	0.055	0.072	0.095	0.107	0.244	0.241

Overall, we confirm our main results showing that firms with protracted CEO successions obtain a positive Carhart (1997) four-factor α, and show that this result is not driven by any alternative observed firm characteristics or variations in risk.

4 Why Do Lame Duck CEOs Outperform?

Section 3 showed that firms undergoing a lame duck CEO period experience significant positives and that this finding is robust to controls for risk and industry and firm characteristics. However, our results raise the question of why such positive returns take place to begin with. In this section, we explore two possible explanations for the unexpected performance of lame duck CEOs: under-reaction to no news of a new CEO and within-firm tournament competition for the new CEO spot.

4.1 Under-reaction to no news

As King James I of England said "No news is better than evil news." The passage of time contains information that relates to the development of the current state.

Because of limited attention or behavioral biases, investors' reactions are different for different types of news. In particular, investors have been shown to under-react to less obvious news (Peng and Xiong, 2006). It is thus reasonable to expect investors to be oblivious to information contained in the mere passage of time. For example, Giglio and Shue (2014) find that during the period between an M&A announcement and its completion, the passage of time contains information on the probability of M&A completion. They document how investors under-react to the information embedded within the mere passage of time, detecting a positive correlation between stock returns and the probability of deal completion, as measured by the hazard rate.

Similar to Giglio and Shue (2014), we also find that investors under-react to "no news" during the "lame duck" period. Following initial announcements that the incumbent CEO will be stepping down, firms enter into the lame duck period with no explicit announcement of the new CEO's identity. We document investors' under-reaction to the (expected) probability of the new CEO's identity being announced.

Following the methodology of Giglio and Shue (2014), Figure 3 Panel A shows that the hazard rate on the probability of announcing the new CEO identity next week conditional on not having declared it yet is hump-shaped.[6] The hazard rate increases from 0.07 during event week 1 to almost

[6] The detail of calculation is in appendix B.

0.2 during event week 29, and then declines afterwards. The different hazard rates throughout the event window indicate that the passage of time indeed contains information relevant to the CEO succession. Figure 3 Panel B shows that firms' stock returns through event weeks also follow a hump-shaped pattern, peaking around the same event time as the hazard rate. From Figure 3, the strong co-movement of hazard rate and stock return indicates a possible channel for investors' under-reaction to a lack of news during the lame duck period.

To formally test the predicted correlation between hazard rate and stock return, we conduct regression analysis in table 8. In Table 8 Panel A, we estimate a regression of weekly returns by event week hazard rate. We add a calendar time fixed effect to control for time-varying unobserved factors. In column (1), we observe a positive and significant correlation between the hazard rate and the weekly return. The result confirms our observation from Figure 3. From column (2) to column (5), we test the relationship between hazard rate and weekly returns across subsamples. In columns (2) and (3), we show that our results are economically more significant for firms that ultimately appoint an internal candidate, but the statistical differences are small. In columns (4) and (5), we show that the positive relationship between stock returns and the hazard rate is concentrated in the subsample in which tournament competition among senior executives is higher than the industry median level. We expand on tournament incentives in the next section.

In Panel B, we construct a calendar-time portfolio and sort firms into two portfolios. One includes firms with higher hazard rates than the median at a given trading time; the other contains firms with lower hazard rates than the median at the same point. If under-reaction to no news generates the excess abnormal return, we should also expect to observe the portfolio containing firms with higher hazard rates to be associated with higher alphas than the portfolio with lower hazard rate firms. Across three different benchmarks, the portfolio with higher hazard rate firms, on average, experiences a 1.4% excess monthly return, which is, on average, twice the size of the portfolio containing firms with low hazard rates.

Overall, our evidence documents that investors' under-reaction to no news explains the positive excess returns for firms undergoing a lame duck period.

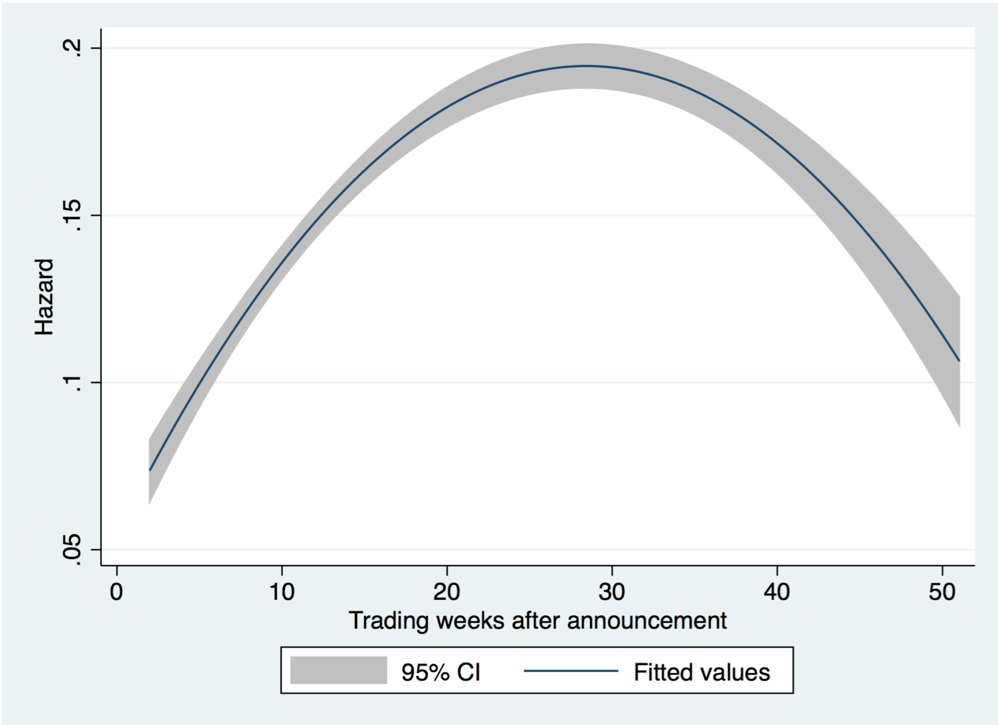
4.2 Internal Tournament

Firms benefit from tournament competition by motivating internal candidates to compete and then promoting the best candidate to the position of CEO (Lazear and Rosen, 1981). [7] Although

[7] Tournament theory also predicts a sabotaging situation between agents, as the most crucial factor is the relative performance between candidates. We argue that candidates' sabotage is of less concern between internal candidates.

Figure 3. Weekly hazard rate and stock return

The top panel shows the estimated weekly hazard rates for all protracted CEO successions over the event time, from the end of the week the firm announces the incumbent CEO's resignation (e_0) through the end of the week that the firm reveals the identity of the successor CEO (e_1). The bottom panel plots the average weekly return and 95% confidence interval, from the end of the week that the firm announces the incumbent CEO's resignation (e_0) through the end of the week that the firm reveals the identity of the successor CEO (e_1).



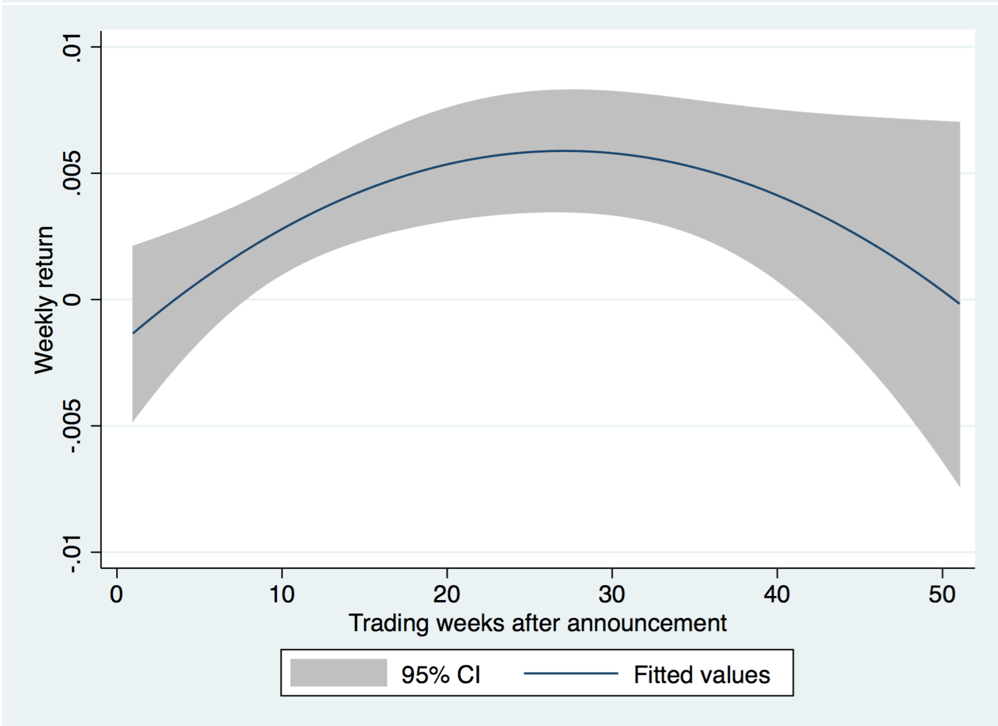


Table 8. Mechanism: Hazard rate

This table Panel A shows the regression of $r_{iwt} = b_0 + b_1 h_w + \gamma_t + \varepsilon_{iwt}$, where i indexes CEO turnovers; t is the calendar time (year-month); γ_t represents a set of calendar time year-month fixed effects. h_w is the event week w's hazard rate. Column (1) shows results for the regression analysis performed on the full sample. Column (2) focuses on firms that appoint internal successors. Column (3) focuses on firms that appoint external successors. Column (4) focuses on firms with high tournament competition levels. Column (5) focuses on firms with low tournament competition levels. Standard errors are clustered at both the calendar year-month level and at the turnover level. Panel B shows results for the monthly regressions of returns to an equally-weighted portfolio on the Carhart (1997) four factors, MKT, SMB, HML, and MOM. The dependent variable is the return for the long-only portfolio of protracted firms less either the risk-free rate, the industry-matched portfolio return, or the characteristics-matched portfolio return. Similar to Giglio and Shue (2014), we sort firms into two portfolios: one containing firms with a hazard rate higher than the median and the other containing firms with a hazard rate lower than the median. We exclude all financial and utility firms. Standard errors are corrected for heteroscedasticity and serial correlation. T-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Panel A: Weekly return regression				
	Full	New CEO		Tournament	
		Internal	External	High	Low
	(1)	(2)	(3)	(4)	(5)
Hazard rate	0.013***	0.018**	0.011***	0.018***	0.006
	(3.886)	(2.331)	(3.080)	(3.741)	(1.054)
Calendar Time FE	Yes	Yes	Yes	Yes	Yes
Observations	9,995	3,531	6,444	5,729	4,144
R-squared	0.058	0.068	0.070	0.057	0.088

	Panel B: Hazard excess returns over		
	Risk-free	Industry	Charact.
	(1)	(2)	(3)
α_{High}	**0.014****	**0.013****	**0.013***
	(2.354)	(2.179)	(1.764)
α_{Low}	**0.005**	**0.003**	**0.010***
	(0.967)	(0.586)	(1.797)
Spread	**0.009**	**0.009**	**0.004**
	(1.320)	(1.331)	(0.328)

the tournament competition will benefit firms, it is also an intangible asset that will not immediately be incorporated into firm value. First, firms are not required to disclose their succession planning in detail. Therefore, it is difficult for external agents to learn ex-ante whether firms will introduce an external talent or promote an internal candidate. Second, until the final announcement, it is not obvious to candidates who is the winner. Therefore, consistent with Edmans (2011); Mueller et al. (2017), the market does not fully capture this intangible information.

When a CEO announces his resignation, other high-ranking executives engage in a competition to claim the (soon to be vacant) position. As predicted by tournament theory (Rosen, 1981; Main et al., 1993), the competition intensity depends on differences in the ex-ante probability of winning the competition among tournament participants: the more equally likely all participants are to win, the higher the aggregated effort. Therefore, we expect the tournament-based consequences of protracted successions to be negatively related to the ex-ante dispersion of candidates' probability of winning. We use the inverse of the standard deviation of compensation among tournament participants in the year prior to the tournament as a proxy for similarity in the ex-ante probability of winning the tournament. We compare this measure with the industry median. We then split our sample between protracted succession with high (above industry median) and low (below industry median) tournament competition levels, respectively.

Table 9 Panel A examines the calendar-time portfolio alphas for firms with high tournament competition and firms with low tournament competition. The high tournament competition portfolio generates significant returns over all benchmarks. The alpha is 1.5% monthly above the risk-free rate, 1.3% monthly controlling for an industry portfolio, and 1.8% monthly controlling for a similar characteristics-matched portfolio. The excess returns are much higher than the low tournament portfolio, and spreads of the excess returns between two portfolios are also substantial.

Moreover, we expect tournament competition to be higher when firms ultimately appoint internal candidates. Although it is impossible for candidates to have this information until the successor CEO's identity is revealed, it is reasonable to assume that candidates can forecast whether the firm will appoint an internal or an external candidate in the end. Therefore, Panel B of Table 9 uses whether the successor CEO was hired externally or internally as a proxy for the tournament. If the new CEO is an internal hire, then the firm is more likely to perform an internal candidate tournament than in cases when the new CEO is an external hire. The portfolio with successor CEOs hired

First, the board of directors will monitor the competition and try to ensure that it does not destroy shareholder value. Second, internal candidates are disciplined by the possibility of external candidates and future career prospects from the external labor market.

