ABSTRACT

Title of Dissertation:	MATCHMAKING OR INFORMATION LEAKAGE? DISCLOSURE BENEFITS AND CONSTRAINTS OF CORPORATE JOB ADVERTISEMENTS
	Yi Cao, Doctor of Philosophy, 2018
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This study examines the benefits and constraints of a special form of corporate voluntary disclosure—job advertisements. Using a novel dataset of over 8 million recruiting advertisements posted by public companies, I follow taxonomy theories and create a continuous measure of information specificity, based upon the level of descriptive detail of skill requirements in job advertisements. Consistent with the theory that labor market disclosure mitigates search frictions, I find job advertisement specificity positively predicts employee satisfaction, productivity, and corporate accounting performance and negatively predicts employee turnover rate. My results further suggest that job advertisement specificity provides incremental information about human capital intangibles and improves the value-relevance of accounting numbers. I also show that the information specificity is constrained by product market competition. Together, my results suggest job advertisement is an

important voluntary disclosure channel and that the content of job advertisements is informative to capital- and product-market participants.

MATCHMAKING OR INFORMATION LEAKAGE? DISCLOSURE BENEFITS AND CONSTRAINTS OF CORPORATE JOB ADVERTISEMENTS

by

Yi Cao

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Advisory Committee:
Associate Professor Shijun Cheng, Chair
Professor Ginger (Zhe) Jin
Associate Professor Michael Kimbrough
Associate Professor Nick Seybert
Assistant Professor Emanuel Zur

Dedication

For my parents, my wife and children. Thank you for walking me through the journey.

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Chapter 1: Introduction

General consensus holds that human capital is "one of the most important assets" (Fulmer and Ployhart, 2013) and affects firms' fundamental performance (e.g., Huselid 1995). Nonetheless, due to a lack of regulation of human capital disclosure, the ways in which firms recruit and manage employees remains largely invisible.[1] While investors show a strong demand for the mandatory reporting of human capital performance,[2] labor economic theories and business psychology experiments hint that a major source of labor-market voluntary disclosure—job advertisements—may complement the limited regulated disclosures that are available. These models suggest that job advertisements can affect employees' perceptions and firms' recruitment outcomes, thus shedding light on the quality of human capital portfolios (e.g., Mortensen 1986; Roberson et al. 2005). However, given the sheer volume of job advertisements created and distributed every day,[3] researchers know surprisingly little regarding whether this special form of disclosure is useful and incrementally informative about firms' fundamentals. This study aims to fill the gap in the literature by empirically examining the disclosure benefits and constraints of corporate job advertisements.

Labor economic theories find that job advertisements enhance hiring outcomes and improve the matching between companies and employees by mitigating the labor

[1] "When Investors Want to Know How You Treat People," by David Creelman and John Boudreau, Feb. 10, 2015, *Harvard Business Review*.
[2] For example, in July 2017, Human Capital Management Coalition (HCMC), which is comprised of a group of institutional investors managing total assets of $2.5 trillion, filed a petition with the U.S. Securities and Exchange Commission (SEC) calling for enhancement of human capital disclosures.
[3] According to Burning Glass Technologies (2017), an average of about 3.4 million online job advertisements are posted daily.

market information asymmetry (e.g., Mortensen 1986; Shimer and Wright 2004). Similarly, business psychology experiments document that more specific job advertisements help candidates form a holistic view of a position, thus improving their perceptions of fit (e.g., Roberson et al. 2005). Consistent with these findings, a recent survey shows that 51% of employees are considering a new job (Workforce Panel, Gallup, Nov. 2015), and 67% of companies believe current low retention rates are due to lack of information about positions *before* candidates begin their jobs (Harris Interactive Survey for Glassdoor, 2014). The evidence collectively suggests that managers want to provide more information to candidates to improve hiring outcomes.

However, media reports suggest that disclosure through job advertisements could be constrained by the potential leakage of proprietary information. For example, on May 16, 2014, several technology news networks[4] reported that Microsoft might be working on the desktop version of its virtual assistant, Cortana, because a job listing specifically sought skills related to artificial intelligence and desktop software development. Their conjecture later proved true, as Microsoft announced Cortana for Windows 10 in January 2015. This example shows that job descriptions can reveal firm-specific plans for products or strategies, thus undermining competitive advantage. Since most managers are concerned about "giving away company secrets" when disclosing (Graham, Harvey, and Rajgopal 2005), the optimal job-advertisement disclosure choice for managers is a trade-off between recruiting the best candidates and revealing as little proprietary information as possible.

