Tweet to the Top?

Social Media Personal Branding and Career Outcomes

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ABSTRACT

This paper studies whether social media personal branding (PB) improves a job candidate's labor market performance in the context of executive employment and compensation. We focus on executives employed by Standard & Poor's 500 constituent companies from 2010 to 2013 and evaluate their PB on social media by analyzing their Twitter accounts. To disentangle the effect of PB from that of personality traits, we exploit a (positive) shock to the effectiveness of PB caused by a series of technology upgrades by Twitter. Estimations from a two-sided matching model suggest that social media PB may benefit executive candidates in job markets. This paper contributes to the literature by initiating the study of the emerging phenomenon of social media PB and testing its effect on job market performance.

Keywords: Personal branding, social media, Twitter, two-sided matching

INTRODUCTION

Since Tom Peters coined and popularized the term *personal branding* (PB) in the now classic article "The Brand Called You" (Peters 1997), the idea has been extensively discussed and widely exploited by practitioners. On Wikipedia, PB is described as "*the ongoing process of establishing a prescribed image or impression in the mind of others about an individual, group, or organization*." The rise of social media platforms, such as Twitter, in the past decade has turned this inspiring idea into a powerful technology within the reach of almost everyone. Job seekers, in particular, could potentially benefit from PB on social media.[1] For managers, PB is probably even more important; as a recent *Forbes* article concluded, "*Personal branding is no longer an option; it's a powerful leadership enabler.*"[2] However, the same article also emphasized that PB on social media is a full-time commitment to the journey of defining oneself as a leader and should be carefully considered before starting. Similarly, a recent article in *MIT Sloan Management Review* argued that a chief executive officer (CEO) tweeting can benefit the company he or she works for in different ways but also carries an inherent risk.[3]

The heightened interest in PB from practitioners in the social media age naturally gives rise to the question of whether individuals' PB activities on social media have any effect on their career outcomes. Current academic literature, however, has been silent on this important question. To fill this gap, we study this research question in the context of the executive job market.

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[1]A recent study found that two out of five employers look at job applicants' social media profiles or activities at the recruitment stage. For details, see https://www.theguardian.com/money/work-blog/2013/dec/11/job-applications-social-media-profiles-scrutiny.
[2]http://www.forbes.com/sites/glennllopis/2013/04/08/personal-branding-is-a-leadership-requirement-not-a-self-promotion-campaign.
[3]http://sloanreview.mit.edu/article/how-ceos-can-leverage-twitter.

The theoretical foundation of PB is strongly related to the theory of product advertising, which suggests two important mechanisms for advertising to affect product demand: the awareness effect and the persuasive effect (Bagwell 2007; Chamberlin 1933). In the labor market, the “products” are job candidates, or, more precisely, the candidates’ skill and commitment. Hence, broadly speaking, PB can be conceptually viewed as the counterpart of product advertising in the labor market. Following the conceptual framework of how product advertising affects product demand through both awareness and persuasive effects, we develop our hypothesis on how PB can affect one’s career outcomes through analogous mechanisms. The awareness effect works similarly for both types of markets and can be explained by employers’ limited attention and search costs. We believe the mechanism of the persuasive effect is rooted in Goffman’s (1959) celebrated work on self-presentation and dramaturgical analysis and the ensuing sociology literature on impression management (IM). Borrowing from the conceptual framework of product advertising and drawing upon the literature in both economics and sociology, we propose the hypothesis that social media PB has a positive effect on career outcomes.

From the empirical perspective, the answer to our research question is far from straightforward, even though the benefits of PB have been touted by practitioners. Not only could the postulated benefits of PB be negligible in practice, but it can also hurt one’s job market performance if it is poorly implemented and causes dislike from potential employers (Turnley and Bolino 2001; Wayne and Ferris 1990). To empirically test the PB hypothesis, we investigate how executives’ PB activities on social media affect their compensation and job acquisition.

Several challenges arise for this empirical task. First, while compensation has been widely used to measure executive job market performance, the measurement of PB on social media is nontrivial. We use the tweets from an executive’s personal Twitter account to measure his or her PB on social media. An executive's personal Twitter account is a natural tool to project an image in the minds of others and is fully controlled by the executive. Indeed, over the years, Twitter has become a popular PB platform used by both celebrities and ordinary people.

Second, we need to disentangle the effect of PB from its correlation with a candidate's unobserved personality traits (e.g., confidence, degree of extroversion, social skills) that could also influence job market performance. To this end, we exploit an exogenous shock to PB effectiveness due to a series of technology upgrades by Twitter. Such a shock enables us to investigate the job market response to PB that is unrelated to personality traits.

When employment outcomes are also used to measure one's job market performance, an additional challenge is to take into account the mutual and exclusive nature of the hiring process. The mutual decision arises from the fact that each firm favors the most talented among a pool of candidates, and each candidate will choose to join the best company among all feasible options. Therefore, evaluating the potential impact of PB on hiring outcomes needs to consider the mutual assortative assignment of firm and candidate characteristics. The exclusivity of the hiring process is because each candidate can work for only a single company and each executive position is typically filled by one candidate. The standard discrete choice framework is inadequate for modeling executive recruiting because of the interdependence among different agents' choices (i.e., the employment records are not i.i.d. samples). For example, in a random coefficient logit model (Berry 1994; Berry et al. 1995), a candidate's choice of one firm over another can be attributed only to the candidate's preference for the former and not to the possibility that the latter position is already filled. Even if we only use compensation as a candidate's job market performance measure, the reduced-form approach based only on compensation does not allow for an estimation of fundamental (i.e., structural) parameters, such as a firm's preference for PB. Rather, it treats the matching and negotiation processes as a black box and estimates output response to input changes for this black box. Although we believe in the value of this approach in establishing causal evidence without imposing many theoretical assumptions, it also falls short of fully extracting valuable information from the data in our research context.

Given our unique research context and the aforementioned challenges, we develop a two-sided matching model to capture the mutual decisions of both sides and explicitly take into account the exclusivity using a one-to-many matching framework. We link the matching model with a compensation model through correlated error terms. By jointly estimating the models, we find evidence that PB enhances candidates' job market performance.

The rest of the paper is organized as follows. First, we review the relevant literature and develop the PB hypothesis, followed by a description of the data and variables. Then, we develop and estimate the structural model. Finally, we conclude the paper by discussing the implications and limitations of the current study.

PERSONAL BRANDING HYPOTHESIS

For traditional products, advertising can affect product demand through two important mechanisms:[4] the awareness effect, also known as the informative view, and the persuasive effect (Bagwell 2007; Chamberlin 1933). The awareness effect refers to the role of advertisements in informing consumers of a product's existence and characteristics (e.g., price, quality). The persuasive effect functions by creating desire through brand development and perception. In a labor market, the buyers are employers seeking candidates, and the

[4] The third perspective is the complementary view. For example, consumers may value "social prestige," and a firm may use advertising to complement its product with such prestige, which consumers enjoy while they use the product. This view is less relevant in our context and therefore is omitted.

products are job candidates, or, more precisely, the candidates' skill and commitment. Within this conceptual framework, PB is analogous to product advertising in traditional marketing, and, correspondingly, the awareness and persuasive effects are two natural mechanisms through which PB can positively affect career outcomes.

The awareness effect of PB could result from both increased awareness of a job candidate and revelation of the candidate's tacit qualifications. Gathering and processing information about potential candidates are both costly processes, whether the cost is financial or cognitive. The psychology literature (Kahneman 1973) has shown that humans pay disproportionately more attention to salient information as a coping mechanism to deal with our limited cognitive resources. The resulting bias, known as the *salience bias*, has been used to understand many human choice puzzles that cannot be easily explained in a rational decision-making framework. For example, Barber and Odean (2008) tested and confirmed that individual investors are more likely to buy attention-grabbing stocks because of their limited attention and the enormous number of stocks available. However, the authors found that the same is not true for stock selling, because investors tend to sell only stocks they own. Through PB, job candidates can increase public awareness of their profiles and are therefore more likely to gain attention from potential employers, which could increase their chance of acquiring new job opportunities.

On social media, the awareness effect of PB might not seem obvious because, unlike in traditional media (where the awareness effect works through the *push* mechanism), users often proactively *pull* content. However, due to limited attention and memory constraints, social media users do not often pay much attention to other users they follow, except when exposed to their content. Therefore, even though the *initial* following decision is pull based, the ensuing content consumption process is still largely push based. In this sense, PB on social media is akin to carefully targeted push-based ads where users self-select in the initial targeting process (i.e., decide whom to follow). In addition, followers often retweet, thereby increasing awareness of the original content and its author among non-followers. In the context of the traditional product market, the literature has found many links between a firm's social media activities and its financial performance (Goh et al. 2013; Hitt et al. 2014; Luo et al. 2013; Rishika et al. 2013). These works suggest that social media has tangible business implications, part of which might be attributed to the awareness effect.

PB may also help job candidates reveal certain qualification information that cannot be easily codified. For jobs involving mostly standard or routine tasks, PB is unlikely to convey additional information that employers would value overmuch. However, for jobs that require tacit knowledge, innovation, and leadership, by observing a job candidate's PB, employers could learn about traits that are not readily available in the candidate's standard profile. Indeed, in most job markets, the personal interview, which essentially enables a job candidate to conduct real-time PB, is a critical step in an employer's evaluation of the candidate, along with reviewing a résumé. In the age of information, an employer often extracts a lot of information from any cue that reveals the candidate's tacit qualifications, to assess the fit between the candidate and the job.

For social media PB, the act itself can also convey additional qualification information for some employers. Over the past decade, corporate communications have started to mirror many aspects of personal communication, such as two-way and real-time communications over the Internet. A candidate's PB on social media could signal an ability to effectively communicate with the public through social media. Therefore, some employers could value a candidate's PB on social media because they expect to benefit from the candidate's ability to manage corporate communications in the social media age.

The persuasive effect of PB is analogous to the way product advertising cultivates brand loyalty in traditional marketing. As the first advocate of the persuasive view of advertising, Robinson (1933) argued that

> The customer will be influenced by advertisement, which plays upon his mind with studied skill, and make him prefer the goods of one producer to those of another because they are brought to his notice in a more pleasing and forceful manner.

Similarly, PB could project a more positive or charming image of the candidate in the minds of potential employers. We believe the theoretical foundation of such a mechanism lies in the sociology literature of impression management, which is rooted in Goffman's (1959) seminal work[5] on self-presentation. In what Goffman calls *dramaturgical analysis*, he uses the metaphor of theatrical performance to understand the acts people put on in their daily life. According to his analysis, people "perform" when they act in the social world, which he calls the "front stage," in contrast with the "back stage," where people can relax and be closer to their "true-selves." When called upon to put on a front in a social setting in the presence of others, individuals will attempt to control or guide the impression that others have of them by changing or fixing their settings, appearances, and manners. Goffman calls such an attempt *impression management*, the goal of which is to project an "idealized image."

This idea of IM is considered a primary contribution of Goffman's theory and has been studied and applied in numerous social interaction settings. The literature defines IM as the process by which people attempt to influence the image others have of them during social interactions, either consciously or unconsciously (Schenkler 1980). IM strategies in the context of the labor market have attracted a great deal of attention from both practitioners and academic researchers in the fields of psychology and management, with a particular focus on

[5] Goffman's (1959) monograph "The Presentation of Self in Everyday Life" is listed by the International Sociological Association as the 10th most important sociological book of the 20th century.

the effectiveness of IM in the interview process. For example, Ellis et al. (2002) studied how IM depends on the question types during a structured interview. Higgins and Judge (2004) studied how two IM tactics, ingratiation and self-promotion, affect recruiter perceptions of fit. Kristof-Brown et al. (2002) investigated the effect of applicant characteristics on the use of IM tactics in interviews and the effect of IM tactics on interviewer perceptions of person–job fit and applicant–interviewer similarity. Tsai et al. (2005) examined how the effectiveness of IM tactics is moderated by the interview structure, customer–contact requirements, and interview length in real employment interviews for actual job openings.

We believe the key difference between IM and PB is that, with the latter, physical proximity in social interaction is no longer a necessary condition. Although Goffman's theory suggests that everyone does IM in daily life, in the age of traditional media, PB was mainly the realm of celebrities and business and political leaders. However, the Internet era has fundamentally changed this inequality. As Tom Peters argued, in the age of individualism, everyone has the power to be their own brand, the CEO of Me, Inc. The rise of social media technology in the past decade has further democratized the power of PB. Today, PB is within almost anyone's reach. Therefore, we believe the idea of PB essentially extends the concept of IM to the digital world and is becoming increasingly important as more social activities are conducted online.

Although Goffman's theory predates the Internet era, his insight on IM only becomes more relevant when we consider PB on social media. Unlike social interactions in the offline world, where everything happens in real time, people online have more time to carefully craft their messages to manage their presence. Hence, despite the lack of face-to-face interaction, PB through social media can be an effective way to project an individual's idealized image in the minds of others. Recent literature suggests that employers are taking notice of people's PB on social media. For example, Caers and Castelyns (2011) found that Facebook and

LinkedIn have become extra tools to recruit applicants, find additional information about them, and decide who will be invited for an interview.

Despite PB's potential to improve one's career outcomes, it is a double-edged sword, because it can be poorly implemented and might not always be well received. For example, PB sometimes backfires by creating social rejection and doubt, as Figure 1 shows. A self-promoter can appear conceited, self-aggrandizing, or narcissistic (Buffardi and Campbell 2008) and, in turn, arouse feelings of dislike (Baumeister and Ilko 1995; Gilmore and Ferris 1989; Miller et al. 1992; Tice et al. 1995).