Table 9. Mechanism: Tournament

This table presents monthly regressions of returns to an equally-weighted portfolio on the Carhart (1997) four factors, MKT, SMB, HML, and MOM. The dependent variable is the return for the long-only portfolio containing protracted firms, less either the risk-free rate, the industry-matched portfolio return, or the characteristics-matched portfolio return. We exclude all financial and utility firms. In Panel A, we sort firms into two portfolios, one containing firms with ex-ante tournament competition levels higher than the industry median and the other containing firms with ex-ante tournament competition levels lower than the industry median. In Panel B we sort firms into two portfolios: one containing firms that hire successor CEOs internally and the other containing firms that hire successor CEOs externally. In Panel C, we only focus on firms that hire successor CEOs internally and sort these into two portfolios: one containing firms with tournament competition levels higher than the industry median and the other containing firms with tournament competition levels lower than the industry median. The αs are excess risk-adjusted returns. Standard errors corrected for heteroscedasticity and serial correlation are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Excess returns over		
	Risk-free	Industry	Charact.
	(1)	(2)	(3)
Panel A: Tournament			
α_{high}	**0.015*** **	**0.013** **	**0.018*** **
	(2.618)	(2.157)	(2.685)
α_{low}	**0.002**	**-0.000**	**0.002**
	(0.599)	(-0.061)	(0.425)
Spread	**0.013***	**0.013** **	**0.016**
	(1.955)	(1.973)	(1.386)
Panel B: New CEO type			
$\alpha_{internal}$	**0.022** **	**0.023** **	**0.028** **
	(2.308)	(2.554)	(2.140)
$\alpha_{external}$	**0.002**	**-0.000**	**0.002**
	(0.682)	(-0.107)	(0.458)
Spread	**0.019** **	**0.023** **	**0.026***
	(2.083)	(2.437)	(1.727)
Panel C: Internal new CEO and tournament			
$\alpha_{internal\&high}$	**0.037***	**0.037***	**0.051***
	(1.893)	(1.904)	(1.894)
$\alpha_{external\&low}$	**-0.004**	**-0.007** **	**-0.003**
	(-0.926)	(-2.076)	(-0.560)
Spread	**0.039** **	**0.043** **	**0.054** **
	(2.054)	(2.302)	(1.999)

internally generates an excess return of more than 2% monthly over different benchmarks and more than twice the value of the excess return from the main result. The monthly excess returns for the portfolio of firms hiring external candidates are insignificant from 0. Panel C presents the portfolio alpha for firms that have high tournament competition and hire their successor CEO internally. The results are 4% monthly excess returns.

Table 10 presents additional evidence of the tournament competition mechanism. From Table 4 we know that firms in the lame duck CEO period are associated with a higher abnormal stock return around earnings announcements. If the tournament competition mechanism is valid, we should also expect to observe the abnormal stock return around earnings announcements to be higher for firms with ex-ante intense tournament competition levels or with successor CEOs hired internally. Our results in column (1) and column (3) confirm our hypothesis. Finally, in columns (5) and (6), we show that the economic significance of our results increases when we focus on high tournament incentives that end up appointing an internal candidates; consistent with our hypothesis.

Table 10. Mechanism: Tournament and earnings announcement

This table shows the results of robustness tests on abnormal returns around earnings announcements from 2005 to 2015. The dependent variable is the cumulative abnormal return within the three-day window around the earnings announcements. Abnormal returns are calculated above a market model with a -255 to -46 day estimation window. Protracted is a dummy variable that has a value of 1 if the firm is undergoing a lame duck CEO period (e1) and 0 otherwise. Columns (1) and (2) split the total sample according to the degree of tournament competition for firms' senior executives below the CEO level. Columns (3) and (4) split the total sample according to whether the new CEO is hired internally or externally. Columns (5) and (6) focus on internal successions and are split based on the level of tournament competition. T-statistics are reported in parentheses. Standard errors are clustered at firm level. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	CAR[-1,+1]					
	Tournament		New CEO type		New CEO type &Tournament	
	High	Low	Internal	External	Internal&High	External&Low
	(1)	(2)	(3)	(4)	(5)	(6)
Protracted	0.015*	0.005	0.021**	0.009	0.039**	0.004
	(1.895)	(1.014)	(2.388)	(1.457)	(2.066)	(0.458)
Ln asset	-0.006***	-0.006**	-0.008***	-0.005	-0.007**	0.005
	(-2.887)	(-2.265)	(-3.853)	(-1.037)	(-2.206)	(0.561)
Market-to-book	0.004***	0.004***	0.003***	0.005***	0.004**	0.010***
	(4.475)	(2.942)	(2.657)	(3.257)	(2.384)	(2.825)
Leverage	-0.009	-0.011	-0.022***	-0.003	-0.022*	0.018
	(-1.344)	(-1.382)	(-2.903)	(-0.332)	(-1.807)	(0.740)
Ind-adj ROA	0.030***	-0.004	0.015***	0.047***	0.021	-0.055
	(3.151)	(-0.334)	(16.604)	(2.608)	(1.061)	(-1.254)
Dividend Payer	-0.010***	-0.007*	-0.009***	-0.017***	-0.012***	-0.029**
	(-3.410)	(-1.724)	(-3.188)	(-2.615)	(-2.669)	(-2.498)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,432	24,752	28,031	8,128	15,295	2,814
R-squared	0.064	0.073	0.042	0.052	0.056	0.101

It is also worth testing whether these two mechanisms are associated with systemic risk change across different portfolio within the group. Table 11 A shows that betas for the Fama-French three factors are not statistically different between portfolios in the same group (with the exception of the beta associated with momentum factor in the hazard rate portfolio).

Table 11. Mechanism: Betas across strategies

This table reports the betas for the Carhart (1997) four-factors for the different portfolio construction strategies, along with a test of the null hypothesis that betas do not vary across the same strategy group, separately for each of the four factors. Panel A tests betas' differences across hazard rate portfolios. Panel B tests the betas' differences across new CEO identity portfolios. Panel C tests the betas' differences across tournament competition portfolios. Standard errors are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Strategy betas				
	mktrf	smb	hml	umd
	(1)	(2)	(2)	(3)
	Panel A: Hazard rate			
Low hazard	1.141***	0.837***	0.023	-0.264***
	(8.310)	(7.238)	(0.157)	(-4.403)
High hazard	1.169***	0.604**	-0.165	-0.718***
	(13.378)	(1.983)	(-0.745)	(-3.768)
Test high hazard = low hazard: p-value	0.8922	0.5038	0.5841	0.0313**
	Panel B: New CEO identity			
Internal	1.120***	0.903***	0.051	-0.386***
	(19.378)	(3.250)	(0.290)	(-3.700)
External	1.182***	0.640***	-0.116	-0.518***
	(10.003)	(7.396)	(-0.789)	(-5.936)
Test Internal = External: p-value	0.3118	0.7200	0.6437	0.3333
	Panel C: Tournament competition			
High tournament	1.107***	0.837***	-0.105	-0.583***
	(10.688)	(3.210)	(-0.400)	(-2.740)
Low tournament	1.225***	0.601***	-0.145	-0.445***
	(8.010)	(3.046)	(-0.789)	(-11.19)
Test high tournament = low tournament: p-value	0.3118	0.7200	0.6437	0.3333

Overall, our results confirm our hypothesis that internal tournament competition is one mechanism explaining the excess positive returns associated with firms undergoing a lame duck CEO period.

5 Discussion

5.1 Alternative explanations

The previous two subsections explored possible mechanisms to explain the positive excess return for firms undergoing a lame duck CEO period. There are still other potential explanations for this phenomenon.

Huson et al. (2004); Taylor (2010) suggest that firms' performances reverse after they fire their incumbent CEOs. In particular, Taylor (2010) predicts a gradual increase in firms' profitability instead of a sharp increase. Therefore, our positive abnormal return may be explained by firms' firing decisions for incompetent outgoing CEOs. If that were the case, then we should observe firms with forced CEO turnover to perform better than firms with voluntary CEO turnover. As in Parrino (1997), we sort firms into two portfolios based on whether the incumbent CEO was fired or not. Table 12 Panel A shows the results. Under different benchmark portfolios, the excess returns for the portfolio with forced (or "fired") CEO turnover does not differ from the excess returns of the portfolio with voluntary CEO turnover. It is thus reasonable to conclude that firms' decisions to forcibly remove incumbent CEOs is not the driving factor leading to excess returns enjoyed during the lame duck CEO period.

Table 12. Mechanism: Discussion

This table reports monthly regressions of returns to an equally weighted portfolio on the Carhart (1997) four factors, MKT, SMB, HML, and MOM. The dependent variable is the return for the long-only portfolio of protracted firms less either the risk-free rate, the industry-matched portfolio return, or the characteristics-matched portfolio return. We exclude all financial and utility firms. In Panel A, we sort firms into two portfolios based on whether the incumbent CEO was forced to leave or left voluntarily, based on the algorithm proposed byParrino (1997). In Panel B, we sort firms into two portfolios based on whether the firm appoints an interim CEO to supervise daily operations following the incumbent's departure. In Panel C, we only focus on firms that appoint interim CEOs and sort firms into two portfolios based on whether the interim CEO was promoted to the permanent position or not. In Panel D, we sort firms into two portfolios based on the size of the board. In Panel E, we sort firms into two portfolios based on whether the board size is too extreme(small and large), or in the medium level. In Panel F, we sort firms into two portfolios based on the ratio of independent directors sitting on the board. The αs are excess risk-adjusted returns. Standard errors corrected for heteroscedasticity and serial correlation are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	Excess returns over		
	Risk-free	Industry	Charact.
	(1)	(2)	(3)
Panel A: Turnover reason			
$\alpha_{voluntary}$	**0.010***	**0.008**	**0.014***
	(1.647)	(1.365)	(1.820)
α_{forced}	**0.010***	**0.008***	**0.011***
	(1.701)	(1.667)	(1.955)
Panel B: Interim CEO			
α_{have}	**0.007*****	**0.005***	**0.005**
	(2.758)	(1.737)	(1.446)
α_{no}	**0.015**	**0.014**	**0.024****
	(1.537)	(1.620)	(2.033)
Panel C: Interim CEO only			
$\alpha_{Promoted}$	**-0.003**	**-0.004**	**-0.013**
	(-0.458)	(-0.585)	(-1.467)
$\alpha_{NotPromoted}$	**0.007***	**0.004**	**0.007**
	(1.794)	(1.201)	(1.299)
Panel D: Board size			
α_{large}	**0.001**	**0.002**	**-0.007**
	(0.107)	(0.382)	(-0.896)
α_{small}	**0.001**	**0.000**	**0.004**
	(0.290)	(0.032)	(0.446)
Panel E: Board size II			
$\alpha_{extreme}$	**0.001**	**0.000**	**-0.002**
	(0.210)	(0.091)	(-0.196)
α_{mediam}	**-0.000**	**-0.002**	**-0.003**
	(-0.070)	(-0.391)	(-0.485)
Panel F: Board independence			
α_{high}	**0.006**	**0.006**	**0.003**
	(1.098)	(1.152)	(0.518)
α_{low}	**-0.004**	**-0.006****	**-0.003**
	(-1.401)	(-2.056)	(-0.768)

Another possible explanation is that during the lame duck CEO period, firms' operations improve. For instance, firms may be using the position of interim CEO to test the most favorable candidates. When interim CEOs perform well, they will be promoted to permanent positions. In our lame duck CEO sample, more than 50% of firms appointed an interim CEO. In Table 12 Panel

B, we show that the magnitude of alpha for firms that appoint interim CEOs is smaller than the alpha for firms that do not appoint interim CEOs. In Panel C, we focus on the subsample of firms that appointed interim CEOs, and sort this into two portfolios based on whether the interim CEO was promoted permanently to the CEO position or not. If the exceptional interim CEOs achieved extremely positive outcomes, then we should observe them being promoted to the permanent position. However, our results indicate the opposite. It is therefore unlikely that the appointment of an interim CEO drives the results.

Similarly, during the lame duck CEO period, the board takes responsibility to protect shareholders. Another alternative explanation is that excess returns during the lame duck period derives from boards that operate extremely effectively: well-functioning board governance generates the positive alpha. This hypothesis is consistent with Gompers et al. (2003); Giroud and Mueller (2011), who show that strong governance is associated with excess returns. We use three different measures for board quality. In Table 12 Panel D, we sort portfolios based on board size. If board quality leads to excess returns, then we should observe that the portfolio containing smaller boards performs better than the portfolio containing larger board, as smaller boards have been shown to be more effective (Yermack, 1996). However, in Panel D, the portfolio containing firms with large boards has an alpha similar to the portfolio with firms with small boards. Coles et al. (2008) has also suggested that board size and firm performance is U shaped. As such, we repeat our analysis for median versus extreme board size values. Panel E shows that our results are indeed not driven by board size. The third measure we use to proxy board quality is an independence ratio, as a higher independence ratio may lead to better monitoring (Guo and Masulis, 2015). If this were the case, then the portfolio containing firms with higher board independence ratios will be the main driver of excess returns in the main result. Table 12 Panel F shows that although the alpha for the portfolio containing firms with high independence ratios is positive, it is not statistically significant or robust to reject the null hypothesis.

Overall, it is unlikely that these three alternative explanations lead to an excess return in the main portfolio containing firms undergoing a lame duck CEO period.