[4] Rich Edmonds, May 16, 2014, windowscentral.com; Lance Whitney, May 16, 2014, cnet.com.

I specifically examine whether information provided in job advertisements affects organizational performance and whether this special form of labor market disclosure is constrained by product market competition. To empirically study the disclosure mechanisms, I exploit novel textual-based Burning Glass Technology (BGT) data to measure the proportion of detailed descriptions in job advertisements. BGT parses nearly 40,000 internet sources daily and collects a comprehensive set of attributes from millions of job advertisements. Because of its coverage and novelty, BGT data is frequently used by labor economists (e.g., Modestino et al. 2015; Modestino et al. 2016) and industry practitioners (e.g., Beyond Point and Click, Oracle Academy, 2016). A unique feature of BGT data is its taxonomy classification of skill requirements. BGT collects skill requirements from each job advertisement and classifies each skill in as much detail as possible along three groups of categorical variables, representing a hierarchical parent-child relationship tree. Based on taxonomy theory (Rye and Choi 2005), I harness the variation in the way firms describe skill requirements and create a job advertisement specificity measure.

I begin my analysis by examining whether job advertisement specificity affects future human capital and financial performance. Although Mortensen (1986) suggests that understanding information provided to job candidates is critical for evaluating labor market efficiencies and calls for study of the way firms advertise their openings, empirical research has not provided a clear link between job advertisements and performance due to limited data availability. The BGT data overcomes these limitations by allowing the direct capture of variation in the way firms describe skill requirements and enabling the creation of my specificity measure. I also parse the employee reviews on Glassdoor.com as a proxy for the outcome of firms' human capital performance and find that job advertisement specificity positively predicts employees' opinion about firms' cultures, senior managers, and business outcomes and negatively predicts employee turnover. I also report that improvements in human capital translate into financial performance by showing job advertisement specificity positively predicts future productivity and unexpected earnings. Overall, my evidence suggests that job advertisement specificity is positively associated with firms' human capital performance and that this disclosure benefit ultimately carries over to financial outcomes.

Since job advertisement specificity is informative about firms' human capital performance, I next examine whether this forward-looking indicator adds to the value-relevance of earnings. A stream of literature documents that the nature of intangibles could distort the periodic matching of costs with revenues under current accounting principles, thus reducing the value-relevance of accounting information (Zeghal and Maaloul 2011; Lev and Zarowin 1999; Lev 2003). Human capital is an essential component of firms' intangible assets (Kaplan and Norton 2004). Thus, if the human capital performance can be inferred from job advertisement specificity, I expect the usefulness of earnings to increase when job advertisements are more specific. Indeed, I find a greater earnings response coefficient (ERC) when firms provide more specific job advertisements. This supports my argument that human capital disclosure enriches firms' information environments and aids resource allocation of the capital markets.

I also examine whether product market competition prevents managers from providing even more specific information about the jobs. Controlling for other firm and industry characteristics, I find the specificity declines when a firm operates in a highly competitive environment. Moreover, consistent with my findings about disclosure benefits, I document that, when labor performance is critical to a firm's growth, managers' concern over proprietary cost is alleviated. Taken together, these findings suggest that job advertisement disclosure is motivated by the need to hire well-matched employees but constrained by the potential leakage of proprietary information.

As job advertisement information is determined by both endogenous and exogenous factors, I estimate an exogenously determined specificity by cross-sectionally regressing specificity on the formation of human capital for each industry, and repeat the main test using the exogenously determined specificity as the main independent variable. Additionally, using the enforcement of Americans with Disability Act Amendment Act (ADAAA) in 2011 as an exogenous increase in the level of details in job descriptions, I find consistent performance implications for the firms that are more affected by ADAAA regulations after the enforcement of the law. All results still hold in both robustness check.