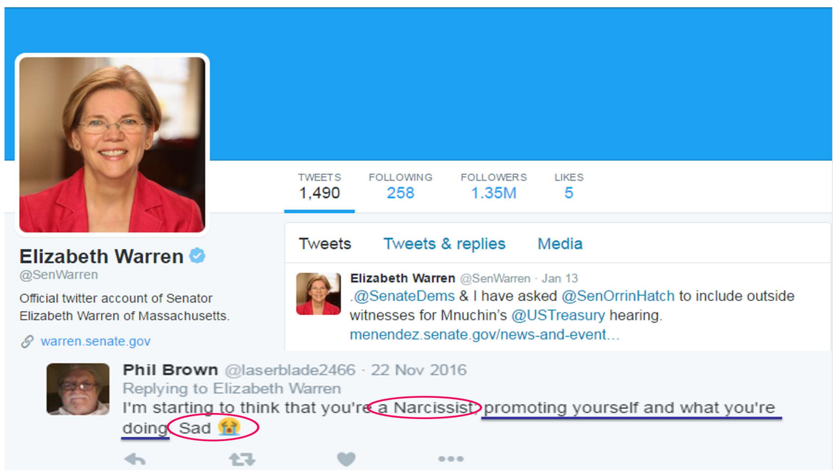

Figure 1. An example where a follower of Senator Elizabeth Warren started to question her overly promoting herself on Twitter

Given the growing popularity of PB on social media, there is clearly a need to empirically assess its real-world implications, especially in terms of an individual's career prospects. Whether PB on social media can improve a candidate's standing among other equally qualified candidates remains unclear. Hence, we propose the following hypothesis for empirical testing.

Personal Branding Hypothesis: A job candidate's social media PB positively affects the candidate's career outcomes.

DATA

In the executive labor market, a hiring firm usually makes the first move in the hiring process. This is because a breach of confidentiality can put executives at risk with their current employer. However, most executives are open to new possibilities. Executive search firms are a well-developed industry. They work for the hiring firms by analyzing their needs, generating a short list, and subtly approaching potential candidates. Once the hiring company has chosen a candidate, the company and the candidate start the negotiation process. During the final steps leading to a mutual agreement, the two parties discuss base salary, performance bonuses, profit sharing, stock options, and so on.

We obtain data on executive employment records and the compensation of S&P 500 constituent companies from 2010 to 2013 from the ExecuComp database. Firm financial data are from the Compustat and CRSP databases. We extract firm characteristics relating to board structure from the GMI Ratings database. Executive characteristics and firm–executive fit information are from BoardEx.

We focus on four executive positions: the overall leader (CEO); the chief marketing and sales-related officer (CMO); the chief technology officer (CTO) and related positions, including the chief information officer; and the chief product and innovation-related officer (CPO). Following the literature (Gao et al. 2013; Jenter and Kanaan 2015), we removed executives who were controlling holders (with at least 5% ownership), and we also excluded certain industrial sectors.[6] Our sample contains 2,014 employment records from 360 different companies. We divide the sample into independent markets and treat each employment record as an observation.

[6] More specifically, we exclude financial corporations (Standard Industrial Classification [SIC] codes 6000–6999) and regulated utilities (SIC codes 4900–4999), because the profitability and valuation data for financial firms are not comparable with firms in other sectors and the profitability and valuation of regulated utilities can be strongly influenced by government policies.

VARIABLES

We use five types of variables: job market outcomes, PB, other executive characteristics, firm characteristics, and firm–candidate interactions. The types of variables in both the compensation negotiation and sorting processes are the same. To compute executive compensation as one of the job market outcomes, we use salary, bonuses, total value of restricted stock, options granted, long-term incentive payouts, and other annual payments.

We identify important control variables by considering literature findings on job search, firm–executive assignment, and executive compensation.

Control variables for firm characteristics include firm size, performance, risk, and corporate governance. In the literature on executive compensation, one consensus is that it increases with firm size. Empirical work has tried to examine this from both the assignment and sorting perspectives (Xavier Gabaix 2008), as well as the agency cost perspective (Gayle and Miller 2009). Pan (2015) also found that a potential employer's size affects the attractiveness of an offer. We use *ln(total assets)* to measure firm size. Matveyev (2016) reveals that another career preference of director candidates is a firm's high return. Therefore, we measure firm performance using the firm's recent stock returns. In addition, theoretical models consider firm risk as another factor affecting compensation, but with conflicting predictions (Banker and Datar 1989). We measure firm risk using the standard deviation of daily stock prices over the past three years. Besides the aforementioned financial variables of a firm, we also include corporate governance variables, using the percentage of inside directors. The literature has found that board independence significantly increases the likelihood of firing CEOs for poor accounting and stock performance (Warner et al. 1988), while weak boards with lesser board independence fail to act against their CEOs when performance is dismal (Jenter and Kanaan 2015).

Control variables for executive characteristics include age, education, unrealized compensation, and recent performance. We use the selectivity[7] of undergraduate institutions to quantify educational background. Unrealized compensation captures the switching cost of job hopping, which is typically the present value of ongoing options the candidate would have had without a job change. For example, an executive voluntarily leaving a current employer will forfeit stock options or the spread if those options are not yet exercisable.[8] We use the sum of the estimated value of in-the-money unexercised unexercisable options and the aggregate value of unearned performance-based shares unvested to measure unrealized compensation. For job changes that happened between years, we consider the latter matching with a compensation amount equaling to the sum of two paychecks.[9]

The most commonly used measure of an executive's performance is the executive's previous employer's returns (Brickley et al. 1999; Coughlan and Schmidt 1985; Fee and Hadlock 2003; Jenter and Kanaan 2015; Kaplan and Reishus 1990; Warner et al. 1988). Extensive evidence (Coughlan and Schmidt 1985; Warner et al. 1988) showed that a firm's stock return affects compensation and management termination decisions. Therefore, we measure the change in annual stock returns during the executive's tenure at the previous employer as the measure of individual performance.

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[7] Following Chatterjee and Hambrick (2007) and Pérez-González (2006), we use Barron's *Profiles of American Colleges* to identify a strong educational background based on the college admission rate. Executives have a strong educational background if their undergraduate institutions are labeled "most competitive," "highly competitive plus," "highly competitive," and "very competitive plus."

[8] Joseph E. Bachelder, "Negotiating Options for New Executives," *New York Law Journal*. October 31, 2001.

[9] The executive's paycheck can contain unusual compensation changes (e.g., payments in the event of involuntary termination of employment) or unobserved switching costs/gains, which both parties to the contract will take into consideration when sorting each other. Since this lump sum adjustment for the ending (initiating) contract is associated with a switch rather than the timing of the switch, the sum of the two payments incorporates this unusual payment fluctuation as a whole. This approach yields a reasonable estimate of the amount a candidate can receive if the candidate has worked in the new company for a whole year.

We construct two firm–candidate interaction variables to measure the suitability of a potential match: industry-specific experience and social capital. A candidate's experience in the industry sector to which a firm belongs is a key determinant of the candidate's fit with the firm. For social capital, we use the proportion of board members in a company who connect with a candidate due to overlapping work experience. In the management literature on job search, the theoretical argument about visibility and the chances of obtaining job offers dates back to the work of Milgrom and Oster (1987). Defining visibility as the amount of information employers can obtain, the authors argued that low visibility results in a lower chance of being hired. Social capital is an important factor affecting one's visibility. For example, Bouwman (2011) found that the level of connections with the board of a target firm affects one's probability of being appointed. There are two explanations. First, social ties and homophily reduce information asymmetry (Granovetter 2005; Westphal et al. 2006) and search costs (McPherson et al. 2001). Second, social ties consider actions in terms of communal norms; facilitate interactions, coordination, and trust (Burt 2005); and lead to favorable interpretations of one's intentions (Uzzi 1996).

To measure executives' PB activities on social media, we use data from Twitter, a leading social media platform. Twitter's social broadcasting nature enables users to easily spread their messages to a wide audience, making it a natural platform for PB. Indeed, many celebrities rely on Twitter to broadcast their messages to millions of people in real time. We did not use Facebook because it is mostly for personal communications among friends, where PB could be less appropriate and also less effective. Friends are more likely to share strong offline connections on Facebook than on Twitter, and PB is most useful when the target audience is not overly informed (Cialdini and De Nicholas 1989). We did not use LinkedIn either, because it is a highly structured online professional network rather than a channel for broadcasting one's leadership image[10] and being very active on LinkedIn is a more proactive approach in considering career possibilities, which could be too explicit and thus not desirable for executives.

We manually collected the personal Twitter account names of the executives in our sample. We excluded firm Twitter accounts and those created by fans. For each personal account, we collected the creation date, number of followers, number of tweets, and textual content of the account's tweets.[11] Figure 2 shows a screenshot of the personal Twitter account of Doug Conant, the former CEO of Campbell Soup and founding CEO of Conant Leadership. We can see that the most recent tweets at the time we collected the data were about his current company, with the business name as the wallpaper on his account.

Figure 2. An Example of a Twitter Account (Doug Conant)

We use three different measures of PB, denoted by PB1, PB2, and PB3, respectively. PB1 is a dummy variable indicating whether a candidate conducts PB on Twitter. PB2 takes into account the intensity of PB. For this measure, we consider tweeting intensity (yearly number of posts) and PB relevance. We measure PB relevance using the similarity between

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[10] LinkedIn started offering people the flexibility of posting unstructured content in 2015, after our sample period.

[11] We retrieved the content in 2015 and were only able to extract the most recent 3,200 tweets for each account. We thus could not retrieve all of the posts of candidates with more than 3,200 tweets during the sample period. Therefore, as a proxy for yearly posts, we use the average number of tweets between snapshots of Twitter accounts from the Internet Archive (https://archive.org). For example, suppose there are two snapshots of an executive's Twitter account 70 days apart; we then use interpolation to fit the data for the remainder of the year.

tweet content and the description of one's firm and job, that is, $PB\ \text{relevance} = \frac{f_{Firm\&JobDesp} \cdot f_{Tweets}}{||f_{Firm\&JobDesp}|| \cdot ||f_{Tweets}||}$, where $f_{Firm\&JobDesp}$ and f_{Tweets} are the term frequency vectors of the firm and job description and post content, respectively.[12] The last PB measure, PB3, further incorporates the candidate's Twitter audience size, which is motivated by the concept of reach (or the number of impressions) in traditional product advertising. Thus, PB3 is operationalized as

$$PB3 = \begin{cases} 0 & \text{no work} - \text{related tweets} \\ quantile\ (\#tweets \times \#followers \times PB\ relevance) & \text{otherwise} \end{cases}$$

We use within-position year quantiles to obtain relative measures of PB, because different positions can have different levels of PB competition. For example, the effectiveness of a CMO candidate's PB is ultimately determined by the competition among the CMO candidates. More importantly, the quantile transformation also imposes a natural upper bound on the PB effect, which is a desirable feature, because PB should have a diminishing effect as its level increases.

Table 1 presents a summary of variable definitions and data sources. We report descriptive statistics of the key variables and their correlations in Tables 2 and 3, respectively.

[12] An alternative measure is based on topic models. Specifically, we use a latent Dirichlet allocation model with 30 topics and treat each candidate's firm and job description and post content as documents and estimate the topic proportion vectors $t_{Firm\&JobDesp}$ and t_{Tweets}, respectively. We then calculate PB as $corr(t_{Firm\&JobDesp}, t_{Tweets})$. The results are consistent with the measure using term frequency. We report the results using term frequency for better intuition and simplicity.

Table 1: Variable Definitions and Data Sources

	Variable Definition	Source
Compensation	(Million USD)	ExecuComp
Executive Characteristics		
Age	Age in 2014	ExecuComp
Edu	Strong educational background (undergraduate institutions labeled "most competitive," "highly competitive plus," "highly competitive," and "very competitive plus")	BoardEx, Barron's *Profiles of American Colleges*
$Unearn_{t-1}$	The sum of the estimated value of in-the-money unexercised unexercisable options and the aggregate value of unearned performance-based shares unvested	ExecuComp
$Perf_{t-1}$	The change in annual stock returns during the executive's tenure at the previous employer	Compustat
PB_{t-1}	The quantile of a product, including the number of tweets, their job relevance, and the number of followers	Twitter API

Firm Characteristics		
Firm Size$_{t-1}$	The total assets	Compustat
Return$_{t-1}$	The average stock return	CRSP
Indep%$_{t-1}$	The percentage of inside directors	GMI Ratings
Firm Risk$_{t-1,t-3}$	The standard deviation of daily stock prices over the most recent three years	CRSP
Firm–Executive Interactions		
Social Capital$_{t-1}$	Overlap (working in the same organization) with the members of a firm's board in the past	BoardEx
Experience$_{t-1}$	Number of years of work experience in the industry sector	BoardEx

Table 2. Summary Statistics of Executive, Firm, and Interactive Attributes

Variable	Mean	Std Dev	N	
Outcome Variable				
$Comp_t$ (Thousand USD)	7999.2025	5865.7040	2014	
Executive Characteristics				
Age	57.5278	6.0487	2012	
Edu	0.1738	0.3790	2014	
$Unearn_{t-1}$	9915.3829	14571.5526	2014	
$Perf_{t-1}$	0.1401	0.6720	2014	
PB3$_{t-1}$	7581.1937	212434.3893	2014	

Firm–Executive Interactive Characteristics				
Social Capital$_{t-1}$	0.9008	0.1155	2014	
Experience$_{t-1}$	18.0050	9.2624	2014	
Firm Characteristics				
$Asset_{t-1}$	9.3230	1.2485	2014	
Ret_{t-1}	0.2512	0.4058	2014	
Indep%$_{t-1}$	0.1352	0.0660	2014	
Firm Risk$_{t-1,t-3}$	11.6827	33.9025	2014	
PB Components				
#Followers	5942.0569	34012.6362	101	
#Yearly Tweets	185.5654	449.3745	101	
PB Relevance	0.0650	0.0560	101	
Job Relevance Adjusted Tweets	9.3840	17.0994	101	
PB Among Positions				
	CEO	CMO	CTO	CPO
Mean	10046.9358	1293.8726	2903.8891	2799.4205
Std	254577.0307	14515.2501	23637.9646	21890.4054
Yearly PB Components and Job Market Outcomes				
	2010	2011	2012	2013
$Comp_t$ (Thousand USD)	7009.5282	8027.6898	8302.6044	8563.7607
PB1	0.0186	0.0346	0.0610	0.0810
PB2	0.0316	0.2053	0.6217	0.9416
PB3	9.6986	254.2838	14013.4222	14344.9432
#Followers	222.9692	799.0488	8730.2540	6954.2754
#Tweets	18.1009	116.3352	177.5758	250.8048

Note: For firm–executive specific social capital, we report the mean and standard deviation of the percentages that a candidate has ever overlapped with a firm's board members in their career paths. All summary statistics are based on raw data.