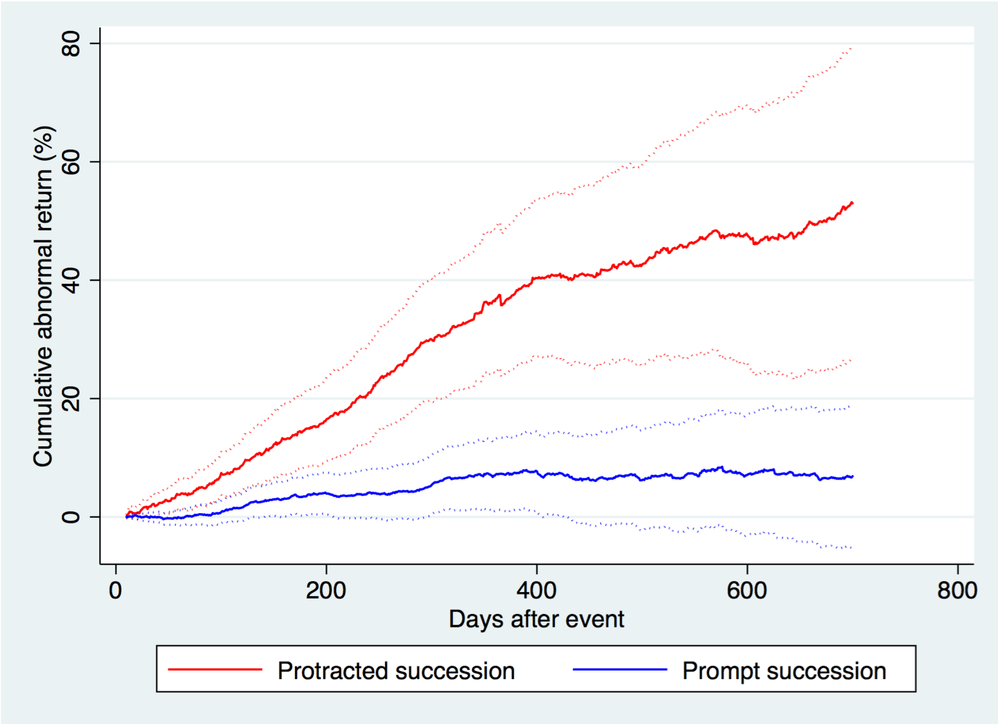
5.2 Long-run performance

We now focus on the long-run performance of firm-CEO matches resulting from a protracted CEO succession. To do so, we calculate the long-run abnormal performance of firms that underwent a protracted CEO succession and compare that to firms that experienced a prompt CEO succession.

We show our results in Figure 4: Firms with either type of succession on average obtain positive long-run abnormal performance. Over three years after CEO succession, firms with joint CEO succession on average experience 10% abnormal returns, and firms with protracted CEO succession on average earn much higher abnormal returns (more than 50%).

Figure 4. Long-run stock performance

This figure shows the abnormal returns from the end of the week that the firm announces the incumbent CEO's resignation for firms under different types of succession. The abnormal return is calculated over the three-year event window [+6, +700], and based on Carhart (1997) four-factor model. The red line represents the cumulative abnormal return associated with protracted succession, while the blue line represents the cumulative abnormal return associated with joint succession. The dashed lines represent the 95% confidence intervals.



We consider this result important for the policy implications of our findings. Protracted CEO successions not only generate a positive alpha during the reign of the "lame duck" CEO, but also lead to a better CEO-firm match that ultimately results in improved performance in the long-run. In other words, when firms take their time to choose their new CEOs, they seem to do a better job at picking the right one.

6 Conclusion

We document that protracted CEO successions are frequent, with 31% of CEO successions for S&P 1500 firms between 2005 and 2014 being protracted and an average lame duck CEO reign of 173 days. Contrary to conventional views, firms with protracted CEO successions experience an annual four-factor alpha of 11% during the lame duck CEOs' reign after controlling for industry-level factors and other observed firm characteristics. We document no significant changes in realized or idiosyncratic return volatility. These findings imply that the market slowly incorporates the information contained in the lame duck CEO event.

The results are consistent with two possible explanations: First, the market under-reaction to the information contained in the passage of time from news of the incumbent CEO's departure to the announcement of the new CEO's identity. We find that the weekly hazard rate for the probability that a new CEO will be announced varies over time after the incumbent CEO steps down, and we document that lame duck firms' abnormal performance correlates with high hazard rates. Second, we find that the internal tournament competition between CEO candidates generates the positive excess returns. This intangible information is hard to incorporate into the market value of firms. We show that abnormal returns are larger for firms with higher tournament competition levels and for firms that ultimately appoint an internal candidate as the successor CEO.

Overall, our results suggest that there is an unwarranted negative connotation associated with lame duck CEOs. Firms over-perform during their reign and long successions lead to healthy competition among candidates, improving overall firm performance.

A Appendix: Variable definition

Variable definitions are below. Compustat variable names are denoted by their Xpressfeed pneumonic and CRSP variable names and IBES names are in bold.

Protracted = 1 if the first news article about the incumbent CEO's resignation takes place before the first news article revealing the new CEO's identity; 0 otherwise. News search conducted using FACTIVA.

mktrf = From WRDS Fama-French & Liquidity Factors

smb = From WRDS Fama-French & Liquidity Factors.

hml = From WRDS Fama-French & Liquidity Factors.

mom = From WRDS Fama-French & Liquidity Factors.

Ln asset = ln(**at**).

Leverage = $\frac{\mathbf{dltt+dlc}}{\mathbf{at}}$.

ROA = $\frac{\mathbf{ebitda}}{\mathbf{at}}$.

Ind-adj ROA = ROA - median Fama-French 48 industry ROA.

Market-to-book = $\frac{\mathbf{prcc\_f*cshpri+dltt+dlc+pstkl-txditc}}{\mathbf{at}}$.

Dividend Payer = 1 if **dvc** > 0; 0 otherwise.

CEO focus = $\frac{\text{\# of news article mentioning incumbent CEO}}{\text{\# of news article cover firm}}$.

Tournament incentive = $\frac{1}{\text{Standard deviation of highest paid four vice-president base salary}}$.

Size = log of the firm's market capitalization (in billions).

Yield = firm's dividend yield (**dvt**).

Ret2-3 = compounded returns in months t-3 to month t-2.

Ret4-6 = compounded returns in months t-6 to month t-4.

Ret7-12 = compounded returns in months t-12 to month t-7.

Volume = trading volume (in millions) (**vol**).

Price = stock price at end of month(**prc**).

Mean forecast error = $\frac{\text{mean of the most resent forecast}-\mathbf{actual}}{\mathbf{actual}}$.

Median forecast error = $\frac{\text{median of the most resent forecast}-\mathbf{actual}}{\mathbf{actual}}$.

B Appendix: Hazard rate

The hazard rate used in this paper is calculated by applying the NelsonAalen nonparametric estimator. The hazard rate measures the probability of finishing the CEO search and announcing the successor at time t, conditional on the firm still having released no explicit information on the new CEO's identity at time $t-1$. We assume the hazard rate draws from the same distribution and for each event time (week), we calculate the hazard rate based on the whole lame duck CEO sample data. In Figure 3 Panel A, we show the shape of the hazard rate within one year of the incumbent CEO's departure announcement. In a longer horizon, the shape of the hazard rate remains similar, except the right tail becomes closer to 0. Similar measures have been used in Giglio and Shue (2014) to estimate the merger completion hazard rate from the time that news of a merger is announced until the merger is completed or withdrawn.

Chapter III

Selection versus Incentives in Incentive Pay

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."[8] 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 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

[8]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."*

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; 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.[9]

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

[9] 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

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. [10] 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 4 outlines the data and discusses the estimation results. Section 4 explores the robustness of our results. Finally, Section 5 concludes.

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

[10] 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.

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.

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
CEOs 1	10	NA	NA
CEOs 2	NA	20	NA
CEOs 3	NA	NA	30

Panel B: All matches

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

Panel C: Performance

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

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)[11]. 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 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.[12]

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

[11] 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)

[12] 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.

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 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:

$$V_{ij} < \overline{V}_{ij}, \forall ij \notin \mu, \quad (2)$$

$$V_{ij} > \underline{V}_{ij}, \forall ij \in \mu. \quad (3)$$

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:

$$V_{ij} = \alpha W_{ij} + \eta_{ij}, \forall ij \in M_t, \tag{4}$$

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 $\eta_{ij} \sim N(0, \sigma_\eta)$.

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:

$$Y_{ij} = \beta X_{ij} + \varepsilon_{ij}, \forall ij \in M_t, \tag{5}$$

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 (5) 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 (5) 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.[13]

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:

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

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 2, 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 $V_{\mu(j)j}$. Following Akkus et al. (2016a), the likelihood function becomes:

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

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

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

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 two-year average change in return on assets 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.[14] 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) I assume the CEO has a multiplicative effect on firm performance. 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).

[14]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.

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 CEO's 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 CEO's 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 CEO's 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

3.2 Naive OLS results

This section presents results for the naive OLS regressions. Table 3 shows associations between CEOs' initial incentive pay and firm performance. I find a strong and positive relationship between changes in firm performance and CEO incentive pay. A 1 percentage point increase in the incentive firms provide to their new CEO will lead to firms' performance increasing in terms of ROA within the range of 1-1.66 percentage points (columns (1), (2), (3) and (4)).

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 three-year average industry-adjusted ROA, it measures the industry adjusted average ROA increases three years after CEO succession year to three years before the CEO succession year. In column (4), firm performance is defined as two-year average industry-adjusted ROA, it measures the industry adjusted average ROA increases two years after CEO succession year to two years before the CEO succession year. 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 three-year ROA			Δ two-year ROA	CEO minimum tenure	
					3 years	4 years
	(1)	(2)	(3)	(4)	(5)	(6)
Incentive pay	0.0061***	0.0095***	0.0103***	0.0092**	0.0290***	0.0468***
	(3.728)	(3.097)	(3.306)	(2.343)	(3.418)	(4.714)
Age		-0.0007	-0.0008	-0.0009*	-0.0063***	-0.0105***
		(-1.512)	(-1.644)	(-1.674)	(-4.264)	(-6.448)
Male		0.0074	0.0077	0.0112	0.0592	0.0727
		(0.569)	(0.636)	(0.833)	(1.116)	(1.211)
MBA		0.0057	0.0022	0.0012	-0.0034	0.0247
		(1.181)	(0.468)	(0.225)	(-0.204)	(1.225)
Total Pay		-0.0014	-0.0021	-0.0033	0.0057	-0.0016
		(-0.420)	(-0.547)	(-0.752)	(0.487)	(-0.124)
Salary		0.0005	-0.0005	0.0016	0.0335*	0.0572***
		(0.110)	(-0.130)	(0.397)	(1.867)	(3.424)
Vega		-0.0063***	-0.0039*	-0.0022	-0.0152**	-0.0160*
		(-2.972)	(-1.750)	(-0.889)	(-1.979)	(-1.690)
Firm size		0.0014	-0.0002	-0.0013	-0.0010	-0.0097
		(0.345)	(-0.064)	(-0.218)	(-0.130)	(-1.078)
Book leverage		0.0881*	0.0823	0.0926	0.0335	0.0550
		(1.755)	(1.547)	(1.324)	(0.906)	(1.332)
Market-to-book		0.0043	0.0037	0.0026	-0.0140**	-0.0110
		(0.832)	(0.746)	(0.374)	(-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	1,623	1,645	1,645
R-squared	0.0078	0.0581	0.1044	0.0736	0.0630	0.0911

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 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.

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 firm's 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	0.2455***	0.2547***	0.2375***
	(18.572)	(14.930)	(11.048)
Age	0.0037**	0.0033	0.0045
	(1.970)	(1.339)	(1.491)
Male	0.0780	0.1456	0.0782
	(1.016)	(1.194)	(0.778)
MBA	0.0113	0.0126	0.0145
	(0.412)	(0.340)	(0.362)
Salary	0.0505**	0.0362	0.0628
	(2.270)	(1.414)	(1.386)
Vega	0.0409***	0.0625***	0.0185
	(3.247)	(3.251)	(1.031)
Total Pay	0.0586***	0.0403*	0.0626**
	(3.476)	(1.793)	(2.350)
Firm size	0.5435***	0.5352***	0.5762***
	(41.193)	(31.444)	(27.393)
Book leverage	-0.5317***	-0.2871***	-0.7448***
	(-8.802)	(-2.811)	(-8.050)
Market-to-book	0.1772***	0.1817***	0.2035***
	(22.626)	(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

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

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 three-year average industry-adjusted ROA, it measures the industry adjusted average ROA increases three years after CEO succession year to three years before the CEO succession year. 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	0.0036**	0.0084***	0.0090***
	(2.169)	(2.760)	(3.282)
Age		-0.0006	-0.0007
		(-1.085)	(-1.391)
Male		0.0062	0.0066
		(0.444)	(0.475)
MBA		0.0066	0.0032
		(1.467)	(0.670)
Total Pay		-0.0019	-0.0025
		(-0.586)	(-0.586)
Salary		0.0006	-0.0005
		(0.133)	(-0.120)
Vega		-0.0061***	-0.0035
		(-2.578)	(-1.520)
Firm size		-0.0009	-0.0028
		(-0.191)	(-0.727)
Book leverage		0.0890	0.0838*
		(1.453)	(1.720)
Market-to-book		0.0032	0.0026
		(0.557)	(0.460)
Matching residual	0.0157***	0.0156***	0.0166***
	(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	0.0201	0.0692	0.1165

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

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.

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 three-year average industry-adjusted ROA, it measures the industry adjusted average ROA increases three years after CEO succession year to three years before the CEO succession year. 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	0.0087**	0.0082**	0.0136**	0.0112**
	(2.287)	(2.264)	(2.562)	(2.008)
Age	-0.0012**	-0.0012**	-0.0001	0.0002
	(-2.094)	(-2.448)	(-0.116)	(0.239)
Male	-0.0070	-0.0068	0.0139	0.0098
	(-0.372)	(-0.349)	(0.761)	(0.512)
MBA	0.0088	0.0095	-0.0070	-0.0070
	(1.291)	(1.297)	(-0.928)	(-0.927)
Total Pay	-0.0036	-0.0036	0.0009	-0.0005
	(-0.693)	(-0.642)	(0.141)	(-0.071)
Salary	-0.0005	-0.0006	0.0010	0.0008
	(-0.145)	(-0.172)	(0.097)	(0.078)
Vega	-0.0037	-0.0037	-0.0052*	-0.0045
	(-1.224)	(-0.853)	(-1.860)	(-1.541)
Firm size	0.0042	0.0033	-0.0063	-0.0107*
	(0.903)	(0.741)	(-1.194)	(-1.885)
Book leverage	0.0583*	0.0602**	0.0890	0.0872
	(1.871)	(2.434)	(1.027)	(1.115)
Market-to-book	0.0022	0.0018	0.0040	0.0023
	(0.580)	(0.636)	(0.273)	(0.165)
Matching residual		0.0068		0.0300***
		(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	0.1291	0.1313	0.1048	0.1388

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 Sarbanes-Oxley 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 motivation effect from CEOs' career concerns (Fama, 1980). If the talent mobility decreases, then, on the one hand, the probability for CEOs jump to better jobs decreases. On the other hand, the firing probability for CEOs also decreases since the cost of firing CEO increases for firms when there is no external talent market. Therefore the career concern for CEO decreases and firms need to provide extra incentive effect relative to selection effect to motivate the same talent level of CEOs when the CEO talent mobility decreases.