This study contributes to the literature in several ways. It has been more than three decades since Dale Mortensen raised the importance of modeling the "process by which firms recruit and specifically how they advertise their openings" (Mortensen 1986). Indeed, relatively little attention has been paid to disclosure directed to stakeholders other than investors (Healy and Palepu 2001). Using a novel dataset with broad coverage of online job advertisements, this study answers the call by empirically examining the informativeness and performance implications of disclosure through job advertisements. My findings imply that investors could rely on job advertisements to obtain insights into firms' human capital when the mandatory disclosure of this information is nearly absent. My findings also suggest that, when there is a lack of capital market perks to motivate disclosure, other incentives, such as human capital performance, may prompt managers to commit to greater disclosure.

An investigation into labor market information is timely and necessary in light of the ongoing push for the SEC to regulate human capital disclosure.[5] The Sustainability Accounting Standards Board (SASB) and several groups of institutional investors[6] have led this initiative, and they aim to promote a more holistic picture of firms' human capital portfolios in mandatory SEC filings. To optimally choose metrics and guidelines, it is important for standard setters and investors to understand when and why firms reveal more about their human capital practice and performance.

Finally, this paper proposes a new taxonomy for measuring information specificity. As a measure of disclosure quality, specificity has been widely adopted in the accounting literature. However, research normally operationalizes specificity as an indicator of whether the information is quantifiable (e.g., Bamber and Cheon 1998; Leone, Rock, and Willenborg 2007). This paper uses a taxonomy approach to extend the measurement of specificity to a continuous variable, and this method provides an intuitive proxy of information quality for future studies.

The rest of the paper is organized as follows. Section 2 reviews the literature and the theories that motivate this study and develops my research hypotheses. Section 3 describes the sample and data and explains the creation of the specificity measure

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[5] "When Investors Want to Know How You Treat People," *Harvard Business Review*, Feb. 10, 2015

[6] According to report from CFO.com on May 20, 2016, the group of institutional investors manages over $4 billion assets in total.

and my research design. Section 4 presents empirical results and discusses the robustness of the results. Section 5 introduces additional analyses, and Section 6 concludes and discusses the implications of this study.

Chapter 2: Related Literature and Hypothesis Development

2.1 Overview of Job Advertisement Creation

Human resource (HR) departments normally coordinate the creation of job descriptions, but anecdotal evidence, collected from several mid-level managers in Fortune 500 companies and international organizations[7] as well as media reports,[8] suggests that the entire process involves different hierarchies within a company. When a headcount budget is available and the team intends to hire, the hiring manager first meets with the divisional chief, to confirm the hiring needs. He or she then discusses them with the HR coordinator and describes the level, salary, and requirements for the openings. At this stage, they normally agree on specific skills listed in the job description, and the hiring manager usually provides a few key items to be included. Sometimes, especially for technical positions, the hiring manager directly drafts the complete requirement section of the job advertisement to ensure candidates understand the team's expectations. Given hiring managers are highly involved in generating the hiring message, it is safe to assume the information provided in the advertisement incorporates both the HR departments' efforts and the hiring managers' discretion. The managers' input is more likely to be found in the description of skill requirements and job responsibilities, as these sections are more technical.

[7] I had private conversations with six mid-level managers (senior manager or director) who are working (or have worked) at U.S. offices of Fortune 500 companies or international organizations such as the World Bank and International Monetary Fund.

[8] Lifting the Curtain on the Hiring Process, Needleman, *The Wall Street Journal*, Jan. 26, 2010.

2.2 Literature Review

2.2.1 Specificity and Information Quality

Taxonomy is a collection of terms organized into a hierarchical-structured tree, and each term in a taxonomy is organized in the way that relates to other terms in a parent-child relationship (Rye and Choi 2006). Taxonomy has been shown to provide an organizational structure to domain knowledge (Burgun and Bodenreider, 2001). Using the hierarchical tree, Rye and Choi (2005) introduce the term “specificity measure,” which represents the informativeness of terms in a domain. It is measured as the location of the term in the taxonomy tree: higher specificity terms tend to locate lower in domain taxonomy terms (Ryu and Choi, 2006). This concept is consistent with implementations in accounting literature as well. Bamber and Cheon (1998) investigate how disclosure-related costs affect the specificity of managers’ forecasts about earnings, which is measured as whether the forecast is open-ended or quantitative. Leone, Rock, and Willenborg (2007) use the specificity of the IPO prospectus, which is operationalized by whether a dollar figure for the use of proceeds is provided. Overall, the concept of “taxonomy specificity” is congruent with the way “specificity” is used in the accounting literature: both capture the degree of detail in the description of a specific topic or object. Accordingly, I measure the specificity of skill requirements in job advertisement as the proportion of skills that are described to the lowest level of the skills’ taxonomy tree. This measure serves as the proxy for the disclosure quality of job advertisement.