Table 3. Correlation Matrices of the Executive and Firm Characteristics

Executive Characteristics					
Variables	$\boldsymbol{Unearn_{t-1}}$	$Perf_{t-1}$	PB_{t-1}	Age	Edu
$Unearn_{t-1}$	1	0.0639	-0.0139	0.0049	0.0690
$Perf_{t-1}$	0.0639	1	-0.0133	-0.0114	0.0246
PB_{t-1}	-0.0139	-0.0133	1	-0.0009	0.0687
Age	0.0049	-0.0114	-0.0009	1	-0.1179
Edu	0.0690	0.0246	0.0687	-0.1179	1
Firm Characteristics					
Variable	$ln(Asset_{t-1})$	$\boldsymbol{Ret_{t-1}}$	Indep%$_{t-1}$	Firm Risk$_{t-1,t-3}$	
$ln(Asset_{t-1})$	1	-0.2147	-0.3380	0.0267	
Ret_{t-1}	-0.2147	1	0.0881	0.0200	
Indep%$_{t-1}$	-0.3380	0.0881	1	0.0333	
Firm Risk$_{t-1,t-3}$	0.0267	0.0200	0.0333	1	

Note: This table presents the correlations of executive and company characteristics using raw data, before any transformations.

IDENTIFICATION

The main confounding factor that impedes the identification of the PB effect is unobserved personality traits, such as extraversion. It is possible that certain personality traits can influence both a candidate's job market performance and PB on social media, thereby leading to an over- or underestimation of the true PB effect. To tackle this identification problem, we exploit a series of exogenous Twitter upgrades that significantly increased the usability of the platform and thus improved the effectiveness of PB on Twitter.

On December 8, 2011, Twitter's Jack Dorsey and Dick Costolo held their *Come See What We're Building* press conference to unveil some of its major technology overhauls. The biggest changes were a redesign and brand new apps focusing on simplicity, discovery, and usability. A design editor stated[13],

> Twitter's redesign turns their website into a true app experience, with smart curves, effortless photo and video viewing, sharp icons, and generous white space. It's not intrusive, or difficult to navigate like a Facebook redesign. It's all really a fresh breath of air.

The four new elements released at the press conference were *Home*, which delivers the user timeline up to 500% faster than before, with a cleaner interface; *Connect*, which shows users all their tweets that have been retweeted and mentions of them by others; *Discover*, which helps users find relevant content through hashtags; and *Me*, which shows users everything going on within their streams and what the people they follow are up to. Twitter on both the web and on mobile apps was redesigned to include these updates.

In July 2012, Twitter started rolling out another upgrade that significantly improved its official apps for iOS and Android. Two of the main features were expanded tweets and push notification. The expanded tweets feature allows users to easily view content with links to texts, images, and videos without the need to click on those links. The real-time push notification feature allows Twitter users to receive alerts whenever their selected followees tweet or retweet them, without the need to filter through their Twitter timelines. The push notification feature significantly increased the clickthrough rate of Twitter content; for example, the marketing software company Kahuna experienced an increase of 40% in its clickthrough rate because of push notification technology. Both features greatly enhanced user experience and improved content delivery efficiency.

In summary, Twitter's technology upgrades from December 2011 through July 2012 significantly improved its usefulness as a platform for PB. This exogenous shock provides a

[13] https://thenextweb.com/twitter/2011/12/08/the-new-twitter-is-all-about-simplicity-discovery-and-usability/

source of identification, because the technology upgrade shock affected different candidates differently. Those who did not use Twitter for PB were not affected; however, for those did rely on it, the more heavily they were using it, the greater the incremental changes in PB effectiveness they should have experienced. Therefore, by comparing the associations of PB and job market performance before and after the shock, we can obtain some causal evidence regarding the PB effect. This identification strategy is especially useful in ruling out an alternative explanation of personality traits, because a potential shift in personality traits, if any, should be unrelated to the shock. We believe this is a reasonable assumption, because people's personality traits and management skills do not change abruptly. Hence, during the four-year period in our study, these potentially confounding factors are likely constant or close to constant.

Based on this identification assumption, we include in our model the upgrade dummy variable ($1_{upgrade}$) and its interaction with the PB variable, where the upgrade dummy takes the value of one only for 2013, because enhancement of the PB effect should manifest itself mostly throughout 2012, when job market outcomes for 2013 were determined. The coefficient of the interaction term can thus provide us with evidence[14] of the PB effect.

STRUCTURAL MODEL ESTIMATION

To use both compensation and employment outcomes as career outcome measures, we develop and estimate a structural model where employment outcomes and compensation are jointly determined. The structural estimation allows us to decompose the PB effect through two mechanisms: sorting and compensation negotiation. The model has two parts.

[14] Due to the statistical power issue, we obtain the causal evidence by comparing the effect of conducting PB in 2012 with the average effects of conducting PB in the years from 2009 to 2011. This is a relatively long span, and we acknowledge this as a limitation of the paper.

The first part models the compensation for any potential firm–candidate pair. Although it resembles the reduced-form model, this part is different because it models not just *realized* pairs but also *counterfactual* ones. The second part is a two-sided matching model, where the overall hiring outcome is determined in equilibrium, by comparing the latent utilities of market participants from all possible matches. The equilibrium concept used in the model is pairwise stability. More specifically, a matching is stable when no two agents prefer to deviate from the assignment and form a new (blocking) pair. Consequently, both the compensation and the matching depend on the characteristics of all the players on the market. We jointly estimate the two parts of the model.

Before presenting the structural model, we briefly review the background of two-sided matching models. Matching theory models the equilibrium of the assignment of two groups. Using the payoffs or utilities of all possible assignments, it produces a stable matching set in which no agents prefer to deviate (Hatfield and Milgrom 2005; Kelso and Crawford 1982; Roth and Sotomayor 1992). The structural estimation of matching games provides powerful tools to address endogenous assignments when analyzing the determinants of economic outcomes (Park 2008; Sørensen 2007). Earlier empirical works on two-sided matching model utility at the pair level and assume a fixed sharing rule of pair-specific utilities between both sides prior to match formation (Park 2008; Sørensen 2007). This approach is restrictive in our research setting, because it does not allow firms to adjust the proportion of total matching utility as a transfer to lure an attractive candidate. In the executive labor market, companies carefully design incentive plans to customize the proportion they would like to pay executives. Therefore, we relax this assumption by modeling the utilities of both sides rather than the total utility for each potential match.

More recently, researchers have developed with-transfer estimators (Akkus 2015; Pan 2015) to incorporate information from observed transfer data and further enhance the performance of the empirical matching model. These models assume only pecuniary utilities for one side of the market and could be oversimplifying candidates' multidimensional utilities. Additionally, that estimation approach does not exploit variations in firm characteristics, since these cancel out when a company compares different candidates. Our model contributes to this stream of research by modeling multidimensional utilities for both sides and drawing inferences from the variations of the attributes on both sides and from the transfer data observed. Moreover, our approach differs from existing methods, since we explicitly model the determinants of compensation and allow for bargaining failure instead of treating it as data.

Model

The two sides of the market are companies and executive candidates, both consisting of a finite number of players. Each candidate can work for one company, and each company can usually recruit one candidate for a given position (in some cases, multiple candidates are possible). Agents compete with each other to match with their most desirable partners.

We define a market based on position and year. The implicit assumption is that the set of players on both sides of each market is exogenously determined, so that the players in the different markets cannot be sorted across markets. This assumption is appropriate for two reasons. First, executive positions are highly specialized; firms that are looking to fill the position of CMO will not be interested in a CTO candidate. Second, we assume candidates always prefer to be matched, since having a gap year without a C-suite role is undesirable. Based on the above assumption, each market contains the firms and executives for a certain position in a year, yielding 16 markets: four positions in each of four years. We describe below the mathematical structure of the model. For ease of notation, we drop the subscript (year and position) for the different markets.

Let the set of companies be F and the set of candidates be E. The set of potential employment relations is therefore $E \times F$. A matching $\mu \subset E \times F$ is a collection of employment records. We denote firm f's employee set by $\mu(f)$ and executive e's employer by $\mu(e)$. There are three equivalent ways of stating a match between firm f and executive e:

$$(e, f) \in \mu \Leftrightarrow e \in \mu(f) \Leftrightarrow f = \mu(e). \tag{1}$$

Following the literature, we impose two assumptions on the preferences of firms and executives (Pan 2015; Sørensen 2007). First, we assume each agent has a complete, transitive, and strict preference over potential partners. Second, we assume the utility of each firm across executives is additively separable. This assumption implies that hiring one candidate will not affect the utility of employing another. There is no coalition of executives in the same position. This assumption suits our research question, since executives in the same position usually have specific focuses, such as geographic segments or business functions. Therefore, they are relatively independent. The assumption then satisfies the gross substitutes condition, following Kelso and Crawford (1982).

As Roth and Sotomayor (1992) proved, a match in our model is group stable if and only if it is pairwise stable. A deviation can arise for a matched firm–executive pair when at least one agent wants to abandon her current partner and successfully finds a new one that prefers her at the same time. In another case, an unmatched pair can block the assignment if they both would be better off by being matched together.

To characterize the equilibrium, let $U^F_{e,f}$ denote firm f's utility of hiring candidate e, and let $U^E_{e,f}$ denote candidate e's utility of joining firm f. We also define two feasible deviation sets for a matched firm–executive pair where subtraction denotes set difference:

$$
\begin{aligned}
D(f) &= \left\{e \in E - \mu(f):\ U^E_{e,f} > U^E_{e,\mu(e)}\right\}, \\
D(e) &= \{f \in F - \mu(e):\ U^F_{e,f} > \min_{e' \in \mu(f)} U^F_{e',f}\}.
\end{aligned}
\tag{2}
$$

Intuitively, $D(f)$ is the set of all executives who are not currently working for firm f (i.e., $e \in E - \mu(f)$) but would prefer *f* to their current employers (i.e., $U^E_{e,f} > U^E_{e,\mu(e)}$). Similarly, $D(e)$ is the set of all possible firms to which executive *e* can switch. In other words, a firm in $D(e)$ evaluates *e* as a more attractive employee than its worst incumbent.

The equilibrium, which always exists for this matching model, is optimal and strategy proof for the firm (i.e., reporting their true preference is a dominant strategy for firms) (Hatfield and Milgrom 2005). The following equilibrium characterization imposes bounds on the latent utilities so that there is no blocking pair. The proof is given in Online Appendix B.

Proposition. A matching μ is stable *if and only if* the following inequality holds:

$$
\begin{cases}
\forall(e,f) \in \mu \Leftrightarrow U^F_{e,f} > \max_{e' \in D(f)} U^F_{e',f} \text{ and } U^E_{e,f} > \max_{f' \in D(e)} U^E_{e,f'} \\
\forall(e,f) \notin \mu, \quad e \in D(f) \Leftrightarrow U^F_{e,f} < \min_{e' \in \mu(f)} U^F_{e',f} \\
\forall(e,f) \notin \mu, \quad f \in D(e) \Leftrightarrow U^E_{e,f} < U^E_{e,\mu(e)}
\end{cases}
$$

This proposition enables us to make a structural inference, given the observed equilibrium of matching assignments. For convenience, we define the following quantities, which will be used later to more concisely express the last two conditions in the proposition:

$$
\overline{U^F_{e,f}} = \begin{cases} \min_{e' \in \mu(f)} U^F_{e',f} & if \quad e \in D(f) \\ \infty & ot \quad erwise \end{cases}, \qquad \overline{U^E_{e,f}} = \begin{cases} U^E_{e,\mu(e)} & if \quad f \in D(e) \\ \infty & ot \quad erwise \end{cases}.
$$

Functional Forms

We model the compensation negotiated between firm *f* and executive candidate *e* with the following function of the observed characteristics of both sides and their interactions:

$$r_{e,f,t} = \alpha_0 + X'_{f,t-1} \cdot \alpha_1 + X'_{e,t-1} \cdot \alpha_2 + PB_{e,t-1} \cdot \alpha_3 + 1_{upgrade} \cdot \alpha_4 + 1_{upgrade} \cdot PB_{e,t-1} \cdot \alpha_5 + A'_{e,f,t-1} \cdot \alpha_6 + c_e + \varepsilon_{e,f,t}$$

$$\equiv W'_{e,f,t-1}\alpha \quad + c_e + \varepsilon_{e,f,t}, \tag{3}$$

where $r_{e,f,t}$ is the observed compensation whenever $e \in \mu(f)$but is otherwise counterfactual and hence latent. The term $\varepsilon_{e,f,t} \sim N(0, \sigma_\varepsilon^2)$ captures unobserved factors in the data. Recent firm and executive characteristics prior to the recruiting decision are denoted by $X_{f,t-1}$and $X_{e,t-1}$, respectively, and $W_{e,f,t}$ denotes all covariates except for the candidate fixed effect c_e, $c_e \sim N(Z'_e\mu_c, \sigma_c^2)$. All time-invariant executive demographic variables (Z_e) are used to construct the prior distributions of the executive fixed effects. We generate the prior mean of candidate fixed effects using this information, since it could be related to unobserved candidate characteristics and not be incorporated elsewhere.

For the sorting process, we model the utility of both sides, $U^F_{e,f,t}$ and $U^E_{e,f,t}$, as latent variables. For an executive candidate $e \in E$, her utility $U^E_{e,f,t}$ of working for firm $f \in F$ depends on the observed firm characteristics $X_{f,t-1}$, the interaction terms $A_{e,f,t-1}$, and the compensation firm *f* promises:

$$U^E_{e,f,t} = r_{e,f,t} \cdot \beta_0 + X'_{f,t-1} \cdot \beta_1 + A'_{e,f,t-1} \cdot \beta_2 + \eta_{e,f,t}$$

$$\equiv r_{e,f,t} \cdot \beta_0 + (X'_{f,t-1}, A'_{e,f,t-1})\beta + \eta_{e,f,t}, \tag{4}$$

where $\eta_{e,f,t} \sim N(0, \sigma_\eta^2)$. The error term $\eta_{e,f,t}$ contains unobserved factors when candidate *e* evaluates firm *f*. Similarly, firm *f*'s willingness to recruit candidate *e* depends on *e*'s characteristics, the interaction terms $A_{e,f,t-1}$, and the compensation:

$$U^F_{e,f,t} = -r_{e,f,t} \cdot \gamma_0 + PB_{e,t-1} \cdot \gamma_{1,} + 1_{upgrade} \cdot \gamma_2 + 1_{upgrade} \cdot PB_{e,t-1} \cdot \gamma_{3,} + X'_{e,t-1} \cdot \gamma_4 + A'_{e,f,t-1} \cdot \gamma_5 + a_e + \delta_{e,f,t}$$

$$\equiv -r_{e,f,t} \cdot \gamma_0 + (\tilde{X}'_{e,t-1}, A'_{e,f,t-1})\gamma + a_e + \delta_{e,f,t}, \tag{5}$$

where $\delta_{e,f,t} \sim N(0, \sigma_\delta^2)$ and $\tilde{X}'_{e,t-1}$ represents all observed executive time-varying variables. The error term $\delta_{e,f,t}$ contains unobserved factors of company *i*'s utility when hiring candidate *e*. We also include candidate fixed effects a_e, $a_e \sim N(Z'_e \mu_a, \sigma_a^2)$. All time-invariant executive characteristics are used to estimate candidate fixed effects.