3.3.3 Industry talent mobility

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 mobility. In Panel A of Table 7, I show the degree of CEO talent mobility in different Fama-French 5 industries. Similar to Cremers and Grinstein (2014), I measure CEO talent mobility 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 talent mobility both increase the importance of the selection effect.

Table 7. Talent mobility

This table presents split sample estimation results based on CEO talent mobility 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 as three-year average industry-adjusted ROA, it measures the industry adjusted average ROA increases three years after CEO succession year to three years before the CEO succession year. 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 mobility 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	0.0058**	0.0054**	0.0279**	0.0233**
	(2.084)	(2.104)	(2.243)	(1.968)
Matching residual		0.0063		0.0473***
		(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	0.0665	0.0697	0.3332	0.3711

4 Robustness

4.1 Alternative market definition

The key assumption on identification is that the distribution of agents in the market is exogenously given. This assumption would not be valid if CEOs or firms choose to participate in a market based on the unobserved characteristics of the market. For instance, if good companies, in general, are more likely to end their CEOs' contracts in even years, then this attracts better candidates to wait and more likely to participate in the labour market in even years. Therefore, if we change the market definition, the estimated coefficients will change compared to the main results because agents select between calendar years.

In Panel A of Table 8, I change the market definition to two calendar years and three calendar years. The estimated coefficients are mostly unchanged. Panel B provides similar test on coefficients difference between naive OLS regressions and selection controlled outcome regressions. The magnitude and statistical significance are similar to the results in In Panel B of Table 5. These results show that the analysis is not sensitive to the specific market definition, and provide evidence on the validation of the identification assumption.

4.2 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 9, 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 9, 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.

Table 8. Robustness: alternative market definition

Panel A presents outcome equation estimation results on firm performance adding the matching residuals in the regression. The matching market is redefined as two calendar years or three calendar years instead of one in main results. The dependent variable is defined as three-year average industry-adjusted ROA, it measures the industry adjusted average ROA increases three years after CEO succession year to three years before the CEO succession year. The year of succession is omitted. The three different specifications are comparable with columns (1)-(3) in Table 3. The matching residuals are computed similar to Table 4 column (1) but with different market definition. 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					
	Two calendar years			Three calendar years		
	(1)	(2)	(3)	(4)	(5)	(6)
Incentive pay	0.0032**	0.0082***	0.0089***	0.0036**	0.0084**	0.0089***
	(2.110)	(3.728)	(3.090)	(2.192)	(2.448)	(3.038)
Age		-0.0006	-0.0007*		-0.0006	-0.0007
		(-1.283)	(-1.733)		(-1.433)	(-1.414)
Male		0.0063	0.0061		0.0055	0.0062
		(0.614)	(0.546)		(0.434)	(0.544)
MBA		0.0067	0.0032		0.0066*	0.0032
		(1.253)	(0.677)		(1.767)	(0.642)
Total Pay		-0.0020	-0.0023		-0.0017	-0.0025
		(-0.524)	(-0.585)		(-0.484)	(-0.673)
Salary		0.0006	-0.0004		0.0006	-0.0004
		(0.130)	(-0.148)		(0.179)	(-0.099)
Vega		-0.0059***	-0.0036*		-0.0062***	-0.0035*
		(-2.884)	(-1.730)		(-3.297)	(-1.647)
Firm size		-0.0013	-0.0029		-0.0008	-0.0029
		(-0.287)	(-0.819)		(-0.161)	(-0.679)
Book leverage		0.0890*	0.0837		0.0887*	0.0837*
		(1.800)	(1.438)		(1.864)	(1.903)
Market-to-book		0.0032	0.0026		0.0033	0.0026
		(0.638)	(0.480)		(0.720)	(0.555)
Matching residual	0.0172***	0.0174***	0.0166***	0.0145***	0.0142***	0.0166***
	(4.028)	(3.257)	(3.562)	(3.233)	(2.695)	(3.108)
Industry FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Location FE	No	No	Yes	No	No	Yes
Observations	1,599	1,599	1,599	1,599	1,599	1,599
R-squared	0.0228	0.0719	0.1165	0.0185	0.0675	0.1165

Panel B: Changes in Incentive pay's coefficients

Difference	0.0029**	0.0013**	0.0014**	0.0025***	0.0011**	0.0014**
Relative change	47.5%	13.7%	13.6%	41.0%	11.6%	13.6%

Table 9. 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 three-year average industry-adjusted ROA, it measures the industry adjusted average ROA increases three years after CEO succession year to three years before the CEO succession year. . 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	0.1252***	0.0032*	0.0074**	0.0080**
	(8.634)	(1.682)	(2.190)	(2.563)
Age	-0.0060***		-0.0009**	-0.0010**
	(-2.638)		(-1.961)	(-2.570)
Male	0.0065		0.0069	0.0073
	(0.076)		(0.452)	(0.518)
MBA	-0.0025		0.0031	-0.0001
	(-0.083)		(0.645)	(-0.020)
Salary	-0.0086		0.0012	-0.0003
	(-0.365)		(0.269)	(-0.089)
Vega	-0.0301**		-0.0058***	-0.0033
	(-2.168)		(-3.550)	(-1.373)
Total Pay	-0.0133		-0.0029	-0.0034
	(-0.834)		(-0.705)	(-0.825)
Firm size	-0.0405***		0.0045	0.0028
	(-3.071)		(1.155)	(0.957)
Book leverage	0.4585***		0.0811**	0.0751*
	(5.800)		(2.158)	(1.747)
Market-to-book	0.3801***		-0.0076	-0.0087
	(33.449)		(-1.176)	(-1.281)
Matching residual		0.0250*	0.0322**	0.0338**
		(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		0.0611	0.1134	0.1601

4.3 Alternative performance measures

In the above analysis, the main measure of firm performance is the change in industry-adjusted return on assets over seven-year window during CEO succession. In order to show the result is not comes from manipulating the estimation window I use return on assets over four-year window during CEO succession as a robust test.

I estimate a matching corrected outcome equation that uses two years' change in return on asset as the performance measure in Table 10 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 10 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.

4.4 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:

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

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

Table 10. 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 firm performance is defined as two-year average industry-adjusted ROA, it measures the industry adjusted average ROA increases two years after CEO succession year to two years before the CEO succession year. The year of succession is omitted. The dependent variable in columns (2) and (3) captures whether the new CEO's 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 two-year ROA	CEO minimum tenure	
		3 years	4 years
	(1)	(2)	(3)
Incentive pay	0.0073**	0.0259***	0.0443***
	(2.086)	(3.196)	(4.998)
Age	-0.0008	-0.0060***	-0.0103***
	(-1.395)	(-4.500)	(-6.886)
Male	0.0098	0.0566	0.0707
	(0.771)	(1.014)	(1.080)
MBA	0.0023	-0.0014	0.0263
	(0.457)	(-0.099)	(1.166)
Salary	0.0017	0.0336**	0.0574***
	(0.307)	(2.448)	(2.964)
Vega	-0.0017	-0.0143**	-0.0153*
	(-0.716)	(-2.190)	(-1.875)
Total Pay	-0.0039	0.0046	-0.0025
	(-1.129)	(0.378)	(-0.153)
Firm size	-0.0048	-0.0072	-0.0146
	(-0.624)	(-0.965)	(-1.470)
Book leverage	0.0942	0.0365	0.0573**
	(1.543)	(0.992)	(2.005)
Market-to-book	0.0013	-0.0165**	-0.0129*
	(0.246)	(-1.988)	(-1.799)
Matching residual	0.0225***	0.0406***	0.0320**
	(2.968)	(3.042)	(2.292)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes
Observations	1,610	1,645	1,645
Observations	1,623	1,645	1,645
R-squared	0.0897	0.0699	0.0940

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:

$$
\begin{aligned}
V_i &= \alpha W_i + \eta_i, \\
Y_i &= \beta X_i + \varepsilon_i,
\end{aligned}
$$

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 agent's 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 11 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 11 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 10 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

Table 11. 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 defined as three-year average industry-adjusted ROA, it measures the industry adjusted average ROA increases three years after CEO succession year to three years before the CEO succession year. 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 three-year 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

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 mobility is higher.

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.

A Appendix: 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 50 CEOs and 50 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: $\beta_c = 0.3$, $\beta_f = 0.3$, $\alpha_c = 0.2$, $\alpha_f = 0.2$ and $\delta = 0.2$. 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.

A1. Single market Monte Carlo exercises

This table presents biased OLS regression and matching corrected regression coefficient estimates based on a simulated dataset containing 50 CEOs and 50 firms in one single market. Results present the findings from 100 replications of a one-to-one matching market. Simulated stable matching is generated from the top-down elimination algorithm. The 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	OLS bias		Matching corrected result bias	
		Mean	RSME	Mean	RSME
	(1)	(2)	(3)	(4)	(5)
α_c	0.2	0.029	0.086	0.002	0.081
α_f	0.2	0.029	0.064	-0.000	0.064
δ	0.2			0.003	0.085

B Appendix: 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, σ.

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

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

Then the estimation procedure is as follows:

- First, draw $V_{ij}, Y^*_{ij} | \beta, \alpha, \delta, \sigma, data$
  - For Y_{ij} observed:

    $$V_{ij}, |\beta, \alpha, \delta, \sigma^2_\xi, data \sim Normal(\alpha W_{ij} + \frac{\delta(Y_{ij} - \beta X_{ij})}{\sigma^2_\varepsilon}, \frac{\sigma^2_\xi}{\sigma^2_\varepsilon}),$$

    and truncated from below at $\underline{V_{ij}}$.
  - For Y_{ij} not observed:

    $$V_{ij}, |\beta, \alpha, \delta, \sigma^2_\xi, data \sim Normal(\alpha W_{ij}, \sigma_\eta),$$

    and truncated from above at $\overline{V_{ij}}$.

    $$Y^*_{ij} | \beta, \alpha, \delta, \sigma^2_\xi, data \sim Normal(\beta X_{ij} + \delta(V_{ij} - \alpha W_{ij}), \sigma^2_\xi)$$

- Second, draw $\beta, \alpha | V_{ij}, Y^*_{ij}, \delta, \sigma^2, data$ from a Bayesian Seeming Unrelated Regression of $[Y^*; V]$ on $[X; W]$ with Normal priors on β and α and know covariance matrix Ω:

$$\beta, \alpha | V_{ij}, Y^*_{ij}, \delta, \sigma, data \sim Normal((C'\Omega^{-1}C + A)^{-1}(C'\Omega^{-1}][Y^*; V] + A\mu), (C'\Omega^{-1}C + A)^{-1}),$$

where A is prior variance matrix and μ is prior mean, also:

$$\Omega = \begin{bmatrix} \sigma_\varepsilon^2 & \delta \\ \delta & \sigma_\eta \end{bmatrix} \bigotimes I_N$$

and

$$C = \begin{bmatrix} X & 0 \\ 0 & W \end{bmatrix}$$

- Third, draw $\delta, \sigma | \beta, \alpha, V, Y^*, data$ from a Bayesian regression of $Y - \beta X$ on $V - \alpha W$, with Normal-IG priors.
- Fourth, repeat. [15]

[15] Based on Sorensen (2007a), and Korteweg (2013).

Chapter IV

The Impact of Broker Reputation on Analyst Forecast Accuracy

1 Introduction

Sell-side analysts play an important role in gathering, analyzing, and distributing information in financial markets. Their behavior attracts the attention of other market participants, particularly when they issue their earnings forecasts. These forecasts are the analysts' most important outputs, and analysts have strong incentives to make better predictions. Mikhail et al. (1999), Hong et al. (2000), and Groysberg et al. (2011) show that more accurate forecasts can help analysts avoid job termination or move down to less reputable brokerage firms, especially for early career analysts. Also, Stickel (1992) and Groysberg et al. (2011) show that analysts with greater forecast accuracy are more likely to be nominated as "All-star" analysts and earn higher compensation.

We find that new analysts working for more reputable brokerage firms are more likely to make greater forecast accuracy. Two confounding effects drive our findings: the direct effect (influence) that more reputable brokerage firms have more resources and help analysts make greater accurate forecasts; and the indirect effect (sorting), whereby more reputable brokerage firms attract more talented analysts, who thus forecast better. Our main contribution is to utilize a two-sided matching model to disentangle these two effects and quantify their relative importance in determining analyst forecast accuracy. We find that both effects are important, and the influence effect accounts for 73% of the total effect of brokerage firms' reputation on analyst forecast accuracy, while the sorting effect accounts for the remaining 27%.

More reputable brokerage houses can help their new analysts improve their forecast accuracy in several ways. First, analysts working for more reputable brokerage firms may have access to better data and research support (Clement, 1999). Better information acquisition and analysis in more reputable brokerage houses lead to more accurate forecast results. Second, analysts working for more reputable brokerage firms may have better personal communication opportunities with the management teams they follow (Clement, 1999), and private interactions with these teams is one of the most influential factors that determine forecast accuracy (Soltes, 2013; Brown et al., 2015). Sorting captures the effect that better-talented analysts are attracted to work for more reputable brokerage firms. Therefore, even if brokerage firms' reputations have no direct impact on analysts' forecast performance, we still observe that analysts who work for higher-reputation brokerage firms perform better, because the sorting effect leads to positive assortative matching between analysts' individual talent and broker reputation.