The proposition imposes the upper/lower bound of the utilities according to whether $(e, f) \in \mu$. Therefore, the assignments depend on all the candidates and all the firms.

Because unobserved factors of executive and firm utilities affect both the rankings in the sorting and compensation negotiation, we model the covariance between error terms as

$$\varepsilon_{e,f,t} = k \cdot \eta_{e,f,t} + \lambda \cdot \delta_{e,f,t} + v_{e,f,t}. \tag{6}$$

We set σ_δ^2 and σ_η^2 to be one to fix the scales, and we exclude constant terms to fix the levels. Thus, the joint distribution of $\eta_{e,f,t}$, $\delta_{e,f,t}$, and $v_{e,f,t}$ is

$$\begin{pmatrix} \varepsilon_{e,f,t} \\ \eta_{e,f,t} \\ \delta_{e,f,t} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \quad \begin{pmatrix} \kappa^2 + \lambda^2 + \sigma_v^2 & \kappa & \lambda \\ \kappa & 1 & 0 \\ \lambda & 0 & 1 \end{pmatrix}\right). \tag{7}$$

Based on the data generation process, the augmented posterior density for a given market is

$$P(\theta|\text{Data}) \propto \prod_{f\in F, e\in E} \Big\{\varphi\big(\frac{1}{\sigma_v}(r_{e,f} - W'_{e,f}\alpha - c_e - \kappa(U^E_{e,f} - r_{e,f} \cdot \beta_0 - (X'_f, A'_{e,f})\beta) - \lambda(U^F_{e,f} + r_{e,f} \cdot \gamma_0 - (\tilde{X}'_e, A'_{e,f})\gamma - a_e)\big)\big) \cdot \varphi(U^E_{e,f} - r_{e,f} \cdot \beta_0 - (X'_f, A'_{e,f})\beta) \cdot \varphi(U^F_{e,f} + r_{e,f} \cdot \gamma_0 - (\tilde{X}'_e, A'_{e,f})\gamma - a_e) \cdot \Big[1_{\{(e,f)\notin\mu\}} 1_{\{U^F_{e,f} < \overline{U^F_{e,f}}\}} 1_{\{U^E_{e,f} < \overline{U^E_{e,f}}\}} + 1_{\{(e,f)\in\mu\}} 1_{\{U^F_{e,f} > \max_{e' \in D(f)} U^F_{e',f}\}} \cdot 1_{\{U^E_{e,f} > \max_{f' \in D(e)} U^E_{e,f'}\}}\Big]\Big\} \cdot \text{Prior}(\theta), \tag{8}$$

where $\theta = (\alpha,\ \beta_0, \beta,\ \gamma_0, \gamma, a_e, c_e, \mu_a, \sigma_a, \mu_c, \sigma_c, \kappa, \lambda, \sigma_v)$ is the vector of all parameters to be estimated, μ is the observed firm–executive matched pairs in the market, $\mathbf{1}(.)$ is the indicator function, and $\text{Prior}(\theta)$ represents the joint prior for all parameters θ. For ease of notation, we drop the year subscript for the different markets.

We estimate the structural model using a Bayesian approach. In the estimation procedure, the prior distributions have means of zero and variances of 100. The parameters of the inverse gamma distributions are set to be 0.01, which are uninformative priors. For most of the estimated parameters, the prior variances are more than 100 times greater than the posterior variances. This result suggests that the posterior distributions learn information from the data well. For the detailed estimation procedure, see Online Appendix C.

ESTIMATION RESULTS

We run two MCMC chains with different initials and use them for posterior inference and convergence diagnostics. The results are based on 30,000 draws from which the initial 15,000 are burn-in. Visual inspection of the trace plots shows that the Gibbs sampling converges to the posterior distribution. To avoid serial correlation between samples, we thin the sample by keeping only one of every five iterations.

Table 4 reports the estimated coefficients of the compensation equation, Equation (3). The coefficient of the interaction between PB and the Twitter upgrade shock is positive and significant. This result reveals a rise in compensation stemming from the exogenous enhancement of PB. The market awards candidates with more related experience and covers unrealized amounts with higher compensation, as the positive and statistically significant estimations suggest. Firm size is positively associated with compensation, which is consistent with the literature (Gayle et al. 2015; Gayle and Miller 2009; Terviö 2008; Xavier Gabaix

2008). We also find that firms with stronger governance tend to come up with higher pay, after controlling for matching. Lastly, firms with better returns and higher risk can either afford or attract candidates with extra pay.

Table 4. Estimates of the Compensation Equations

Firm Characteristics		Executive Characteristics	
$ln(Asset_{t-1})$	0.7115*** (0.2240)	$Unearn_{t-1}$	0.3892*** (0.0377)
Ret_{t-1}	0.0301** (0.0147)	$Perf_{t-1}$	-0.0058 (0.0236)
$Indep\ \%_{t-1}$	-0.5772*** (0.0618)	PB_{t-1}	0.0204 (0.0500)
$Firm\ Risk_{t-1,\ t-3}$	0.1990*** (0.0165)	$PB_{t-1} \cdot 1_{upgrade}$	0.4037*** (0.0104)
Firm–Executive Characteristics			
$Experience_{t-1}$	0.2875*** (0.0195)		
$Social\ Capital_{t-1}$	0.5135 (0.4344)		
$\boldsymbol{c_e}$	Yes		
$1_{upgrade}$ $(Fixed\ Effect)$	Yes		

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The estimated standard deviations of the posterior distribution for each coefficient are in parentheses.

Table 5 reports the estimation results for the firm utility equation. The estimates of the matching process provide evidence of sorting on the observed variables. The values of the utilities represent agents' preferences over all potential matches, involving sorting on both observed and unobserved characteristics and compensation. The average PB effect before the shock is suggested as positive with a credible interval of 90%. The interaction between PB and the shock is significantly positive, which suggests that PB makes candidates more competitive in the job market. The estimates for performance are positive and statistically significant, revealing a preference for candidates with outstanding past performance. Finally, the coefficients of social capital and experience in the industry are positive and significant. In other words, firms are more likely to recruit candidates with connections to their board members and more experience in the specific sector. Compared with the estimated coefficient of social capital in Table 4, our structural model reveals that social capital, while it does not necessarily help increase compensation, does seem to improve a candidate's standing.

Table 5. Firm Utilities

	Coefficient	Marginal Probability Advantages
$-Comp_t$	0.0627*** (0.0102)	0.0354
$Unearn_{t-1}$	-0.0008 (0.0164)	
$Perf_{t-1}$	2.0321** (0.9708)	0.7740
PB_{t-1}	0.1119* (0.0607)	
$PB_{t-1} \cdot 1_{upgrade}$	1.1635*** (0.1655)	0.3187
Firm–Executive Variables		
$Experience_{t-1}$	0.1764*** (0.0471)	0.0992
$Social\ Capital_{t-1}$	0.7067*** (0.0072)	0.3827
$\boldsymbol{a_e}$	Yes	

Note: *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. The estimated standard deviations of the posterior distribution for each coefficient are in parentheses.

In the matching process, all estimates are only identified up to scale and normalized by the variance of the error terms. Therefore, we cannot interpret the estimated coefficients directly. To better interpret the economic magnitudes of the coefficients in the utility equations, we define and calculate the marginal probability advantage of every covariate with a coefficient that is significant with a credible interval of 95% or above. This measure captures the marginal advantage of excelling for an otherwise identical competitor in the job search. Consider a firm facing a choice between two candidates with identical observed characteristics; the choice is entirely determined by comparing the candidates' unobserved capabilities. Therefore, the probability of one being preferred over the other is 50%.

Suppose one candidate's PB in 2012 is in the 75th percentile, whereas the other's is in the 25th percentile. The probability that a firm prefers the candidate with more (less) PB is 65.9% (34.1%). We define the marginal probability advantage of PB by the difference 65.9% - 34.1% = 31.8%. Formally, the marginal probability advantages for observed executive characteristics are calculated as

$$Pr(U_{e,f}^{F} > U_{e^{'},f}^{F}) - Pr(U_{e^{'},f}^{F} > U_{e,f}^{F}) = 2 \times \Phi\left(\frac{X_{e.f}'\cdot\tilde{\gamma} - X_{e^{'},f}'\cdot\tilde{\gamma}}{\sqrt{2}}\right) - 1 \ , \tag{9}$$

where $X_{e,f}^{'}$ denotes all the covariates in determining firm utilities, except for individual fixed effects. Their coefficients are represented by $\tilde{\gamma} = \begin{pmatrix} \gamma_0 \\ \gamma \end{pmatrix}$. We estimate the expectation of Equation (9) using posterior draws. Note that, for continuous variables without natural ranges, the marginal probability advantage measures the advantage a candidate can obtain with a change of one standard deviation. For social capital, it measures the change in utility between the best and worst possible cases. For the impact of the technology upgrade–induced PB enhancement, we report the difference in advantages between candidates whose PB activity levels are in the first and third quartiles. We also similarly define and calculate the marginal probability advantage for observed firm characteristics. The marginal probability advantages reported in Table 5 show that firms have clear preferences in terms of performance, industry-related experience, and social capital. A more PB-active candidate is more likely to be hired than a less active one, since the former has a marginal probability advantage of 31.87%.

Table 6 reports the estimation results for the utility equation of executives. Candidates prefer firms that offer generous packages, since the estimate of compensation is significant at the 1% level. The coefficient for firm size is positive and statistically significant, suggesting that large firms are more attractive to candidates for executive positions. Finally, we find the strongest sorting over firm characteristics to be in terms of industry experience and social capital, with marginal probability advantages of 65.4% and 60.7%, respectively. This result suggests that executives strongly prefer staying in the industry in which they have experience and working with familiar board members.

Table 6. Executive Utilities

	Coefficient	Marginal Probability Advantages
$Comp_t$	0.5273*** (0.0084)	0.2908
$ln(Asset_{t-1})$	0.7996*** (0.1256)	0.4267
Ret_{t-1}	0.1448 (0.3776)	
$Indep\ \%_{t-1}$	-0.5747* (0.3124)	
$Firm\ Risk_{t-1,\ t-3}$	0.5994 (1.3489)	
Firm–Executive		
$Experience_{t-1}$	1.3751*** (0.3622)	0.6536
$Social\ Capital_{t-1}$	1.2082*** (0.0606)	0.6067

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The estimated standard deviations of the posterior distribution for each coefficient are in parentheses.

The sorting on unobserved variables results in correlations between the error terms in the utility and compensation equations. When an unobserved candidate characteristic leads to a positive shock to firm utility, the candidate becomes more attractive, resulting in a positive shock in the compensation equation. This is confirmed by a statistically significant and positive estimate of 0.8022 for λ, with standard deviation of 0.0272.

As a robustness check against potential serial correlation of error terms over the years, we conduct two tests using subsets of data consisting of observations three years apart (2010 and 2013) and two years apart (2011 and 2013), respectively. We also merged these tests with another robustness check by applying a logarithmic transformation to the number of followers; the results are qualitatively the same with or without the transformation. The estimation results reported in Table 7, which are largely consistent with our main results, suggest that the serial correlation of error terms is unlikely to be a major concern.

Table 7. Estimations of Variables of Interest

	Three Years Apart	Two Years Apart
	Compensation	
$PB_{t-1} \cdot 1_{upgrade}$	0.3159*** (0.1033)	0.5040*** (0.0575)
	Firm Utilities	
$PB_{t-1} \cdot 1_{upgrade}$	1.3083** (0.6146)	0.9482*** (0.1039)
$\frac{dP}{PB_{t-1} \cdot 1_{upgrade}}$	0.3563	0.2625

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The estimated standard deviations of the posterior distribution for each coefficient are in parentheses.

CONCLUSIONS

Although the phenomenon of PB is now prevalent on social media, there has been little empirical evidence of its labor market implications. We fill this literature gap by studying the impact of social media PB on job market performance, using executive employment data from 2010 to 2013. By exploiting an exogenous series of technology upgrades by Twitter, we detect evidence that PB can improve an executive candidate's job market performance.

This paper contributes to the IS literature in three important aspects. First, to the best of our knowledge, this is the first academic paper to study the effect of PB on job market performance. Given the new and growing phenomenon of PB in social media, this paper may open up a new stream of exciting, high-impact research in both information systems and related fields. Second, by drawing the analogy between product advertising and PB and adapting Goffman's theory of self-presentation and IM to the digital era, we propose a theoretical foundation of social media personal branding. Third, through a shock-based identification strategy, we present the first empirical evidence of the PB effect.

Practitioners can also benefit from our research findings. Our empirical results suggest that job seekers can generally consider social media PB to improve their job market performance. For those aspiring to become executives or executives seeking to further boost their careers, the firm preferences revealed by the structural model could be particularly relevant. For social media platforms that help unleash the power of PB, this research also reveals a potential new business model. To a certain degree, LinkedIn's business model is already an example. However, we believe a more successful business model for a PB platform should go beyond that highly structured format and incorporate a social broadcasting feature.

Interestingly, at the time of writing, Twitter is essentially providing its PB platform for free, even to those enjoying the verified account status, which is a premium version that certifies the authenticity of the account owner. However, those who produce high-quality[15] content for free on Twitter are also likely to benefit the most from Twitter's PB functionality. In this sense, the free–free equilibrium could reflect a win–win situation for Twitter and its PB-active users. Whether and how to incorporate a PB-based business model into its overall business strategy is an interesting question.

This paper has several limitations. First, we examine only the labor market for executives. Investigating the effect of social media personal branding in other types of labor markets can further our understanding of the scope of the PB effect. Second, the current study does not consider the heterogeneous effects of PB. Research on how PB affects different types of candidates differently would be both theoretically interesting and practically

[15] By high-quality content, we mean content that attracts user attention.

relevant. Finally, despite our efforts to offer causal evidence of the PB effect, our identification strategy has its own limitations. Future studies using more fine-grained data and better identification strategies can further tease out potential confounding factors.

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Tweet to the Top?

Social Media Personal Branding and Career Outcomes

Online Appendices

APPENDIX A: REDUCED-FORM ANALYSES

While the structural approach fits the two-sided market nature of our research context well, its credibility relies on the theoretical assumptions researchers impose on agent behavior, especially the matching process associated with the executive market. On the other hand, the reduced-form approach, despite its inability to reveal the "fundamental mechanism" (i.e., microeconomic model), can offer causal evidence with fewer theoretical assumptions. Hence, we further investigate the PB effect on observed compensation through reduced-form analyses. This robustness check is in line with a special case of our structural model—when sorting and compensation bargaining are independent. We use two identification strategies for the reduced-form analyses.

First, similar to the identification strategy of the structural model, we exploit the exogenous Twitter upgrade shock and estimate the following difference-in-difference (DID) specification.

$$r_{e,f,t} = \alpha_0 + X'_{f,t-1} \cdot \alpha_1 + X'_{e,t-1} \cdot \alpha_2 + PB_{e,t-1} \cdot \alpha_3 + 1_{upgrade} \cdot PB_{e,t-1} \cdot \alpha_4 + A'_{e,f,t-1} \cdot \alpha_5 + c_e + d_t + \varepsilon_{e,f,t} \quad . \tag{A1}$$

In the above specification, $X_{f,t-1}$ and $X_{e,t-1}$ denote firm and executive characteristics respectively; $r_{e,f,t}$ denotes observed compensation; $A_{e,f,t-1}$ represents firm-executive pair-specific variables; and $1_{upgrade}$ is a dummy variable for the year 2013. We also introduced placebo treatments of the other years in one of our tests to verify our shock validity.

Our main goal is to test the PB effect by investigating whether the incremental impact of PB brought by platform upgrades increases compensation.

To alleviate the omitted variable bias concern, we adjust our samples so that PB-active candidates are similar to inactive ones with regard to observed characteristics. In particular, we use a propensity score matching method of four nearest neighbors with a caliper of 0.2. We use all executive-related variables in Equation (A1) to estimate the propensity. Table A1 reveals the performance of the propensity score matching method for control variables. T-tests show that the treatment and control groups are statistically indistinguishable for control variables after matching. The propensity score matching obtained a balance matching sample for adopting PB.

Table A1. Balance Check After the Propensity Score Matching

2010				
	Mean		T-test	
	Treated	Control	t	p > |t|
$ln(\boldsymbol{Asset_{t-1}})$	-0.8011	-0.8438	0.11	0.914
$\boldsymbol{Ret_{t-1}}$	1.1223	1.3303	-0.30	0.766
$\boldsymbol{Indep\ \%_{t-1}}$	0.1438	-0.0256	0.42	0.684
$Firm\ \ Risk_{t-1,\,t-3}$	-0.0917	-0.0414	-0.43	0.670
$\boldsymbol{Unearn_{t-1}}$	-0.1268	-0.1313	0.01	0.990
$\boldsymbol{Perf_{t-1}}$	1.3730	1.4825	-0.23	0.823
$Experience_{t-1}$	-0.6363	-0.8223	0.58	0.573
$Social\ Capital_{t-1}$	0.9738	0.9803	-0.28	0.782
2011				
	Mean		T-test	
	Treated	Control	t	p > |t|
$ln(\boldsymbol{Asset_{t-1}})$	-0.5786	-0.5421	-0.10	0.918
$\boldsymbol{Ret_{t-1}}$	0.7145	0.5147	0.39	0.697
$\boldsymbol{Indep\ \%_{t-1}}$	0.1562	0.2027	-0.13	0.895
$Firm\ \ Risk_{t-1,\,t-3}$	-0.0334	-0.0564	0.25	0.803
$\boldsymbol{Unearn_{t-1}}$	-0.2148	-0.2781	0.32	0.752
$\boldsymbol{Perf_{t-1}}$	-0.6169	-0.5133	-0.25	0.803
$Experience_{t-1}$	-0.1962	-0.0646	-0.43	0.668
$Social\ Capital_{t-1}$	0.9467	0.9474	-0.02	0.981

2012				
	Mean		T-test	
	Treated	Control	t	p > |t|
$ln(\boldsymbol{Asset_{t-1}})$	-0.1852	-0.2682	0.34	0.733
$\boldsymbol{Ret_{t-1}}$	-0.7455	-0.8328	0.60	0.553
$\boldsymbol{Indep\ \%_{t-1}}$	-0.0013	-0.1481	0.74	0.464
$Firm\ Risk_{t-1,\ t-3}$	0.1070	0.1193	-0.07	0.944
$\boldsymbol{Unearn_{t-1}}$	-0.0689	0.1007	-0.63	0.533
$\boldsymbol{Perf_{t-1}}$	-0.8562	-0.8605	0.02	0.986
$Experience_{t-1}$	-0.0354	-0.0745	0.16	0.875
$Social\ Capital_{t-1}$	0.8684	0.8721	-0.08	0.937
2013				
	Mean		T-test	
	Treated	Control	t	p > |t|
$ln(\boldsymbol{Asset_{t-1}})$	0.1565	0.2197	-0.26	0.799
$\boldsymbol{Ret_{t-1}}$	-0.1556	-0.1342	-0.16	0.873
$\boldsymbol{Indep\ \%_{t-1}}$	-0.0349	-0.0659	0.16	0.871
$Firm\ Risk_{t-1,\ t-3}$	0.1663	0.2022	-0.07	0.945
$\boldsymbol{Unearn_{t-1}}$	0.2612	0.4104	-0.46	0.649
$\boldsymbol{Perf_{t-1}}$	0.1533	0.1435	0.10	0.924
$Experience_{t-1}$	0.0120	0.2418	-1.04	0.302
$Social\ Capital_{t-1}$	0.9194	0.9214	-0.09	0.928

For simplicity and ease of interpretation with the propensity score matching method, we use PB1 to measure PB. We test the impact of PB on compensation using two specifications, the results of which are reported in Table A2. In both specifications, the estimated coefficients of the interaction term$PB_{t-1} \cdot 1_{upgrade}$ are positive and significant, which offers causal evidence supporting the PB hypothesis. Comparing the results of both specifications, it seems unlikely that the PB effect is driven by potential fluctuation in year trends[1]. The second specification also provides a formal test of the parallel trend assumption and a direct comparison of the overall PB effect over the years.

Table A2. Shock-based Analysis

	(1)	(2)
$ln(Asset_{t-1})$	-0.3868 (0.3108)	-0.3865 (0.3275)
Ret_{t-1}	-0.0362 (0.0855)	-0.0331 (0.0867)
$\boldsymbol{Indep\ \%_{t-1}}$	0.0917 (0.0837)	0.1004 (0.0936)
$Firm\ Risk_{t-1,\,t-3}$	0.3454** (0.1574)	0.3511** (0.1632)
$Unearn_{t-1}$	0.4835*** (0.1612)	0.4732*** (0.1671)
$Perf_{t-1}$	0.1038 (0.0631)	0.1017 (0.0658)
PB_{t-1}	0.0019 (0.1078)	
$PB_{t-1} \cdot 1_{year=2011}$		0.2374 (0.2175)
$PB_{t-1} \cdot 1_{year=2012}$		0.1953 (0.1973)
$PB_{t-1} \cdot 1_{upgrade}$	0.2732*** (0.0803)	0.4617** (0.2286)
$Experience_{t-1}$	0.6484 (0.6401)	0.6885 (0.7044)
$Social\ Capital_{t-1}$	-0.0975 (0.2849)	-0.0959 (0.3066)

[1] Due to the statistical power issue, we obtain the causal evidence by comparing the effect of conducting PB in 2012 with the average effects of conducting PB in the years from 2009 to 2011. This is a relatively long span, and we acknowledge this as a limitation.

Executive Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	364	364
R^2	0.2487	0.2539

Note: Robust standard errors are reported in parentheses in this session. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

We conducted several falsification tests for other executive characteristics in Table A3 by interacting the shock with other executive attributes. We find that their interactions with the technology upgrade dummy are statistically insignificant.

Table A3. Falsification Tests: Technology Upgrades and Other Executive Traits

	(1)	(2)	(3)	(4)
$ln(Asset_{t-1})$	0.1778*** (0.0547)	0.1785*** (0.0562)	0.1782*** (0.0688)	0.1776** (0.0689)
Ret_{t-1}	-0.0023 (0.0350)	-0.0025 (0.0352)	0.0022 (0.0637)	-0.0066 (0.0607)
$Indep\%_{t-1}$	-0.0518** (0.0250)	-0.0513** (0.0244)	-0.0521 (0.0472)	-0.0511 (0.0461)
$Firm\ \ Risk_{t-1,\mathrm{t}-3}$	-0.0358*** (0.0115)	-0.0361*** (0.0109)	-0.0321* (0.0172)	-0.0347** (0.0143)
PB_{t-1}	0.0292 (0.0546)	0.0298 (0.0547)	0.0270 (0.0933)	0.0284 (0.0922)
$Unearn_{t-1}$	0.4348*** (0.1172)	0.4424*** (0.0383)	0.4429*** (0.0713)	0.4480*** (0.0705)
$Perf_{t-1}$	0.0192 (0.0631)	0.0170 (0.0743)	0.0098 (0.0674)	0.0210 (0.0637)
Age	-0.0350 (0.0248)	-0.0343 (0.0253)	-0.0039 (0.0475)	-0.0344 (0.0584)
Edu	0.0337	0.0319	0.0368	-0.0448

	(0.0883)	(0.0801)	(0.1142)	(0.1208)
$Unearn_{t-1} \cdot 1_{upgrade}$	0.0108 (0.1225)			
$Perf_{t-1} \cdot 1_{upgrade}$		0.0114 (0.1065)		
$Age \cdot 1_{upgrade}$			-0.0689 (0.0920)	
$Edu \cdot 1_{upgrade}$				0.1917 (0.1781)
$Experience_{t-1}$	0.0366 (0.0839)	0.0368 (0.0823)	0.0368 (0.0444)	0.0318 (0.0456)
$Social\ \ Capital_{t-1}$	-0.7184* (0.3972)	-0.7243* (0.4009)	-0.7261** (0.3392)	-0.6903** (0.3413)
Market Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	363	363	363	363
R^2	0.4873	0.4873	0.4888	0.4897

Note: Robust standard errors are reported in parentheses in this session. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Our second identification strategy for the reduced-form analyses is to resort to instrumental variables. We use political advertising expenditures in the US Senate and House races in the same state, at the same time, as an IV for PB. Each advertisement promotes a specific political candidate. Political advertising is a suitable instrument for executive PB activities for several reasons. First, exposure to political advertisement increases one's awareness of the PB strategy. Indeed, political advertisements by candidates running for offices are probably the most visible examples of PB in public life.[2] Witnessing PB by

[2]Politicians' PB strategies are often analyzed and commented on the Internet. For example, following the 2016 presidential election, numerous blog articles on Donald Trump's PB strategy were posted and widely shared. See the following articles:
https://medium.com/your-brand/donald-trumps-campaign-personal-branding-case-study-cb111a978018

political candidates may stimulate executive job candidates to consider and explore PB for their own careers. On the other hand, there is no obvious reason why political advertisements could directly affect[3] the career outcomes of executive job candidates.

The advertisement expenditure data come from the Wesleyan Media Project for the 2010 and 2012 Senate and House races (Fowler 2015). The dataset tracks political advertisements aired on all television and cable networks in the US. It identifies the candidate promoted in each piece and estimates the cost. We construct the IV using the cost of political advertisements attributed to races that happened in the state with the firm's headquarters. The cost of political advertisements is set to 0 when there are no political races.

Table A4 reports three sets of IV estimations for all measures of PB. First-stage estimations in all sets of results confirm that political advertising expenditure in the same state positively correlates with executive PB activities. The coefficients of political advertisements are significant at the 5% level using all PB measures. From the second-stage estimations, we see that PB is associated with higher compensation, with statistical significance at the 1% level. Therefore, the IV estimations also offer causal evidence supporting the PB hypothesis.

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https://www.inc.com/marla-tabaka/4-personal-branding-lessons-you-need-to-learn-from-donald-trump-and-hillary-clin.html
https://www.inc.com/nicolas-cole/how-donald-trumps-personal-brand-won-him-the-presidency.html
https://www.huffingtonpost.com/entry/what-we-can-learn-about-personal-branding-from-donald_us_5873bb02e4b0eb9e49bfbd95

[3] Even if political election outcomes can affect executive career outcomes through certain new policies, there typically exists a significant delay between a policy proposal and its responses from firms. Hence, we believe political advertisement should be a valid IV for an executive candidate's PB activities.