Distinguishing these two effects is challenging. Brokerage firm reputation becomes endogenous when better-talented analysts work for more reputable firms, and analysts' talent cannot be perfectly measured. The unobserved part of talent can then be correlated with the brokerage firm reputation measure, and the estimated direct effect of brokerage firm reputation will be biased upward. This concern increases when we focus on new analysts where the datasets contain little information on their abilities. The ideal solution to this endogeneity problem is to find an instrumental variable that correlates with brokerage firms' reputation and is independent of analyst forecast accuracy through other channels. However, the matching decision between analysts and brokerage firms are mutual choices, and it is a complicated process involving a number of observable and unobservable factors. No valid instruments currently exist.

Instead, we use a structural approach similar to Sorensen (2007a) to overcome this missing IV problem. Our structural model contains two key elements: first, an outcome equation that models the determinants of analysts forecast accuracy, and second, a one-to-many associative matching model that controls for sorting. The matching model explicitly models the matching process between analysts and brokerage firms and allows for matching decisions to interact with different agents. The matching decision interaction between agents creates difficulties in estimating the model, but also provides a rank order property that is useful for identification. The rank order property of the two-sided matching model means that the matching decision depends on the relative ranking of the agents in the market. Therefore, it not only depends on the characteristics of the matched agents themselves, but also on the other agents' characteristics. If the agents' characteristics vary exogenously across the market, we can identify the sorting effect by comparing the performance difference between analysts of different quality but match with brokerage firms with similar reputations in different markets. Similarly, we can identify the influence effect by comparing the performance difference between analysts with similar quality but match with brokerage firms with different reputation in different markets.

The key identification assumption is that agents are exogenously assigned across different markets. That is, we need sufficient variation across the new analyst labour market, and agents cannot choose to participate in a particular market for reasons correlated with the agents' characteristics in that market. In this study, we assume the new analyst labour market is segregated by the calendar year and geographically. A similar identification assumption has been made in Sorensen (2007a), Park (2013), Chen (2014), Ni and Srinivasan (2015), Pan (2015), Akkus et al. (2016a), and Xia (2018).

Agents' matching decisions interact, so any analysis of the likelihood function of one agent's decision must also take account of other agents' decisions. The likelihood function then becomes a high dimensional integral function and it cannot be factored out, as in the standard Heckman selection model (Heckman, 1979) where agents' decisions are independent of each other. To overcome the numerical difficulty in solving the high dimensional integration problem, we apply a Bayesian approach, use the Markov Chain Monte Carlo (MCMC) method to transform the integration problem into a simulation problem to make estimation feasible (Tanner and Wong, 1987; Albert and Chib, 1993; Sorensen, 2007a; Park, 2013; Chen, 2014; Ni and Srinivasan, 2015).

Our research contributes first to the literature on the determinants of analyst forecast accuracy. Brokerage firm resources have been found to affect analyst forecast accuracy (Clement, 1999; Kothari et al., 2016), and because of the lack of an identification strategy the sorting effect cannot be disentangled from the total impact. Therefore, the influence on analyst forecast accuracy is unknown. Our results not only provide the first quantitative estimates of the influence effect of the brokerage firm but also quantify the relative importance of the influence and the sorting effects.

Second, our study contributes to the literature that uses the two-sided matching model to understand the incentives for agents to match and the outcomes of the matching results in markets such as the venture capital market (Sorensen, 2007a; Akkus et al., 2016a; Fox et al., 2018), the labour market (Agarwal, 2015; Pan, 2015; Matveyev, 2016; Xia, 2018), M&A market (Park, 2013; Akkus et al., 2016b), and the bank lending market (Chen and Song, 2013; Schwert, 2018).

The results of our study also help to understand workers' incentives to work for firms with good reputations, and the incentives for firms to maintain their reputations. Edmans (2011) finds that firms with better reputations on average perform better, and our results suggest that the reputation of a firm can serve as a sorting mechanism to attract talented employees, which is beneficial for firm performance. More talented employees also like to work for firms with good reputations, because they can scale their ability by using the firms' resources and achieve better personal performance and better future career outcomes. Our results suggest that for new analysts the influencing effect of firms' reputations is 2.7 times larger than the sorting effect. Therefore, the benefit of working for high-reputation firms is particularly attractive for new workers.

The remainder of the paper is organised as follows. In Section 2 the data and the OLS estimation results are discussed. Section 3 presents the theoretical and empirical model and a discussion of identification. Section 4 provides the estimation results. Section 5 concludes the paper.

2 Data and OLS results

2.1 Sample selection and key variables construction

We consider new hires by brokerage firms in each year between 1996 and 2013. Our data comes from the Institutional Brokers Estimate System (I/B/E/S) database, which collects analysts' earnings forecasts and recommendations for companies worldwide. We use the I/B/E/S Detail Recommendations File to identify the brokerage firm an analyst is employed by in any given year. The recommendation file starts in 1992 and expands its coverage over the first three years, so we only consider analysts who started in 1996 or later. We classify an analyst as a new hire in a given year if she appears for the first time in the dataset in that year, and stays at least for the subsequent four years in the dataset and works for the same brokerage firm. We cross-check with the I/B/E/S Detail Earnings History File to further exclude analysts who had previously issued any earnings forecasts, and those who do not issue any earnings forecasts at all. We manually search for the location of the brokerage firms and remove analysts employed by foreign broker houses that do not have any offices in the U.S. Our final sample consists of 1,815 analysts hired by 284 brokerage firms for the period between 1996 and 2013.

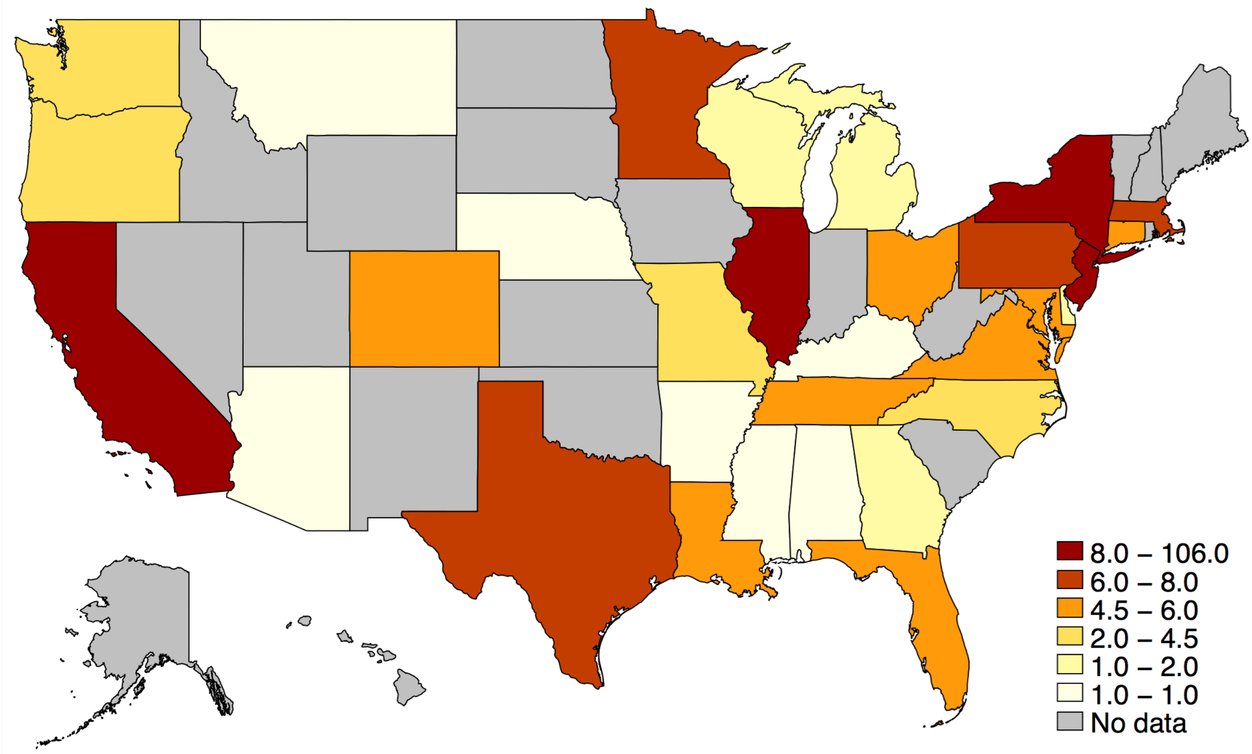
Figure 1 illustrates the geographic distribution of brokerage houses from our sample. We plot the number of firms in each state. A clear geographic clustering on the demand side can be clearly seen in the Northeastern states such as NY and MA, accounting for roughly 65% of our sample. We therefore divide the analysts into 36 markets: Northeastern states and the remaining states for 18 years from 1996 to 2013. Note that pooling the other states together into one labour market each year is less of a concern under the assumption that those small local markets are independent of each other.[16]

To measure an analyst's performance, we first determine her accuracy for each stock she covers in a given year and then take the average of this accuracy across all coverage stocks over the first five years of her tenure. Specifically, for analyst i making a forecast for the earnings of fiscal year t of stock j, we compare her absolute forecast error to the average absolute forecast error

[16]We also run our analysis by considering all of the states as one big market in each year, and the results are similar.

Figure 1. Geographic distribution of brokerage firms

This figure shows the distribution of the US brokerage firms' headquarters in different states. The darker the states, the more brokerage firms are located in that state.



of other analysts covering the same stock during the same time period. We rank all available absolute forecast errors from small to large and assign a rank that corresponds to the relative ranking of analyst i's forecast error for that stock-year. The analyst ranked n-th (where the most accurate/smallest error is ranked 1st and the least accurate/largest error is ranked Nth) is assigned.

$$rank_{ijt} = 1 - \frac{n_{ijt}}{N_{jt} + 1}. \tag{6}$$

The lower the rank, the less accurate the forecast. We aggregate those accuracy ranks for analyst i to determine her overall accuracy as

$$Accuracy_i = \frac{1}{5} \sum_{t=\tau}^{\tau+4} \left(\frac{1}{|J_{it}|} \sum_{j \in J_{it}} rank_{ijt} \right),$$

where J_t denotes analyst i's coverage in year t.

The brokerage firm prestige is measured by using Carter and Manaster (CM) ranking. This ranking measure is based on the order of brokerage firms in firms' IPO tombstone announcements. The measure is developed by Carter and Manaster (1990) and extended by Carter et al. (1998) and Loughran and Ritter (2004). We obtain the data from Jay Ritter's website. On a scale of 0 to 9, the higher the rank, the more prestigious the brokerage firms. Morgan Stanley, Goldman Sachs, JPMorgan, Deutsche Bank, and CITI Group are among the most frequently listed in the highest reputable brokerage groups.

Table 1 presents the summary statistics of our variables. The mean growth rate for these brokerage firms is 14.5% yearly, and the median growth rate is 5%. These firms are on average expanding through the sample period. The newly hired analysts on average start by covering slightly more than 8 stocks, less than the average number of stocks covered by analysts in the whole I/B/E/S universe, which is 14. Most of the analysts cover less than three different industries. The financial analyst labour market is racially dominated by white analysts, based on the surname search, and in our sample we classify less than 17% as nonwhite analysts. Analysts do not cluster in the main industries they cover in our sample. The largest group of analysts (27.9% of the total sample) cover firms in the high-tech industry, followed by 26.8% who mainly cover industries other than those listed in the table. As over half of the U.S. publicly listed firms from 1996 to 2013 are classified in the high-tech industry or in "other" industries, this is a reasonable assumption.

Table 1. Summary statistics

This table reports summary statistics of the main variables. We consider an analyst's tenure as her first five years working for the brokerage firm. Broker reputation is the Carter and Manaster rank on a scale of 0 to 9, and the higher the rank the more prestigious the brokerage firm. Broker growth is the percentage of brokerage size increase from last year. Number of stocks and industries is the average number of firms and industries she covers during her tenure. Log(Market Cap) is the logarithm of the total market cap an analyst covers in her first year. Ethnicity indicates whether the analyst is white Caucasian or not based on the analyst's surname (1 indicates not, 0 indicates yes). To include the focus industry fixed effects, we define industries using the Fama-French five industry classifications, and classify an analyst's focus industry as the one in which she covers the most stocks. We indicate the following four industries: Consumer (including retails & wholesales), Manufacturing & Energy, High Tech, and Health. Num IPO indicates the total number of IPOs made in a specific year.

	N	Mean	St. Dev	Percentile				
VARIABLES				10th	25th	50th	75th	90th
Accuracy	1,815	0.514	0.082	0.410	0.473	0.521	0.567	0.609
Broker Reputation	1,815	5.948	3.112	0	5.001	7.001	8.501	9.001
Broker Growth	1,815	0.145	0.467	-0.181	-0.066	0.052	0.191	0.500
Log(Market Cap)	1,815	8.642	1.974	6.052	7.260	8.602	10.119	11.952
Num Stocks	1,815	8.511	4.780	2.6	5	8	11.4	14.75
Num Industries	1,815	1.683	0.771	1	1	1.5	2	2.8
Ethnicity	1,815	0.167	0.374	0	0	0	0	1
I.Consumers	1,815	0.141	0.348	0	0	0	0	1
I.Manuf & Energy	1,815	0.196	0.397	0	0	0	0	1
I.High Tech	1,815	0.279	0.449	0	0	0	1	1
I.Health	1,815	0.116	0.320	0	0	0	0	1
Num IPO	1,815	168.047	148.497	38	60	131	223	384

2.2 OLS results

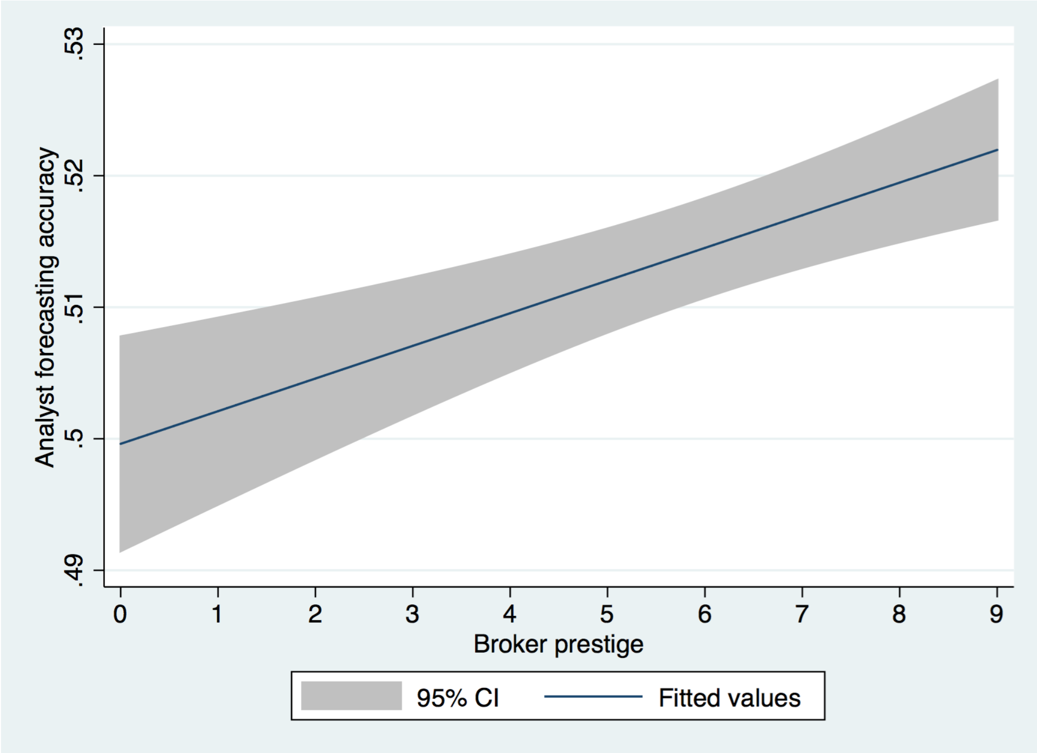
In this subsection, we document a robust and strong empirical correlation between brokerage reputation and newly hired analysts' forecast performances. According to the level of brokerage prestige, we first plot the correlation between brokerage prestige and analyst performance.

Figure 2 illustrates strong positive correlations between broker prestige and analysts' accuracy and their likelihood of becoming an all-star analyst. Analysts who start with the lowest prestige brokerage firms on average exhibited performance of 0.493, while those who start with the highest prestige firms on average exhibited performance of 0.522, and those analysts are on average 6% more accurate.

To investigate these relations more formally, we estimate an OLS model for analyst accuracy. Table 2 shows that for the entire 1996 - 2013 period, analysts work for higher prestige brokerage firms on average have greater forecast accuracy. The magnitude does vary when we include other broker and analyst characteristics in column (2) and market fixed effect in column (3). In column (4) and column (5) we repeat the analysis on subsamples from 1996 - 2004 and 2005 - 2013. Here, broker reputation is also positively correlated with analyst forecast accuracy. Overall, the positive correlation between broker prestige and analyst forecast accuracy is robust to different controls

Figure 2. Relation between brokerage firm prestige and analyst performance

This figure shows the correlation between brokerage firms' reputations and newly hired analysts' forecast accuracy from 1996 to 2013. Our sample is grouped into 10 bins according to broker prestige. The shadow area represents a 95% confidence interval.



and split sample regressions. If an analyst moves from the lowest to the highest reputable group of brokerage firms, the analyst forecast accuracy will increase by 0.025.

In addition to broker prestige, other factors affect newly hired analyst forecast accuracy. From Table 2, we observe that the more stocks analysts cover, the more accurate their forecasts are. This observation may appear to contradict previous findings that the more complex the portfolios that analysts are covering, the less accurate their forecasts are. We argue this is less of a concern because our sample only contains newly hired analysts, so the number of stocks analysts cover also contains information on analysts' ability. Another critical factor explaining analyst forecast accuracy is the ethnicity of the analyst. In the whole sample, non-white analysts constitute less than 17% of the total sample but on average they perform better than white analysts. This outperformance is particularly strong in the first half of the sample, possibly because sell-side analyst jobs used to be occupied by white candidates and so the entry bar is higher for non-white candidates. For non-white candidates to get a job, their ability must be better than average, and thus they perform better[17].

[17]Similar evidence has been found in the asset management industry, where the entry bar is higher for candidates with low-income family backgrounds. Consequently, to become fund managers these candidates need to be significantly better than those from wealthy families (Chuprinin and Sosyura, 2018)

Table 2. Naive OLS Regression

This table reports estimation results of the OLS model for analyst accuracy. Columns (1) to (3) present this relationship by using the whole sample from 1996 to 2013. Column (4) analyzes this relationship using the first half of the sample and column (5) analyzes the relationship using the second half of the sample. Parentheses include the corresponding standard errors. ***,**, and * denote significance at the 10%, 5%, and 1% levels, respectively. Variables are defined in Table 1.

	Analyst forecasting accuracy				
	Whole sample			1996 - 2004	2005 - 2013
VARIABLES	(1)	(2)	(3)	(4)	(5)
Broker prestige	0.0025***	0.0025***	0.0026***	0.0022**	0.0031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Broker growth		0.0005	-0.0032	-0.0045	-0.0017
		(0.005)	(0.005)	(0.006)	(0.008)
Log(Market cap)		0.0006	0.0005	0.0020	-0.0011
		(0.001)	(0.001)	(0.002)	(0.002)
Num stocks		0.0017***	0.0015***	0.0019**	0.0013**
		(0.000)	(0.000)	(0.001)	(0.001)
Num industries		0.0017	0.0022	0.0012	0.0033
		(0.002)	(0.002)	(0.004)	(0.003)
Ethnicity		0.0075	0.0099*	0.0230***	0.0016
		(0.005)	(0.005)	(0.008)	(0.007)
Num IPOs		0.0000**	-0.0002***	-0.0001	-0.0005**
		(0.000)	(0.000)	(0.000)	(0.000)
Market dummy	No	No	Yes	Yes	Yes
Observations	1,815	1,815	1,815	785	1,030
R-squared	0.0088	0.0212	0.0490	0.0570	0.0458

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As we explain in the introduction, the quality of brokerage firms becomes endogenous when sorting and causes more reputable brokerage houses to employ analysts who are better, along with many dimensions unobserved in the data. Analysts with better unobserved characteristics, as captured by the error term in the regression, match with brokers of better quality. The error term becomes positively correlated with broker size and broker accuracy, and the coefficient estimates are biased upwards relative to the brokers' actual influence. As no obvious instrumental variable is independent of analyst outcome but is related to the quality of the brokerage firm employing this analyst, we adopt the structural model developed by Sorensen (2007a) that exploits the implications of sorting to separate sorting from influence. Sorting implies that in a market with better broker firms, a given firm is pushed down the relative ranking and is left with worse analysts. Hence, a broker's new hire decisions depend on the characteristics of other agents in the market. Nevertheless, the outcome of the analyst is independent of these other characteristics, and the other brokers' characteristics serve as a source of exogenous variation. We now discuss the model in more detail.

3 Model

3.1 Two-sided matching model

An essential feature of the equity analyst labour market is that the matching between new equity analysts and brokerage firms is a mutual decision, as both of the parties have the decision power to determine whether they want to match. In addition, one analyst can only work for one firm, but one firm can hire multiple analysts. These features are best captured by a one-to-many two-sided matching market, which contains two types and a finite number of agents on each side of the market. The model used in this study is similar to the variation of the college admission model suggested by Sorensen (2007a), and shares similar assumptions: first, as discussed above, the new equity analyst labour market is a one-to-many two-sided matching market. Second, in one market, brokerage firms are restricted in the number of new analysts they can hire. This is a reasonable assumption because brokerage firms' resources limit their hiring decisions and time invested in organising interviews. Therefore, brokerage firm hiring capacity is capped. Third, each possible match has a valuation (V), which represents the discounted expected future payoff of the possible matched pair, and the brokerage firm receives λ fraction of the valuation, and the analyst expects to receive $1 - \lambda$ fraction, where λ is fixed for all possible matches in a market and thus guarantees the model has a unique equilibrium. This assumption also rules out transfers, and is also reasonable. First, we do not observe analyst compensation in general. Second, most compensation is paid in the form of a bonus, which is high when a firm's bonus pool expands and low when it shrinks (Groysberg et al., 2011). Therefore, analysts are sharing profits from the firm. Third, we focus on newly hired analysts, who have little bargaining power at the beginning of their career, so it is unlikely that these analysts can negotiate on pay. Therefore, their compensation structure is mostly fixed, and they cannot match more reputable firms by being offered a lower profit share by the firm.

3.1.1 Agents

The matching model has two types of agents: newly hired analysts and brokerage firms. In market m, a set I_m contains all of the new analysts, and a set J_m contains all brokerage firms that hire analysts. Each new analyst works for one brokerage firm, and one brokerage firm can hire a limited number of analysts. Let brokerage firm j's quota be q_j, where $q_j > 0$. The set M_m contains all possible matches of analysts and firms in market m, therefore $M_m = I_m \times J_m$. A matching contains observed hirings in market m denoted as μ_m, where $\mu_m \subset M_m$. Denoting that μ_j contains all of the analysts firm i hires and μ_i is the brokerage firm analyst i works for, then a match between firm i and analyst j can be expressed as: $(i, j) \in \mu$, $i = \mu(j)$, or $j \in \mu(i)$.

Agents on both sides of the market choose their matched partners to maximise the matching value, which represents the expected latent joint utility at the time of hiring. Let each possible match have a matching value and let the value of the match i, j be denoted as $V_{i,j}$ regardless of whether i, j is a matched pair or not. The matching values are assumed to be distinct to avoid the possibility that agents can be indifferent between two matches. The matching utility is divided between the brokerage firms and analysts. Firms receive λ share of the matching value and the analysts receive $(1 - \lambda)$ share, and λ is fixed for all matches and $\lambda \in (0, 1)$.

3.1.2 Equilibrium

A matching is an equilibrium if it is stable and no pair of agents would like to deviate from their current matches and form a new match together to become a blocking pair. The stable equilibrium always exists (Gale and Shapley, 1962) and under the fixed sharing rule of the matching value the equilibrium is unique (Sorensen, 2007a). The unique equilibrium is characterised by a set of inequalities based on the no blocking pairs condition.

For i, j to be a stable match, we need no blocking pair to exist for i, j, that is, the opportunity cost of analyst i remaining match with firm j or the opportunity cost of firm j remaining match with analyst i has to be smaller than the matching value of i, j, $V_{i,j}$.

The opportunity cost of analyst i is the maximum value that analyst i can get from the feasible set of deviations of analyst i instead of working for the firm j. The opportunity cost of brokerage firm j is the maximum value that firm j can get from the feasible set of deviations of firm j instead of hiring analyst i. The fixed sharing rule means that finding the maximum value that agents on one side of the market can get is equivalent to find the maximum matching value that a pair of agents can achieve together. We denote OC_i as the corresponding matching value for analyst i's opportunity cost and OC_i is the corresponding matching value for brokerage firm j's opportunity cost. That is,

$$V_{i,j} < max[OC_i, OC_j],$$

where

$$OC_i \equiv max[V_{i,j'}], \forall j' \in J \cap (V_{i,j'} > V_{\mu(j'),j'}),$$
$$OC_j \equiv max[V_{i',j}], \forall i' \in I \cap (V_{i',j} > \min_{i'' \in \mu(j)} V_{i'',j}).$$

If in other circumstances analyst i and brokerage firm j are not matched, then (i, j) cannot become the blocking pair for their current matches. Then it is sufficient that,

$$V_{i,j} > max[V_{i,\mu(i)}, \min_{i''' \in \mu(j)} V_{i''',j}].$$

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

$$V_{i,j} < \overline{V}_{i,j}, \forall (i, j) \notin \mu, \tag{7}$$

$$V_{i,j} > \underline{V}_{i,j}, \forall (i, j) \in \mu. \tag{8}$$

3.2 Empirical Model

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

$$V_{i,j} = \alpha W_{i,j} + \eta_{i,j}, \forall (i,j) \in M, \tag{9}$$

where $W_{i,j}$ contains characteristics of analyst i and firm j that are observed by econometricians. $\eta_{i,j}$ contains characteristics of analyst i and firm j that are not observed by econometricians but are known for every agent in the market and $\eta_{i,j} \sim N(0, \sigma_\eta)$.

The second part of the model is the outcome equation. This determines the outcome of all possible matches, which is only observable to those matches that are realised. The outcome of analyst i and brokerage firm j can be written as:

$$Y_{i,j} = \alpha X_{i,j} + \varepsilon_{i,j}, \forall (i,j) \in M, \tag{10}$$

where $X_{i,j}$ contains characteristics of analyst i and firm j that are observed by econometricians. $\varepsilon_{i,j}$ contains characteristics of analyst i and firm j that are not observed by econometricians but known for every agent in the market and $\varepsilon_{i,j} \sim N(0, \sigma_\varepsilon)$.[18]

Directly estimating the outcome equation leads to biased results, as the matching decision between analyst i and firm j is not random but correlated with the error term in the outcome equation, which cannot be observed by econometricians. This problem is captured by a third equation determining the correlation between the error terms in the valuation equation and the outcome equation:

$$\varepsilon_{i,j} = \delta \eta_{i,j} + \xi_{i,j}, \tag{11}$$

where $\xi_{ij} \sim N(0, \sigma_\xi)$. If there is no correlation between the two error terms then $\delta = 0$.

3.3 Identification and estimation

In this subsection we briefly discuss how we identify and estimate the parameters in the outcome equation. The main feature of the matching market is that the agents' decisions on matching interact with each other, and this leads to better-talented analysts sorting by brokerage quality. If analyst A is hired by brokerage firm 1, then brokerage firm 2 cannot approach analyst A, simply because A is not available anymore. Also, if brokerage firm 1 has used up its hiring quota, then other analysts with relatively lower quality than analyst A cannot match with broker 1. Therefore, in one market, each agent's matching decision is correlated with other agents' characteristics, and also leads to better-talented analysts matching with more reputable brokerage firms.