Table A4. Instrumental Variable Analyses

	PB1		PB2		PB3	
	First-Stage	Second-Stage	First-Stage	Second-Stage	First-Stage	Second-Stage
Political Ads	0.0149** (0.0030)		0.0116** (0.0026)		0.0099** (0.0030)	
$ln(Asset_{t-1})$	-0.0093 (0.0073)	0.3186*** (0.0432)	-0.0021 (0.0055)	0.2903** (0.0506)	-0.0005 (0.0060)	0.2820** (0.0571)
$\boldsymbol{Ret_{t-1}}$	-0.0013 (0.0192)	0.0748 (0.0893)	-0.0006 (0.0063)	0.0722 (0.0436)	0.0001 (0.0064)	0.0691 (0.0491)
$\boldsymbol{Indep\ \%_{t-1}}$	0.0007 (0.0060)	0.0469 (0.0323)	0.0022 (0.0040)	0.0382 (0.0282)	0.0035 (0.0044)	0.0273 (0.0319)
$Firm\ Risk_{t-1,\,t-3}$	0.0078 (0.0041)	-0.0806** (0.0175)	0.0046 (0.0029)	-0.0723** (0.0171)	0.0044 (0.0027)	-0.0751** (0.0186)
PB_{t-1}		4.2886*** (0.5663)		5.4817*** (0.4372)		6.4515*** (0.5286)
$\boldsymbol{Unearn_{t-1}}$	0.0147 (0.0080)	0.3653** (0.0696)	0.0041 (0.0044)	0.4060*** (0.0371)	0.0028 (0.0043)	0.4105*** (0.0392)
$\boldsymbol{Perf_{t-1}}$	-0.0065 (0.0196)	-0.0230 (0.0752)	-0.0015 (0.0068)	-0.0428 (0.0354)	-0.0019 (0.0069)	-0.0386 (0.0427)
Age	-0.0339* (0.0108)	0.1793* (0.0613)	-0.0203* (0.0068)	0.1450* (0.0475)	-0.0202* (0.0071)	0.1642* (0.0592)
Edu	0.0400 (0.0247)	-0.0912 (0.1239)	0.0296 (0.0176)	-0.0815 (0.1131)	0.0292 (0.0174)	-0.1076 (0.1317)
$Experience_{t-1}$	0.0046 (0.0064)	0.0268 (0.0446)	0.0030 (0.0053)	0.0300 (0.0453)	0.0028 (0.0054)	0.0283 (0.0504)
$Social\ Capital_{t-1}$	0.0463 (0.0866)	-0.7665 (0.4492)	0.0029 (0.0497)	-0.5841 (0.3458)	-0.0013 (0.0480)	-0.5594 (0.3721)
Market Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
First-Stage	52.841		240.170		219.496	

F Score						
Observations	2,012		2,012		2,012	

Note: This table presents IV estimation results using three different PB measures. For brevity, estimated constants are not reported. *,**,and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

APPENDIX B: PROOF OF THE PROPOSITION

For brevity, we dropped the subscript for market and time in the notation.

Case 1: For any matched pair (*e,f*), any agent's deviation will break the equilibrium. That means the equilibrium fails if at least one of the following inequalities holds: (1) if firm *f* could employ a better executive e' from all the candidates who prefer to have joined firm *f*: $U^F_{e,f} < \max_{e' \in D(f)} U^F_{e',f}$ or (2) if executive *e* prefers to work for a more desirable and feasible firm f': $U^E_{e,f} < \max_{f' \in D(e)} U^E_{e,f'}$.

We define $\underline{U^F_{e,f}}$ and $\underline{U^E_{e,f}}$ as follows:

$$\underline{U^E_{e,f}} = \max_{f' \in D(e)} U^E_{e,f'}\ ,\ \underline{U^F_{e,f}} = \max_{e' \in D(f)} U^F_{e',f}\ . \tag{B1}$$

Therefore, neither executive *e* nor firm *f* will block the pair *if and only if* $U^E_{e,f} > \underline{U^E_{e,f}}$ and $U^F_{e,f} > \underline{U^F_{e,f}}$.

Case 2: For any unmatched pair (*e,f*), the deviation from the equilibrium is when firm *f* is willing to hire executive *e* instead of its current worst employee in the same position *and e* is better off by joining *f*. This can be translated to $e \in D(f)$ and $f \in D(e)$. Therefore, (*e,f*) is not a blocking pair *if and only if* $U^E_{e,f} < U^E_{e,\mu(e)}$ or $U^F_{e,f} < \min_{e' \in \mu(f)} \left(U^F_{e',f}\right)$. Recall that in the main paper, we define the $\overline{U^E_{e,f}}$ and $\overline{U^F_{e,f}}$ as follows:

$$\overline{U^F_{e,f}} = \begin{cases} \min_{e' \in \mu(f)} U^F_{e',f} & if \quad e \in D(f) \\ \infty \quad ot \quad erwise \end{cases}, \qquad \overline{U^E_{e,f}} = \begin{cases} U^E_{e,\mu(e)} & if \quad f \in D(e) \\ \infty \quad ot \quad erwise \end{cases} \tag{B2}$$

So, equivalently, (*e,f*) is not a blocking pair *if and only if* $U^E_{e,f} < \overline{U^E_{e,f}}$ and $U^F_{e,f} < \overline{U^F_{e,f}}$.

APPENDIX C: ESTIMATION PROCEDURE

There are three major estimation techniques for structural empirical matching games: inequality methods (maximum score estimator), simulated methods of moments (SMM), and full likelihood methods. The maximum score estimator (e.g., Fox 2017; Pan 2015) is derived from the necessary condition of pairwise stability but cannot guarantee the preference it discovers can generate the observed stable matching in expectation. In addition, sorting on non-interactive variables, such as executive performance or firm characteristics, cannot be identified because both the actual and counterfactual pairs evaluate them in the same way[4]. SMM (e.g., Matveyev 2016) is an optimization approach. It requires solving the model a certain number of times for each iteration of an outer optimization. Depending on the optimization techniques, there is often no guarantee that it can lead to a global minimum, making the results less reliable numerically. Our structural inference uses the exact likelihood with data augmentation, which is similar to Park (2008) and Sørensen (2007). We treat the unobserved payoff of each match as auxiliary parameters and integrate out using a blocking structure in MCMC estimation.

The computational challenge arises from the sorting and interaction between agents on both sides of the markets. When an executive signs a contract with a firm, it will prohibit or greatly reduce the probability that other candidates can take the same position, due to the quota of each company. As a result, we cannot analyze each candidate's decision independently. The likelihood function cannot factor into a product of the individual choice likelihoods, and we have to integrate over all error terms simultaneously. The maximum likelihood function will suffer from the curse of dimensionality and is impossible for estimation. However, Bayesian estimation using Gibbs sampling and data augmentation

[4] Or at least the characteristics of one side are canceled out when the transfer data is used, such as in Pan (2015).

transforms this high dimensional integration problem into a simulation problem and makes the estimation feasible. The procedure we use is an extension of Gelfand and Smith (1990), Geweke (1999), and Geweke et al. (2003), with data augmentation as in Albert and Chib (1993).

Let $\theta = (\alpha, \beta_0, \beta, \gamma_0, \gamma, a_e, c_e, \mu_a, \sigma_a, \mu_c, \sigma_c, \kappa, \lambda, \sigma_v)$ and, given the functional forms below,

$$
\begin{array}{rcl}
U^E_{e,f} & = & r_{e,f} \cdot \beta_0 + \left(X'_f, A'_{e,f}\right)\beta + \eta_{e,f}, \\
U^F_{e,f} & = & -r_{e,f} \cdot \gamma_0 + \left(\widetilde{X}'_e, A'_{e,f}\right)\gamma + a_e + \delta_{e,f}, \\
r_{e,f} & = & W'_{e,f}\alpha + c_e + \varepsilon_{e,f}, \\
\varepsilon_{e,f} & = & k \cdot \eta_{e,f} + \lambda \cdot \delta_{e,f} + v_{e,f}, \\
\eta_{e,f} & \sim & N(0,1), \\
\delta_{e,f} & \sim & N(0,1), \\
v_{e,f} & \sim & N(0, \sigma_v^2), \\
a_e & \sim & N(Z'_e\mu_a, \sigma_a^2), \\
c_e & \sim & N(Z'_e\mu_c, \sigma_c^2).
\end{array}
\tag{C1}
$$

we can write the posterior distribution as proportional to the following:

$$
\begin{aligned}
P(\theta|\text{Data}) \quad \propto \quad & \prod_{f\in F, e\in E} \Big\{\varphi\big(\frac{1}{\sigma_v}(r_{e,f} - W'_{e,f}\alpha - c_e - \\
& \kappa\left(U^E_{e,f} - r_{e,f} \cdot \beta_0 - \left(X'_f, A'_{e,f}\right)\beta\right) - \lambda\left(U^F_{e,f} + r_{e,f} \cdot \gamma_0 - \left(\tilde{X}'_e, A'_{e,f}\right)\gamma - a_e\right)\big)\big) \\
& \cdot \varphi\left(U^E_{e,f} - r_{e,f} \cdot \beta_0 - \left(X'_f, A'_{e,f}\right)\beta\right) \cdot \varphi\left(U^F_{e,f} + r_{e,f} \cdot \gamma_0 - \left(\tilde{X}'_e, A'_{e,f}\right)\gamma - a_e\right) \\
& \cdot \left[1_{\{(e,f)\notin\mu\}} 1_{\{U^F_{e,f} < \overline{U^F_{e,f}}\}} 1_{\{U^E_{e,f} < \overline{U^E_{e,f}}\}} + 1_{\{(e,f)\in\mu\}} 1_{\{U^F_{e,f} > \underline{U^F_{e,f}}\}} 1_{\{U^E_{e,f} > \underline{U^E_{e,f}}\}}\right]\Big\} \\
& \cdot \text{Prior}(\theta).
\end{aligned}
\tag{C2}
$$

E (F, respectively) includes executives (firms) for potentially multiple times, depending on their presences in the job markets in our data. For instance, for an executive candidate who was on the job market in 2010 and 2012, set E would contain two elements corresponding to the two job searches. Based on the posterior distribution in Equation (C2), we derive the Gibbs sampling for the proposed model specified in Equation (C1). Note that for the specification of the firm utilities, the technology upgrade dummy cancels out when firms compare candidates from the same year. Therefore, we do not need to sample this particular parameter.

Conditional Posterior Distributions of Compensation and Latent Utilities:

Update $\boldsymbol{r_{e,f}}$ for $(\boldsymbol{e},\boldsymbol{f}) \notin \boldsymbol{\mu}$:

$$P(r_{e,f}|-) \quad \propto \quad \varphi(r_{e,f}\left(\frac{1+\kappa\beta_0-\lambda\gamma_0}{\sigma_v}\right)+\Delta^1_{r_{e,f}})\cdot\varphi(\beta_0 r_{e,f}+\Delta^2_{r_{e,f}})\cdot\varphi(\gamma_0 r_{e,f}+\Delta^3_{r_{e,f}}), \text{ (C3)}$$

where

$$\begin{aligned}
\Delta^1_{r_{e,f}} &= \frac{1}{\sigma_v}(-c_e - W'_{e,f}\alpha - \kappa(U^E_{e,f}-(X'_f, A'_{e,f})\beta) \\
&\qquad -\lambda(U^F_{e,f}-(\tilde{X}'_{e,}, A'_{e,f})\gamma - a_e)) \\
\Delta^2_{r_{e,f}} &= -U^E_{e,f}+(X'_f, A'_{e,f})\beta \\
\Delta^3_{r_{e,f}} &= U^F_{e,f}-\left(\tilde{X}'_{e,}, A'_{e,f}\right)\gamma - a_e.
\end{aligned}$$

And so

$$r_{e,f}|-\sim N(\mu^{post}_{r_{e,f}}, (\sigma^{post}_{r_{e,f}})^2),$$

where

$$\begin{aligned}
\left(\sigma^{post}_{r_{e,f}}\right)^2 &= [\left(\frac{1+\kappa\beta_0-\lambda\gamma_0}{\sigma_v}\right)^2+\beta_0^2+\gamma_0^2]^{-1} \\
\mu^{post}_{r_{e,f}} &= -\left(\sigma^{post}_{r_{e,f}}\right)^2\left[\left(\frac{1+\kappa\beta_0-\lambda\gamma_0}{\sigma_v}\right)\Delta^1_{r_{e,f}}+\beta_0\Delta^2_{r_{e,f}}+\gamma_0\Delta^3_{r_{e,f}}\right].
\end{aligned}$$

Update $\boldsymbol{U^E_{e,f}}$:

The correlation between the error terms provides additional information about the latent utilities. From the full likelihood, we get the conditional distribution:

$$
\begin{aligned}
P(U^E_{e,f}|-) \quad \propto \quad & \varphi(\frac{1}{\sigma_v}(r_{e,f} - c_e - W'_{e,f}\alpha - \kappa(U^E_{e,f} - \beta_0 r_{e,f} - (X'_f, A'_{e,f})\beta) - \\
& \lambda(U^F_{e,f} - a_e + \gamma_0 r_{e,f} - (\tilde{X}'_{e,}, A'_{e,f})\gamma))) \\
& \cdot \varphi(U^E_{e,f} - \beta_0 r_{e,f} - (X'_f, A'_{e,f})\beta) \cdot (1_{\{(e,f)\notin\mu\}} 1_{\{U^E_{e,f} < \overline{U^E_{e,f}}\}} + 1_{\{(e,f)\in\mu\}} 1_{\{U^E_{e,f} > \underline{U^E_{e,f}}\}}) \\
\propto \quad & \varphi(\frac{-\kappa}{\sigma_v} U^E_{e,f} + \Delta^1_{U^E_{e,f}}) \cdot \varphi(U^E_{e,f} + \Delta^2_{U^E_{e,f}}) \cdot (1_{\{(e,f)\notin\mu\}} 1_{\{U^E_{e,f} < \overline{U^E_{e,f}}\}} + 1_{\{(e,f)\in\mu\}} 1_{\{U^E_{e,f} > \underline{U^E_{e,f}}\}}),
\end{aligned}
\tag{C4}
$$

with

$$
\begin{aligned}
\Delta^1_{U^E_{e,f}} \quad = \quad & \frac{1}{\sigma_v}(r_{e,f} - c_e - W'_{e,f}\alpha - \kappa(-\beta_0 r_{e,f} - (X'_f, A'_{e,f})\beta) - \\
& \lambda(U^F_{e,f} - a_e + \gamma_0 r_{e,f} - (\tilde{X}'_{e,}, A'_{e,f})\gamma)) \\
\Delta^2_{U^E_{e,f}} \quad = \quad & -\beta_0 r_{e,f} - (X'_f, A'_{e,f})\beta.
\end{aligned}
$$

This leads to

$$
U^E_{e,f}| - \sim N(\mu^{post}_{U^E_{e,f}}, (\sigma^{post}_{U^E_{e,f}})^2) \cdot (1_{\{(e,f)\notin\mu\}} 1_{\{U^E_{e,f} < \overline{U^E_{e,f}}\}} + 1_{\{(e,f)\in\mu\}} 1_{\{U^E_{e,f} > \underline{U^E_{e,f}}\}}),
$$

where

$$
\begin{aligned}
(\sigma^{post}_{U^E_{e,f}})^2 \quad & = \quad [1 + \frac{\kappa^2}{\sigma_v^2}]^{-1} \\
\mu^{post}_{U^E_{e,f}} \quad & = \quad -(\sigma^{post}_{U^E_{e,f}})^2 [\frac{-\kappa}{\sigma_v} \Delta^1_{U^E_{e,f}} + \Delta^2_{U^E_{e,f}}].
\end{aligned}
$$

These are the normal distributions that are truncated from above (below). The expressions for $\overline{U^E_{e,f}}$ and $\underline{U^E_{e,f}}$ are given in equations (B2) and (B1) in this appendix.