[18]If the outcome is binary, there will be a third part containing a binary outcome function, i.e. $O_{i,j} = 1[Y_{i,j} > 0]$

The sorting and interaction feature helps in identification. As mentioned earlier, the endogeneity problem can occur when better-talented analysts sort on brokerage firm reputation and the talent cannot be measured or observed completely. The estimated impact from brokerage firm reputation will then be biased upward. Sorting and interaction in the market can be viewed as we rank all of the new analysts and all brokerage firms based on their characteristics in each market, with the top-ranked analyst candidate matched with the top-ranked brokerage firm. We continue to match the second highest ranked analyst candidate with the top-ranked brokerage firm until the hiring quota is entirely filled, and then we continue to form matches between analysts with the second highest ranked brokerage firm until we fill all of the vacancies in the market. This rank-order property means the matching decision is determined by the relative ranking of the agents on two sides of the market, and partly depends on the agents' own characteristics, and partly on the characteristics of other agents. If markets conditions vary exogenously, this will lead to similar-quality analysts being matched with brokerage firms with different reputations for exogenous reasons, and can help to identify the parameters in the outcome equation.

The cross-market variation means that same-quality brokerages and same-quality analysts cannot match in two different markets. Assume in market 1, brokerage i and analyst j are matched. In market 2, brokerage i' has the same quality as brokerage i, but assume market 2 contains similar brokerage firms but with more talented analysts. Therefore, an analyst j' with the same quality as analyst j will rank much lower in market 2, and cannot match with brokerage i', and instead is matched with another brokerage firm with lower quality. Brokerage house i' can match with another analyst k who has better quality than analyst j'. The effect from matching is different, but the impact from the brokerage firm influence is the same, and this will lead to differences between outputs from analyst j and analyst k. This will help us identify the effect of matching.

More formally, let Y_{ij}^* denote the observed match (i, j)'s outcome in one market, and then to estimate the coefficients based on the empirical model we have:

$$
\begin{aligned}
E[Y_{i,j}|X_{i,j}] &= E[Y^*_{i,j}|X_{i,j},(i,j)\in\mu] \\
&= E[Y^*_{i,j}|X_{i,j},V_{i,j} > \underline{V}_{i,j}] \\
&= \beta + E[\varepsilon_{i,j}|\alpha W_{i,j} + \eta_{i,j} > \underline{V}_{i,j}] \\
&= \beta + E[\delta\eta_{i,j} + \xi_{i,j}|\eta_{i,j} > \underline{V}_{i,j} - \alpha W_{i,j}] \\
&= \beta + \delta E[\eta_{i,j}|\eta_{i,j} > \underline{V}_{i,j} - \alpha W_{i,j}].
\end{aligned}
$$

The first equality comes from the equilibrium condition of the matching model, and the fourth equality comes from the error term correlation structure. Therefore, the exogenous variation in this expression identifies outcome equation parameters β, and the expression varies with $\underline{V}_{i,j}$. As $\underline{V}_{i,j}$ is determined by the other agents' characteristics in the market, if the allocation of the other agents in the market is exogenously given, then the parameters in the outcome equation are identified. [19]

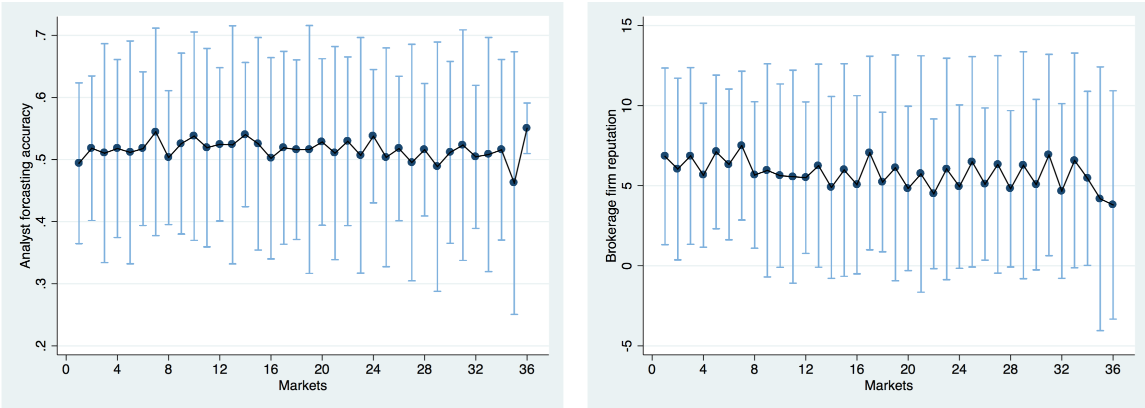
The key identification assumption is that agents are allocated exogenously across markets, which is reasonable because the new analyst labour market is likely to be influenced by macro or financial industry factors instead of agents' sort on different markets (i.e., waiting to hire later because they know there will be better candidates one year later). Figure 3 shows that even though the average is reasonably consistent across markets, there are significant variations of main variables within each market, and this variation fluctuates from market to market. Thus, it is reasonable to assume the agents are exogenously allocated across markets.

The estimation method we use is the Bayesian estimation with Markov Chain Monte Carlo (MCMC). The sorting and interaction feature of the model makes estimation difficult. The likelihood function for one pair of agents' matching decisions also depends on the other agents' choices, so all of the error terms must be integrated simultaneously. To circumvent this high-dimensional integration problem, we take advantage of the Bayesian method with MCMC (Tanner and Wong, 1987; Geweke et al., 1994; Albert and Chib, 1993), and instead of solving the integration problem, we augment the observed data with the simulated value of the latent matching value and the performance of the counterfactual matches. The simulated distribution converges to the augmented posterior distribution. The detailed simulation procedure can be found in Appendix A.

[19] A complete discussion of the identification strategy can be found in Sorensen (2007b).

Figure 3. Variation in main variables across markets

This figure shows the cross and within market variation of the key Y variable: analyst forecast accuracy, and the key X variable: broker reputation. Each subgraph depicts the average of the variable (black solid line) and one standard deviation around the mean (light blue error bar). Subgraph (a) shows the variation of analyst accuracy across different markets. Subgraph (b) shows the variation of brokerage reputation across different markets.



(a) Analyst forecast accuracy

(b) Broker reputation

4 Estimation results

4.1 Main result

In this section, we estimate the structural model. In Table 3 Panel B, the coefficients estimated represent agents' preferences. The results show that an analyst prefers to work for brokerage firms with higher reputations and higher growth rates, and brokerage firms prefer to hire analysts who can cover large value portfolios, cover fewer stocks, have less industry focus, and are from a non-white background. Thus, firms prefer non-white analysts who can cover a limited amount of large firms and span less industries. The probability of an analyst match with a broker with the highest reputation score is 90.6%. The probability that brokerage firms prefer a non-white analyst is 55.13%. Compared with a new analyst who can only cover the lowest ten percentile of the portfolio market size, brokerage firms prefer analysts who cover the top ten percentile of the portfolio market size by a probability of 59.5%. Overall, the results from the matching equation suggest analysts have strong preferences in terms of broker reputation, rather than other observed factors that brokerage firms have on analysts. Broker reputation is the most important factor in measuring brokerage firms' quality, while the analysts' ethnicity or portfolio sizes are simply indirect measures of their quality.

Panel C of Table 3 represents the effect of sorting on unobserved characteristics. If there is no sorting between unobservables, a matching model is not needed. The result shows δ is positive

Table 3. Bayesian estimate of the matching model and the outcome equation

This table reports Bayesian estimation results of two equations from the structure model. The dependent variable in the outcome equation is analyst forecast accuracy, and the dependent variable in the valuation equation is the latent matching value. A detailed description of the variables is given in Table 1. Mean, Median, and Standard Dev. are the statistics of the simulated posterior distributions of the parameters. Marginal effects of the valuation equation represent the probability of choosing two matches with only marginal change in one variable, and are calculated by following Sorensen (2007a). Estimates are based on 110,000 simulations of the posterior distribution. The initial 11,000 simulations are discarded for burn-in. ***,**,and * denote that zeros are not contained in the 10%, 5%, and 1% credible intervals, respectively. Variables are defined in Table 1.

	Dependent variable: Analyst forecasting accuracy				
	Mean	Median	Marginal effect	Standard Dev.	95% HPD
VARIABLES	(1)	(2)	(3)	(4)	(5)
Panel A: Outcome equation					
Broker reputation	0.0019***	0.0019		0.0007	[0.0006, 0.0033]
Broker growth	-0.0044	-0.0044		0.0043	[-0.0130, 0.0041]
Log(Market cap)	-0.0002	-0.0002		0.0011	[-0.0024, 0.0019]
Num stocks	0.0013***	0.0013		0.0005	[0.0004, 0.0022]
Num industry	-0.0031	-0.0031		0.0027	[-0.0084, 0.0023]
Ethnicity	0.0036	0.0037		0.0052	[-0.0070, 0.0140]
Num IPO	0.0000*	0.0000		0.0001	[-0.0000, 0.0001]
Panel B: Matching equation					
Broker reputation	0.1439***	0.1409	0.0406	0.0261	[0.0974, 0.1952]
Broker growth	0.0651	0.0663	0.0184	0.1219	[-0.1732, 0.3010]
Log(Market cap)	0.0569***	0.0560	0.0161	0.0149	[0.0284, 0.0868]
Num stocks	-0.0095	-0.0091	-0.0027	0.0068	[-0.0233, 0.0034]
Num industry	-0.1763***	-0.1753	-0.0497	0.0316	[-0.2381, -0.1145]
Ethnicity	0.1820***	0.1786	0.0513	0.0664	[0.0556, 0.3115]
Panel C: Variance					
δ	0.0063***	0.0063		0.0037	[8.89e-07, 0.0131]

and 0 is not contained in the 99% highest posterior distribution, and that the sorting effect exists and is significant, indicating that unobserved agents' characteristics affect matching values and also matching outcomes. This also highlights the key point of the study: controlling for matching is crucial given its significant effect.

Panel A of Table 3 shows the estimated coefficients in the outcome equation after controlling for endogenous matching. The coefficient associated with broker reputation is positive and 0 is not contained in the 95% highest posterior distribution, which suggests after controlling for sorting, the effect of brokerage reputation is crucial in explaining analyst forecast accuracy. This finding is consistent with channels suggested by Clement (1999) that brokerage resources (proxied by brokerage reputation in this study) are important in determining analyst forecast accuracy.

4.2 Relative importance

Although the above analysis clearly shows that broker reputation has a significant direct impact on analyst forecast accuracy, because sorting on unobservables also has a significant impact on the outcome, the relative importance of the direct effect of broker reputation, and the indirect effect from sorting is unknown..

In determining the relative importance, we compare the OLS and Bayesian estimated results in Table 4. Column (1) presents the OLS regression results, and column (2) the Bayesian estimation results. From these two columns, the total impact of broker reputation on analyst forecast accuracy estimated by OLS regression is 0.0026, and the direct impact of broker reputation on analyst forecast accuracy is 0.0019. The direct impact takes 73% of the total impact, and thus the remainder is the sorting effect. In column (4), we calculate and test whether the average sorting effect is statistically significant. The magnitude of the average sorting effect on broker reputation is 0.0007, which represents 27% of the average total impact, and it is statistically different from 0. Although the absolute value of the sorting effect is small, the economic magnitude is huge. By comparing two similar quality analysts matched with two distinct brokerage firms, where one belongs to the lowest reputable group and the other to the highest reputable group, the difference in analyst forecast accuracy is found to be 0.007, which represents 15 years' working experience for the average analyst. Thus, although the sorting effect does not represent the majority of the total impact of broker reputation, it is still huge in economic terms and should therefore be considered.

Table 4. Bayesian estimate of alternative market and comparison

This table compares the outcome equations from models with different market definitions and compares the coefficient estimated from the naive OLS regression for analyst accuracy. Bayesian estimates are based on 110,000 simulations of the posterior distribution. The initial 11,000 simulations are discarded for burn-in and a tune-in factor of 10. Parentheses represent the corresponding t-statistics. ***,**,and * denote significance at the 10%, 5%, and 1% levels, respectively. Variables are defined as in Table 1.

	Dependent variable: Analyst forecasting accuracy				
	OLS	Bayesian estimation		Difference with OLS	
		Main	Expended states	Main	Expended states
VARIABLES	(1)	(2)	(3)	(4)	(5)
Broker reputation	0.0026	0.0019	0.0019	0.0007**	0.0007**
				(2.3459)	(2.3459)
Broker growth	-0.0032	-0.0044	-0.0004	0.0012	-0.0028
				(0.5741)	(-1.3397)
Log(Market cap)	0.0005	-0.0002	0.0001	0.0008	0.0005
				(1.4906)	(0.8518)
Num stocks	0.0015	0.0013	0.0009	0.0002	0.0006***
				(0.9377)	(2.8132)
Num industry	0.0022	-0.0031	-0.0034	0.0053***	0.0056***
				(5.3979)	(5.7035)
Ethnicity	0.0099	0.0036	-0.0031	0.0063***	0.0130***
				(2.6854)	(5.5420)
Num IPO	-0.0002	0.0000	0.0000	-0.0002***	-0.0002***
				(-9.5108)	(-9.5108)
δ		0.0063	0.0074		
Markets	36	36	18		

4.3 Alternative market

In our main analysis, our definition of new analyst labour market is by one calendar year but segregated by geographical locations. The market segregation is a critical identification assumption, and will fail if new analyst candidates or brokerage firms choose to participate in the specific market, based on unobserved characteristics of other agents in that market. For example, if the Northeast of the US has more reputable brokerage firms and if that reputation is sufficient to attract analyst candidates, this will lead to analysts sorting between different locations, and so a more appropriate definition of the market is to consider the whole US as a single market.

In this subsection, we expand the market definition to evaluate the robustness of the estimation results. In Column (3) of Table 4, we treat the Northeast and the rest of the US as the same market and repeat the analysis. The estimated coefficients are at a similar magnitude and significance level, particularly the key variables of broker reputation and δ. The magnitude of the coefficient associated with broker reputation is robust to different specifications and the statistical significance is also similar. The magnitude of δ increases but the statistical significance is similar. This indicates that minor sorting exists between the geographical locations in the same year, but the baseline Bayesian estimation does not capture this minor effect. For our main purpose of estimating the direct effect of broker reputation, this is less of a concern because this cross-location sorting appears to have little correlation with broker reputation. Overall, the results provide an intuitive robustness test that confirms that the identification assumption is valid and our estimation results are not sensitive to different market definitions.

5 Conclusion

Our study focuses on the new analyst labour market. We find new analysts working for firms with higher reputations perform better. This total effect is a combination of the direct influence effect, in which reputable firms can help analysts perform better, and the sorting effect, in which brokerage firms with high reputations can attract more talented analysts. To disentangle these two effects, we utilise a one-to-many two-sided matching model to circumvent the need to find the instrumental variable. The features of the matching model can capture how agents' matching decisions interact, and how the other agents' characteristics determine the relative ranking of the agents' matching decisions, but the other agents' characteristics do not have an effect on the agents' performance. Therefore, the exogenous variation of the other agents' characteristics helps to identify the coefficients of the outcome equation.

In the sample of 1815 new analyst-brokerage firm matched pairs from 1996 to 2013, we find that both the influence effect and the sorting effect have a significant impact on analyst forecast accuracy. The influence effect accounts for 73% of the total impact, and the sorting effect for 27%.

The results of the study have more general implications for understanding the incentives for workers to choose more reputable firms to work for and the incentives for firms to spend resources in maintaining their reputation. High reputation firms provide resources for workers and help them perform better, and in our results the forecast difference between analysts of the same quality working for the lowest and the highest reputation firms is equivalent to 15 years of experience. A firm's reputation is valuable, as it not only motivates current workers but also attracts more talented new workers. Both of these effects are important in understanding the benefit of firms' reputation on workers performances.

A Appendix: MCMC estimation procedure

Let the markets be indexed by $m = 1, \ldots, N$, latent valuation variables be $V_m \equiv \{V_{ij}, ij \in M_m\}$, matching characteristics $W_m \equiv \{W_{ij}, ij \in M_m\}$, and exogenous explanatory variables be $X_m \equiv \{X_{ij}, ij \in M_m\}$, for all potential matches $ij \in M_m$ in each market m. The following algorithm shows how to draw from the posterior the distribution of the parameters augmented with the latent valuation variable, V_{ij}, and the missing observations y^*_{ij} for unobserved matches. We are interested in estimating the parameters α, β, and δ. The Markov chain is generated by drawing each individual dimension of the joint posterior distribution conditional on the draws of the other dimensions as follows:

1. Start Gibbs-sampler for $g = 1 : G_{burn-in} + G_{sample}$ total runs.
2. Initialise the sampling by drawing α, β, δ, and σ^2_ξ from prior distributions: $\alpha \sim N(\alpha_0, A^{-1}_\alpha = 10I_k)$, $\beta \sim N(\beta_0, A^{-1}_\beta = 10I_p)$, $\delta|\sigma^2_\xi \sim N(\delta_0, \sigma^2_\xi/A_\delta)$, and $\sigma^2_\xi \sim IG(a = 2.1, b = 1)$.
3. Draw latent valuation variables V_{ij} for all potential matches in each market m, and draw outcome variable Y_{ij} for unobserved matches in each market m, from distributions conditional on parameters $\alpha, \beta, \delta, \sigma^2_\xi$.
4. Update α, β by drawing from a Bayesian Seemingly Unrelated Regression (BSUR) of $[V; Y]$ on $[W; X]$ conditional on δ, σ^2_ξ.
5. Update δ, σ^2_ξ by drawing from a Bayesian regression of $Y - X\beta$ on $V - W\alpha$, conditional on α, β.
6. Go back to step 3 and repeat.

We now describe how to draw from each conditional distribution.

A.1 Conditional distribution of valuation variables V_{ij}

The conditional augmented posterior distribution of V_{ij} depends on whether brokerage firm i and analyst j are matched or not:

1. when $ij \notin \mu_m$, we draw V_{ij} from $N(W'_{ij}\alpha, 1)$ truncated from above at $\overline{V}_{ij}$;
2. when $ij \in \mu_m$, we draw V_{ij} from

$$V_{ij}|\alpha, \beta, \delta, \sigma^2_\xi, Y_{ij} \sim N\left(W'_{ij}\alpha + (Y_{ij} - X'_{ij}\beta)\frac{\delta}{\delta^2 + \sigma^2_\xi}, \frac{\sigma^2_\xi}{\delta^2 + \sigma^2_\xi}\right)$$

truncated from below at $\underline{V}_{ij}$.

The expressions for $\overline{V}_{ij}$ and $\underline{V}_{ij}$ are given in the equation.

A.2 Conditional distribution of unobserved outcome variables Y_{ij}

We only need to simulate the outcome variable Y_{ij} if $ij \notin \mu_m$, i.e., for unobserved matches. We draw Y_{ij} from

$$Y_{ij}|\alpha, \beta, \delta, \sigma_\xi^2, V_{ij} \sim N\left(X_{ij}'\beta + \delta(V_{ij} - W_{ij}'\alpha), \sigma_\xi^2\right).$$

A.3 Conditional distribution of α and β

We apply a BSUR of [V; Y] on [W;X] to sample α and β,

$$\alpha, \beta|V_{ij}, Y_{ij}, \delta, \sigma_\xi^2 \sim N\left(M^{-1}N, M^{-1}\right),$$

where

$$M = \begin{pmatrix} \Omega_{1,1}^{-1}W'W & \Omega_{1,2}^{-1}W'X \\ \Omega_{2,1}^{-1}X'W & \Omega_{2,2}^{-1}X'X \end{pmatrix} + A, \quad N = \begin{pmatrix} A_\alpha\alpha_0 \\ A_\beta\beta_0 \end{pmatrix} + \begin{pmatrix} \Omega_{1,1}^{-1}W'V & \Omega_{1,2}^{-1}W'Y \\ \Omega_{2,1}^{-1}X'V & \Omega_{2,2}^{-1}X'Y \end{pmatrix},$$

and

$$\Omega = \begin{pmatrix} 1 & \delta \\ \delta & \delta^2 + \sigma_\xi^2 \end{pmatrix}.$$

A.4 Conditional distribution of δ and σ_ξ^2

Draw $\delta, \sigma_{xi}^2|\alpha, \beta, V, Y$ from a Bayesian regression of $\varepsilon = Y - X\beta$ on $\eta = V - W\alpha$:

1. Draw $\sigma_\xi^2 \sim IG(a+N, b+S)$, where N is the number of all potential matches from all markets, and $S = (\varepsilon - \eta d)'(\varepsilon - \eta d) + (d - \delta_0)'A_\delta(d - \delta_0)$, and $d = (\eta'\eta + A_\delta)^{-1}(\eta'\varepsilon + A_\delta\delta_0)$.

2. Draw $\delta|\sigma_\xi^2 \sim N\left(d, \sigma_\xi^2(\eta'\eta + A_\delta)^{-1}\right)$, truncated from below at 0.

Summary

This thesis investigates three questions relates to CEOs and financial analysts: (1) What are the impact of lame-duck CEOs on firms performances? (2) What is the relative importance of incentive pay's incentive effect and selection effect on CEO performance? (3) What is the relative importance of brokerage firm reputation's sorting effect and influence effect on analysts forecast accuracy?

Chapter 2 shows that the protracted succession is common in U.S. S&P 1500 firms. Among 1739 CEO turnovers from 2005 to 2014, 31% of them are experiencing the protracted succession form of match friction. In protracted successions, firms announce incumbent CEOs' leaving news without identifying successors' name, and then incumbent CEOs become lame-ducks. The average period of the protracted succession lasts for six months. During this period, a monthly rebalanced long-only portfolio add firm into the portfolio when the successors' identity has not been publicly announced and sale firm when the successor is publicly known. This portfolio generates monthly 4-factor alpha of 11%. Moreover, during the reign of lame-duck CEOs, firms also experience positive abnormal returns associated with earnings announcements. This positive market reaction is likely to be driven by two mechanisms: Investors under-react to the lack of new of new CEO identify and the underestimation of the positive effects of the tournament competition among CEO candidates.

The task in chapter 3 is trying to distinguish between the two forces that will lead to new CEOs receive higher incentive pay performance better. The two forces are direct incentive effect that higher incentive pay motivates CEOs to work harder and firms perform better, and selection effect that better-talented CEOs are matched with firms provide higher incentive pay and leads to better firm performance. This chapter utilizes a one-to-one two-sided matching model to control for the selection effect and identify the incentive effect. This method takes advantage of the fact that agents matching decisions not only depend on their own characteristics but also on other agents characteristics in the market, these other agents characteristics are not likely to impact on matched pairs' performance. The exogenous variation on agents' characteristics in different markets helps to disentangle the incentive and selection effect of CEO incentive pay. The incentive effect accounts for 83% of the total impact and the selection effect accounts for 17% of the total impact. The selection effect becomes more important in industries where talent mobilities are higher and in more recent years.

Chapter 4 uses a similar approach in chapter 3 to understand the impact of brokerage firm's

reputation on financial analysts' forecast accuracy. On one hand, brokerage firms with high reputation are always associated with better research support, better opportunity to communicate with the management team, and these resources can help analysts to forecast better (influence effect). On the other hand, better reputable brokerage firms attract better-talented analysts to work for them, therefore forecast better (sorting effect). This chapter uses a one-to-many two-sided matching model to identify the influence effect and the sorting effect. The result shows that the incentive effect accounts for 73% of the total impact and the sorting effect accounts for 27% of the total impact.

Samenvatting

Dit proefschrift onderzoekt drie vragen met betrekking tot CEO's en financiële analisten: (1) Wat zijn de gevolgen van CEO's van lamé-eenden voor de prestaties van bedrijven? (2) Wat is het relatieve belang van het stimulerende effect van het stimuleringsbeleid en het selectie-effect op de prestaties van de CEO? (3) Wat is het relatieve belang van de sorteringseffecten en het invloedseffect van makelaarsfirma's op de nauwkeurigheid van voorspellingen van analisten?

Hoofdstuk 2 laat zien dat de langdurige opvolging gebruikelijk is in Amerikaanse S&P 1500-kantoren. Van 1739 CEO-omzet van 2005 tot 2014 ervaart 31% de langdurige opvolgingsvorm van match-frictie. In langdurige opvolgingen kondigen bedrijven aan dat zittende CEO's nieuwtjes achterlaten zonder de naam van de opvolger te identificeren, en dan worden zittende CEO's lamé-eenden. De gemiddelde duur van de langdurige opvolging duurt zes maanden. Gedurende deze periode voegt een maandelijkse, opnieuw gebalanceerde, lange portefeuille de onderneming toe aan de portefeuille wanneer de identiteit van de opvolger niet openbaar is aangekondigd en de verkooporganisatie niet bekend is wanneer de opvolger publiek bekend is. Deze portfolio genereert maandelijks 4-factor alfa van 11%. Bovendien ervaren bedrijven tijdens de regering van CEO's van lamme eendjes ook positieve abnormale rendementen in verband met aankondigingen van inkomsten. Deze positieve marktreactie zal waarschijnlijk worden aangedreven door twee mechanismen: beleggers reageren onvoldoende op het ontbreken van nieuwe CEO's en identificeren de positieve effecten van de toernooicompetitie onder CEO-kandidaten.

De taak in hoofdstuk 3 probeert een onderscheid te maken tussen de twee krachten die ertoe zullen leiden dat nieuwe CEO's hogere prikkelprestaties beter ontvangen. De twee krachten hebben een direct stimulerend effect dat hogere prikkelbeloningen bestuurders motiveren harder te werken en bedrijven beter presteren, en selectie-effect dat beter getalenteerde CEO's gepaard gaan met bedrijven hogere prikkelbeloningen bieden en leiden tot betere bedrijfsprestaties. Dit hoofdstuk maakt gebruik van een één-op-één model voor tweezijdige matching om het selectie-effect te controleren en het stimulerende effect te identificeren. Deze methode maakt gebruik van het feit dat agents die beslissingen matchen niet alleen afhankelijk zijn van hun eigen kenmerken, maar ook van andere kenmerken van agenten in de markt, en dat deze andere kenmerken van agenten waarschijnlijk niet van invloed zijn op de prestaties van overeenkomende paren. De exogene variatie op de kenmerken van agents in verschillende markten helpt om het incentive- en selectie-effect van CEO incentive-beloning te ontwarren. Het stimulerend effect is goed voor 83% van de totale impact en

het selectie-effect vertegenwoordigt 17% van de totale impact. Het selectie-effect wordt belangrijker in bedrijfstakken waar talentmobiliteiten hoger zijn en in recentere jaren.

Hoofdstuk 4 gebruikt een vergelijkbare aanpak in hoofdstuk 3 om inzicht te krijgen in de impact van de reputatie van beursvennootschappen op de nauwkeurigheid van de voorspellingen van financiële analisten. Enerzijds worden beursvennootschappen met een hoge reputatie altijd geassocieerd met betere onderzoeksondersteuning, betere mogelijkheden om met het managementteam te communiceren en deze bronnen kunnen analisten helpen voorspellen wat beter is (invloedseffect). Aan de andere kant trekken beter gereputeerde beursvennootschappen analisten aan die beter in staat zijn om voor hen te werken en daarom beter voorspellen (sorteringseffect). In dit hoofdstuk wordt een één-op-veelzijdig model voor tweezijdig matchen gebruikt om het invloedseffect en het sorteringseffect te identificeren. Het resultaat toont aan dat het stimulerend effect 73% van de totale impact uitmaakt en dat het sorteringseffect goed is voor 27% van de totale impact.

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