Update $U^F_{e,f}$:

We observe that

$$
\begin{aligned}
P(U^F_{e,f}|-) \quad \propto \quad & \varphi(\frac{1}{\sigma_v}(r_{e,f} - c_e - W'_{e,f}\alpha - \kappa(U^E_{e,f} - \beta_0 r_{e,f} - (X'_f, A'_{e,f})\beta) - \\
& \lambda(U^F_{e,f} - a_e + \gamma_0 r_{e,f} - (\tilde{X}'_{e,}, A'_{e,f})\gamma))) \\
& \cdot \varphi(U^F_{e,f} - a_e + \gamma_0 r_{e,f} - (\tilde{X}'_{e,}, A'_{e,f})\gamma) \cdot [1_{\{(e,f)\notin\mu\}} 1_{\{U^F_{e,f} < \overline{U^F_{e,f}}\}} + 1_{\{(e,f)\in\mu\}} 1_{\{U^F_{e,f} > \underline{U^F_{e,f}}\}}] \\
\propto \quad & \varphi(\frac{-\lambda}{\sigma_v} U^F_{e,f} + \Delta^1_{U^F_{e,f}}) \cdot \varphi(U^F_{e,f} + \Delta^2_{U^F_{e,f}}) \cdot [1_{\{(e,f)\notin\mu\}} 1_{\{U^F_{e,f} < \overline{U^F_{e,f}}\}} + 1_{\{(e,f)\in\mu\}} 1_{\{U^F_{e,f} > \underline{U^F_{e,f}}\}}],
\end{aligned}
\tag{C5}
$$

setting

$$\begin{aligned}\Delta^1_{U^F_{e,f}} &= \tfrac{1}{\sigma_v}(r_{e,f} - c_e - W^{'}_{e,f}\alpha - \kappa(U^E_{e,f} - \beta_0 r_{e,f} - (X^{'}_f, A^{'}_{e,f})\beta) - \\ &\quad \lambda(\gamma_0 r_{e,f} - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma - a_e)) \\ \Delta^2_{U^F_{e,f}} &= -a_e + \gamma_0 r_{e,f} - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma.\end{aligned}$$

Thus,

$$U^F_{e,f}| - \sim N(\mu^{post}_{U^F_{e,f}}, (\sigma^{post}_{U^F_{e,f}})^2) \cdot [1_{\{(e,f)\notin\mu\}} 1_{\{U^F_{e,f} < \overline{U^F_{e,f}}\}} + 1_{\{(e,f)\in\mu\}} 1_{\{U^F_{e,f} > \underline{U^F_{e,f}}\}}],$$

where

$$\begin{aligned}(\sigma^{post}_{U^F_{e,f}})^2 &= [1 + \tfrac{\lambda^2}{\sigma_v^2}]^{-1} \\ \mu^{post}_{U^F_{e,f}} &= -(\sigma^{post}_{U^F_{e,f}})^2 [\tfrac{-\lambda}{\sigma_v}\Delta^1_{U^F_{e,f}} + \Delta^2_{U^F_{e,f}}].\end{aligned}$$

Update α:

$$\begin{aligned}P(\alpha|-) &\propto \prod_{e\in E, f\in F} [\varphi(\tfrac{1}{\sigma_v}(r_{e,f} - c_e - W^{'}_{e,f}\alpha - \kappa(U^E_{e,f} - \beta_0 r_{e,f} - (X^{'}_f, A^{'}_{e,f})\beta) - \\ &\quad \lambda(U^F_{e,f} - a_e + \gamma_0 r_{e,f} - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma)))] \\ &\quad \cdot \text{Prior}(\alpha) \\ &\propto \prod_{e\in E, f\in F} [\varphi(-\tfrac{1}{\sigma_v} W^{'}_{e,f}\alpha + \Delta_{\alpha,e,f})] \cdot \; exp\left(-\tfrac{1}{2}(\alpha - \mu_\alpha)^T \Sigma^{-1}_\alpha (\alpha - \mu_\alpha)\right),\end{aligned} \tag{C6}$$

with

$$\begin{aligned}\Delta_{\alpha,e,f} &= \tfrac{1}{\sigma_v}(r_{e,f} - c_e - \kappa(U^E_{e,f} - \beta_0 r_{e,f} - (X^{'}_f, A^{'}_{e,f})\beta) - \\ &\quad \lambda(U^F_{e,f} - a_e + \gamma_0 r_{e,f} - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma)).\end{aligned}$$

We obtain

$$\alpha|-: N(\mu^{post}_\alpha, \Sigma^{post}_\alpha),$$

where

$$\begin{aligned}\Sigma_\alpha^{post} &= [\sum_{e\in E,f\in F}\frac{1}{\sigma_v^2}W_{e,f}W_{e,f}^{'}+\Sigma_\alpha^{-1}]^{-1}\\ \mu_\alpha^{post} &= -\Sigma_\alpha^{post}[\sum_{e\in E,f\in F}\left(\frac{-1}{\sigma_v}\Delta_{\alpha,e,f}\right)W_{e,f}-\Sigma_\alpha^{-1}\mu_\alpha].\end{aligned}$$

Update $\boldsymbol{\beta_0}$:

$$\begin{aligned}P(\beta_0|-) &\propto \prod_{e\in E,f\in F}[\varphi(\frac{1}{\sigma_v}(r_{e,f}-c_e-W_{e,f}^{'}\alpha-\kappa(U_{e,f}^E-\beta_0 r_{e,f}-(X_f^{'},A_{e,f}^{'})\beta)\\ &\qquad -\lambda(U_{e,f}^F-a_e+\gamma_0 r_{e,f}-(\tilde{X}_{e,}^{'},A_{e,f}^{'})\gamma)))\\ &\qquad \cdot\varphi(U_{e,f}^E-\beta_0 r_{e,f}-(X_f^{'},A_{e,f}^{'})\beta)]\cdot\mathrm{Prior}(\beta_0)\\ &\propto \prod_{e\in E,f\in F}[\varphi(\frac{\kappa r_{e,f}}{\sigma_v}\beta_0+\Delta_{\beta_0,e,f}^1)\cdot\varphi(-r_{e,f}\beta_0+\Delta_{\beta_0,e,f}^2)]\cdot\varphi\left(\frac{\beta_0-\mu_{\beta_0}}{\sigma_{\beta_0}}\right),\end{aligned}\tag{C7}$$

where

$$\begin{aligned}\Delta_{\beta_0,e,f}^1 &= \frac{1}{\sigma_v}(r_{e,f}-c_e-W_{e,f}^{'}\alpha-\kappa(U_{e,f}^E-(X_f^{'},A_{e,f}^{'})\beta)-\\ &\qquad \lambda(U_{e,f}^F-a_e+\gamma_0 r_{e,f}-(\tilde{X}_{e,}^{'},A_{e,f}^{'})\gamma)),\\ \Delta_{\beta_0,e,f}^2 &= U_{e,f}^E-(X_f^{'},A_{e,f}^{'})\beta.\end{aligned}$$

As a result,

$$\beta_0|-\sim N(\mu_{\beta_0}^{post},(\sigma_{\beta_0}^{post})^2),$$

with parameters given by

$$\begin{aligned}(\sigma_{\beta_0}^{post})^2 &= [\sum_{e\in E,f\in F}\left(\frac{\kappa^2 r_{e,f}^2}{\sigma_v^2}+r_{e,f}^2\right)+\frac{1}{\sigma_{\beta_0}^2}]^{-1}\\ \mu_{\beta_0}^{post} &= -(\sigma_{\beta_0}^{post})^2[\sum_{e\in E,f\in F}\left(\frac{\kappa r_{e,f}}{\sigma_v}\Delta_{\beta_0,e,f}^1\right)+\sum_{e\in E,f\in F}\left(-r_{e,f}\right)\Delta_{\beta_0,e,f}^2-\frac{1}{\sigma_{\beta_0}^2}\mu_{\beta_0}].\end{aligned}$$

Update $\boldsymbol{\beta}$:

$$\begin{aligned}P(\beta|-) &\propto \prod_{e\in E,f\in F}[\varphi(\frac{1}{\sigma_v}(r_{e,f}-c_e-W_{e,f}^{'}\alpha-\kappa(U_{e,f}^E-\beta_0 r_{e,f}-(X_f^{'},A_{e,f}^{'})\beta)-\\ &\qquad \lambda(U_{e,f}^F-a_e+\gamma_0 r_{e,f}-(\tilde{X}_{e,}^{'},A_{e,f}^{'})\gamma)))\\ &\qquad \cdot\varphi(U_{e,f}^E-\beta_0 r_{e,f}-(X_f^{'},A_{e,f}^{'})\beta)]\cdot\mathrm{Prior}(\beta)\\ &\propto \prod_{e\in E,f\in F}[\varphi(\frac{\kappa(X_f^{'},A_{e,f}^{'})}{\sigma_v}\beta+\Delta_{\beta,e,f}^1)\cdot\varphi(-(X_f^{'},A_{e,f}^{'})\beta+\Delta_{\beta,e,f}^2)]\\ &\qquad \cdot\ exp\left(-\frac{1}{2}\left(\beta-\mu_\beta\right)^T\Sigma_\beta^{-1}\left(\beta-\mu_\beta\right)\right),\end{aligned}\tag{C8}$$

where

$$
\begin{aligned}
\Delta^1_{\beta,e,f} &= \frac{1}{\sigma_v}(r_{e,f} - W^{'}_{e,f}\alpha - c_e - \kappa(U^E_{e,f} - \beta_0 r_{e,f}) \\
&\quad -\lambda(U^F_{e,f} - a_e + \gamma_0 r_{e,f} - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma)) \\
\Delta^2_{\beta,e,f} &= U^E_{e,f} - \beta_0 r_{e,f},
\end{aligned}
$$

which implies

$$\beta| - \sim N(\mu^{post}_\beta, \Sigma^{post}_\beta)$$

with

$$
\begin{aligned}
\Sigma^{post}_\beta &= [\sum_{e\in E, f\in F}(\frac{\kappa^2}{\sigma^2_v}+1)(X^{'}_f, A^{'}_{e,f})^{'}(X^{'}_f, A^{'}_{e,f}) + \Sigma^{-1}_\beta]^{-1} \\
\mu^{post}_\beta &= -\Sigma^{post}_\beta[\sum_{e\in E, f\in F}\Delta^1_{\beta,e,f}\frac{\kappa(X^{'}_f, A^{'}_{e,f})^{'}}{\sigma_v} - \sum_{e\in E, f\in F}\Delta^2_{\beta,e,f}(X^{'}_f, A^{'}_{e,f})^{'} - \Sigma^{-1}_\beta\mu_\beta].
\end{aligned}
$$

Update γ_0:
We note that

$$
\begin{aligned}
P(\gamma_0|-) &\propto \prod_{e\in E, f\in F}[\varphi(\frac{1}{\sigma_v}(r_{e,f} - c_e - W^{'}_{e,f}\alpha - \kappa(U^E_{e,f} - \beta_0 r_{e,f} - (X^{'}_f, A^{'}_{e,f})\beta) \\
&\quad -\lambda(U^F_{e,f} - a_e + \gamma_0 r_{e,f} - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma))) \\
&\quad \cdot\varphi(U^F_{e,f} + \gamma_0 r_{e,f} - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma - a_e)]\cdot \text{Prior}(\gamma_0) \\
&\propto \prod_{e\in E, f\in F}[\varphi(\frac{-\lambda r_{e,f}}{\sigma_v}\gamma_0 + \Delta^1_{\gamma_0,e,f})\cdot\varphi(\gamma_0 r_{e,f} + \Delta^2_{\gamma_0,e,f})]\cdot\varphi\left(\frac{\gamma_0 - \mu_{\gamma_0}}{\sigma_{\gamma_0}}\right),
\end{aligned}
\tag{C9}
$$

setting

$$
\begin{aligned}
\Delta^1_{\gamma_0,e,f} &= \frac{1}{\sigma_v}(r_{e,f} - c_e - W^{'}_{e,f}\alpha - \kappa(U^E_{e,f} - \beta_0 r_{e,f} - (X^{'}_f, A^{'}_{e,f})\beta) - \\
&\quad \lambda(U^F_{e,f} - a_e - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma)), \\
\Delta^2_{\gamma_0,e,f} &= U^F_{e,f} - a_e - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma.
\end{aligned}
$$

This implies

$$\gamma_0| - \sim N(\mu^{post}_{\gamma_0}, (\sigma^{post}_{\gamma_0})^2),$$

with parameters given by

$$
\begin{aligned}
(\sigma_{\gamma_0}^{post})^2 &= [\sum_{e\in E,f\in F}\left(\frac{\lambda^2 r_{e,f}^2}{\sigma_v^2}+r_{e,f}^2\right)+\frac{1}{\sigma_{\gamma_0}^2}]^{-1}\\
\mu_{\gamma_0}^{post} &= -(\sigma_{\gamma_0}^{post})^2[\sum_{e\in E,f\in F}\left(\frac{-\lambda r_{e,f}}{\sigma_v}\Delta_{\gamma_0,e,f}^1\right)+\sum_{e\in E,f\in F} r_{e,f}\Delta_{\gamma_0,e,f}^2-\frac{1}{\sigma_{\gamma_0}^2}\mu_{\gamma_0}].
\end{aligned}
$$

Update γ:

We see that

$$
\begin{aligned}
P(\gamma|-) \;&\propto \prod_{e\in E,f\in F}[\varphi(\frac{1}{\sigma_v}(r_{e,f}-c_e-W_{e,f}^{'}\alpha-\kappa(U_{e,f}^E-\beta_0 r_{e,f}-(X_f^{'},A_{e,f}^{'})\beta)\\
&\quad -\lambda(U_{e,f}^F-a_e+\gamma_0 r_{e,f}-(\tilde{X}_{e,}^{'},A_{e,f}^{'})\gamma)))\\
&\quad \varphi(U_{e,f}^F-a_e+\gamma_0 r_{e,f}-(\tilde{X}_{e,}^{'},A_{e,f}^{'})\gamma)]\cdot \mathrm{Prior}(\gamma)\\
&\propto \prod_{e\in E,f\in F}[\varphi(\frac{\lambda}{\sigma_v}(\tilde{X}_{e,}^{'},A_{e,f}^{'})\gamma+\Delta_{\gamma,e,f}^1)\cdot\varphi(-(\tilde{X}_{e,}^{'},A_{e,f}^{'})\gamma+\Delta_{\gamma,e,f}^2)]\\
&\quad \cdot\, exp\left(-\frac{1}{2}(\gamma-\mu_\gamma)^T\Sigma_\gamma^{-1}(\gamma-\mu_\gamma)\right),
\end{aligned}
\tag{C10}
$$

using the notation

$$
\begin{aligned}
\Delta_{\gamma,e,f}^1 &= \frac{1}{\sigma_v}(r_{e,f}-c_e-W_{e,f}^{'}\alpha-\kappa(U_{e,f}^E-\beta_0 r_{e,f}-(X_f^{'},A_{e,f}^{'})\beta)-\\
&\quad \lambda(U_{e,f}^F-a_e+\gamma_0 r_{e,f})),\\
\Delta_{\gamma,e,f}^2 &= U_{e,f}^F-a_e+\gamma_0 r_{e,f}.
\end{aligned}
$$

Then,

$$
\gamma \;\; |-\sim N(\mu_\gamma^{post},\Sigma_\gamma^{post}),
$$

where

$$
\begin{aligned}
\Sigma_\gamma^{post} &= [\sum_{e\in E,f\in F}\left(\frac{\lambda^2}{\sigma_v^2}+1\right)(\begin{matrix}\tilde{X}_e\\ A_{e,f}\end{matrix})(\tilde{X}_{e,}^{'},A_{e,f}^{'})+\Sigma_\gamma^{-1}]^{-1}\\
\mu_\gamma^{post} &= -\Sigma_\gamma^{post}[\sum_{e\in E,f\in F}\left(\frac{\lambda}{\sigma_v}\Delta_{\gamma,e,f}^1\right)\begin{pmatrix}\tilde{X}_e\\ A_{e,f}\end{pmatrix}-\sum_{e\in E,f\in F}\Delta_{\gamma,e,f}^2\begin{pmatrix}\tilde{X}_e\\ A_{e,f}\end{pmatrix}-\Sigma_\gamma^{-1}\mu_\gamma].
\end{aligned}
$$

Update κ and λ:

The densities of these conditional distributions are normal distributions. The conditional posterior distributions are

$$\kappa \sim N(\mu_k^{post}, (\sigma_k^{post})^2), \;\; \lambda \sim N(\mu_\eta^{post}, (\sigma_\eta^{post})^2),$$

where

$$\begin{aligned}
\mu_k^{post} &= (\sigma_k^{post})^2 \cdot \sum_{e\in E, f\in F} [\frac{(U_{e,f}^E-(X_f^{'},A_{e,f}^{'})\cdot\beta-\beta_0\cdot r_{e,f})\cdot(r_{e,f}-c_e-W_{e,f}^{'}\alpha}{\sigma_v^2} \\
&\qquad \frac{-\lambda(U_{e,f}^F-a_e-(\tilde{X}_{e,}^{'},A_{e,f}^{'})\gamma+r_{e,f}\cdot\gamma_0))}{}] \\
(\sigma_k^{post})^2 &= \left[\sum_{e\in E, f\in F}\left(\frac{U_{e,f}^E-(X_f^{'},A_{e,f}^{'})\cdot\beta-\beta_0\cdot r_{e,f}}{\sigma_v}\right)^2+\frac{1}{\sigma_k^2}\right]^{-1} \\
\mu_\lambda^{post} &= (\sigma_\lambda^{post})^2 \cdot \sum_{e\in E, f\in F}\frac{(U_{e,f}^F-a_e-(\tilde{X}_{e,}^{'},A_{e,f}^{'})\gamma+\gamma_0\cdot r_{e,f})}{\sigma_v^2}\cdot \\
&\qquad (r_{e,f}-c_e-W_{e,f}^{'}\alpha-\kappa(U_{e,f}^E-(X_f^{'},A_{e,f}^{'})\cdot\beta-\beta_0 r_{e,f})) \\
(\sigma_\lambda^{post})^2 &= \left[\sum_{e\in E,\ f\in F}\left(\frac{U_{e,f}^F-a_e-(\tilde{X}_{e,}^{'},A_{e,f}^{'})\gamma+\gamma_0\cdot r_{e,f}}{\sigma_v}\right)^2+\frac{1}{\sigma_\lambda^2}\right]^{-1}.
\end{aligned} \tag{C11}$$

Update σ_v^2:

The conditional posterior distribution of σ_v^2 is $InvG(a_{\sigma_v^2}^{post}, b_{\sigma_v^2}^{post})$, which is updated using the compensation as

$$\begin{aligned}
a_{\sigma_v^2}^{post} &= a_{\sigma_v^2}+\frac{|E\times F|}{2} \\
b_{\sigma_v^2}^{post} &= b_{\sigma_v^2}+\sum_{e\in E, f\in F}(r_{e,f}-c_e-W_{e,f}'\alpha-\kappa\cdot(U_{e,f}^E-(X_f',A_{e,f}')\cdot\beta-\beta_0\cdot r_{e,f}) \\
&\qquad -\lambda(U_{e,f}^F-a_e-(\tilde{X}_{e,}',A_{e,f}')\gamma+\gamma_0\cdot r_{e,f}))^2/2 \\
|E\times F|&: \quad \textit{The total number of possible matches across markets.}
\end{aligned} \tag{C12}$$ [5]

Sampling a_e[6]:

We notice that

[5] Note: The same assignments in different years are treated as different matches.

[6] Note: We use a_e and c_e to denote the fixed effects of the different executives across different markets. The same value applies for the same executive across markets.

$$
\begin{aligned}
P(a_e|-) \quad \propto \quad & \prod_{f\in F_e} [\varphi(\frac{1}{\sigma_v}(r_{e,f} - c_e - W'_{e,f}\alpha - \kappa(U^E_{e,f} - \beta_0 r_{e,f} - (X'_f, A'_{e,f})\beta) \\
& \qquad -\lambda(U^F_{e,f} - a_e + \gamma_0 r_{e,f} - (\tilde{X}'_{e,}, A'_{e,f})\gamma))) \\
& \qquad \cdot \varphi(U^F_{e,f} + \gamma_0 r_{e,f} - a_e - (\tilde{X}'_{e,}, A'_{e,f})\gamma)] \cdot \text{Prior}(a_e) \\
\propto \quad & \prod_{f\in F_e} [\varphi(\frac{\lambda}{\sigma_v} a_e + \Delta^1_{a_e}) \cdot \varphi(-a_e + \Delta^2_{a_e})]\varphi(\frac{a_e - Z'_e\mu_a}{\sigma_a}),
\end{aligned}
\tag{C13}
$$

where $F_e = \bigcup_{t\in T} F_{t,pos(e)}$, if $e \in E_{t,pos(e)}$. $E_{t,pos(e)}$ represents the job market that executive e participated in year t, for the position, which is denoted by pos(e). Therefore, $F_{t,pos(e)}$ denotes the set of unique firms that were recruiting on that market $E_{t,pos(e)}$. By convention, for all markets that candidate e did not participate, $F_{t,pos(e)}$ is the empty set.

Thus we have

$$
\begin{aligned}
\Delta^1_{a_{e,f}} \quad &= \quad \frac{1}{\sigma_v}(r_{e,f} - c_e - W^{'}_{e,f}\alpha - \kappa(U^E_{e,f} - \beta_0 r_{e,f} - (X^{'}_f, A^{'}_{e,f})\beta) \\
& \qquad -\lambda(U^F_{e,f} + \gamma_0 r_{e,f} - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma)), \\
\Delta^2_{a_{e,f}} \quad &= \quad U^F_{e,f} + \gamma_0 r_{e,f} - (\tilde{X}^{'}_{e,}, A^{'}_{e,f})\gamma.
\end{aligned}
$$

Therefore,

$$
a_e| - \sim N\left(\mu^{post}_{a_e}, (\sigma^{post}_{a_e})^2\right),
$$

with

$$
\begin{aligned}
(\sigma^{post}_{a_e})^2 \quad &= \quad [\sum_{f\in F_e} \left(\frac{\lambda^2}{\sigma_v^2} + 1\right) + \sigma_a^{-2}]^{-1} \\
\mu^{post}_{a_e} \quad &= \quad -(\sigma^{post}_{a_e})^2 \left[\sum_{f\in F_e} \left[\Delta^1_{a_e,f}\frac{\lambda}{\sigma_v} - \Delta^2_{a_e,f}\right] - \sigma_a^{-2} Z^{'}_e \mu_a\right].
\end{aligned}
$$

Sampling c_e:

We observe that

$$
\begin{aligned}
P(c_e|-) \quad \propto \quad & \prod_{f\in F_e} [\varphi(\tfrac{1}{\sigma_v}(r_{e,f} - c_e - W_{e,f}^{'}\alpha - \kappa(U_{e,f}^{E} - \beta_0 r_{e,f} - (X_f^{'}, A_{e,f}^{'})\beta) \\
& -\lambda(U_{e,f}^{F} - a_e + \gamma_0 r_{e,f} - (\tilde{X}_{e,}^{'}, A_{e,f}^{'})\gamma)))] \\
& \cdot \operatorname{Prior}(c_e) \qquad \text{(C14)} \\
\propto \quad & \prod_{f\in F_e} [\varphi(-\tfrac{1}{\sigma_v} c_e + \Delta_{c_e})] \cdot \operatorname{Prior}(c_e),
\end{aligned}
$$

where

$$
\begin{aligned}
\Delta_{c_e,f} \quad = \quad & \tfrac{1}{\sigma_v}(r_{e,f} - W_{e,f}^{'}\alpha - \kappa(U_{e,f}^{E} - \beta_0 r_{e,f} - (X_f^{'}, A_{e,f}^{'})\beta) \\
& -\lambda(U_{e,f}^{F} - a_e + \gamma_0 r_{e,f} - (\tilde{X}_{e,}^{'}, A_{e,f}^{'})\gamma)).
\end{aligned}
$$

Hence,

$$
c_e| - \sim N\left(\mu_{c_e}^{post}, (\sigma_{c_e}^{post})^2\right),
$$

where

$$
\begin{aligned}
(\sigma_{c_e}^{post})^2 \quad = \quad & [\sum_{f\in F_e} \tfrac{1}{\sigma_v^2} + \sigma_c^{-2}]^{-1} \\
\mu_{c_e}^{post} \quad = \quad & -(\sigma_{c_e}^{post})^2 \left[\sum_{f\in F_e} \Delta_{c_e,f} \tfrac{-1}{\sigma_v} - \sigma_c^{-2} Z_e^{'} \mu_c\right].
\end{aligned}
$$

Sampling μ_a:

Clearly,

$$
\begin{aligned}
P(\mu_a|-) \quad \propto \quad & [\prod_{e\in E^{'}} P(a_e|\mu_a, \sigma_a^2)] \cdot \operatorname{Prior}(\mu_a), \\
\propto \quad & [exp\left(-\sum_{e\in E^{'}} \tfrac{(a_e - Z_e^{'}\mu_a)^2}{2\sigma_a^2}\right)] \cdot \ exp\left[-\tfrac{1}{2}\left(\mu_a - \mu_{\mu_a}\right)^T \Sigma_{\mu_a}^{-1}\left(\mu_a - \mu_{\mu_a}\right)\right]. \qquad \text{(C15)}
\end{aligned}
$$

$E^{'}$: the total number of unique candidates across markets.
So

$$
\mu_a|-: N\left(\mu_a^{post}, \Sigma_a^{post}\right),
$$

with

$$
\begin{aligned}
\Sigma_a^{post} &= [\sum_{e \in E'} Z_e Z_e' \frac{1}{\sigma_a^2} + \Sigma_{\mu_a}^{-1}]^{-1} \\
\mu_a^{post} &= -\Sigma_a^{post}\left[\sum_{e \in E'} -\frac{Z_e a_e}{\sigma_a^2} - \Sigma_{\mu_a}^{-1}\mu_{\mu_a}\right].
\end{aligned}
$$

Sampling μ_c:

Clearly,

$$
\begin{aligned}
P(\mu_c|-) &\propto [\prod_{e \in E'} P(c_e|\mu_c, \sigma_c^2)] \cdot \text{Prior}(\mu_c), \\
&\propto [exp\left(-\sum_{e \in E'} \frac{(c_e - Z_e'\mu_c)^2}{2\sigma_c^2}\right)] \cdot exp\left[-\frac{1}{2}(\mu_c - \mu_{\mu_c})^T \Sigma_{\mu_c}^{-1}(\mu_c - \mu_{\mu_c})\right]. \quad \text{(C16)}
\end{aligned}
$$

And so

$$\mu_c| - \sim N(\mu_c^{post}, \Sigma_c^{post}),$$

with

$$
\begin{aligned}
\Sigma_c^{post} &= [\sum_{e \in E'} Z_e Z_e' \frac{1}{\sigma_c^2} + \Sigma_{\mu_c}^{-1}]^{-1} \\
\mu_c^{post} &= -\Sigma_c^{post}\left[\sum_{e \in E'} -\frac{Z_e c_e}{\sigma_c^2} - \Sigma_{\mu_c}^{-1}\mu_{\mu_c}\right].
\end{aligned}
$$

Sampling σ_a^2:

By simple conjugacy

$$\sigma_a^2| - \sim InvG(a_{\sigma_a}^{post}, b_{\sigma_a}^{post}),$$

where

$$a_{\sigma_a}^{post} = a_{\sigma_a} + |E'|/2, \quad b_{\sigma_a}^{post} = b_{\sigma_a} + \frac{1}{2}\sum_{e=1}^{|E'|} (a_e - Z_e'\mu_a)^2, \qquad \text{(C17)}$$

Sampling σ_c^2:

As in the previous case

$$\sigma_c^2| - \sim InvG(a_{\sigma_c}^{post}, b_{\sigma_c}^{post}),$$

where

$$a_{\sigma_c}^{post} = a_{\sigma_c} + |E^{'}|/2, \quad b_{\sigma_c}^{post} = b_{\sigma_c} + \frac{1}{2}\sum_{e=1}^{|E^{'}|} (c_e - Z_e^{'}\mu_c)^2. \qquad \text{(C18)}$$

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