2.2.2 Search Frictions and Information Asymmetry in Labor Market

Diamond (1982a), Mortensen (1982a,b), and Pissarides (1984a, b) lay the cornerstone for the analysis of labor market, based on search and matching frictions. Their model (DMP model hereafter) assumes an inherent friction in the labor market, which is defined as "… the costly delay in the process of finding trading partners and determining the term of trade …" (Pissarides 2011). The DMP model suggests that the fundamental reason for the co-existence of unemployment and job vacancies is the search frictions preventing the labor market from reaching a clearing equilibrium. Any deterioration of matching efficiency will increase the level of unemployment at equilibrium and make it more difficult for workers to find a job.

The DMP model has spurred a large literature investigating how market frictions affect the efficiency of matching. One stream of analysis investigates the inefficiencies, or the "mismatch," arising in the presence of information asymmetry. Acemoglu (1995) studies the matching efficiencies when the worker is not informed and the firm is well-informed. The worker makes a bargaining offer and, if rejected, the worker could make another offer in the next period. Acemoglu suggests that matching could be inefficiently delayed because the worker may choose a wage that is too high when she lacks information, and thus, in later periods, she must reduce her offer gradually until she reveals herself to be a low productivity type. Shimer and Wright (2004) likewise find, when both the firm and the worker are uninformed, matching could be delayed because its probability is reduced by the asymmetric information. Additionally, Mortensen (2000) and Pissarides (2000) study the positive effect of information in labor market and offer a channel through which information could mitigate search frictions—search cost. They find, when search cost is low, firms and workers could simultaneously conduct multiple searches. As a result, the reserved level of quality for the matching will rise, and the lowest level of productivity acceptable to the firm and the lowest wage acceptable to the worker both then increase. Mortensen (1986) specifically mentions recruiting and advertising and suggests advertising helps reduce search costs and frictions, thus reducing the social equilibrium unemployment rate. Overall, labor economic theories suggest that lack of disclosure in the labor market reduces matching efficiency.

One type of the search friction is the qualitative mismatch, which represents the misalignment between the human capital and firms' needs (Sattinger 2012). This mismatch has received significant attention from policymakers (OECD Handbook, 2013) in recent years, and the European Centre for the Development of Vocational Training (CEDEFOP) has listed the measurement of skill and skill mismatch as one of its research priorities (CEDEFOP 2009). The concept of qualitative mismatch is consistent with the research setting of this paper, where the measure of information specificity is built upon the skill requirements of firms. In particular, this idea comports with the work of Mortensen (1986), who suggests job advertisement information can reduce the search frictions. By providing evidence on the relationship between specificity, human capital, and financial performance, this study empirically tests the qualitative mismatch theory.

2.2.3 Job Advertisement Information and Employee Perceptions

An extensive body of human resource management literature suggests that the first phase of recruitment—an applicant's job search—is the most critical in the entire hiring process for both applicants and hiring organizations (e.g., Barber 1998). Barber et al. (1994) argue that, from the applicants' perspective, job search, which is the information collection process for potential openings (Steffy, Shaw and Noe, 1989), determines the opportunity set for job choices. From the perspective of hiring organization, this stage is important too, because the ability to attract the attention from matching candidates is key to the economic utility of recruiting efforts (Boudreau and Rynes 1985). As a result, a series of papers focuses on the role of information in the job advertisement and examines how it affects hiring outcomes such as person-organization (PO) and person-job (PJ) fit.

Theories of person-environment (PE) fit propose that, when individuals fit or match the environment, they provide positive feedback and generate better economic outcomes (e.g., Dawis and Lofquist 1984). PO and PJ fit are two most common forms of PE fit in recruiting and represent the match between the individual type and that of the organization or position (Carless 2005). During the job search, information asymmetry prevents candidates from directly observing potential PO and PJ fit. Accordingly, they rely on observable attributes of the job and the organization to decide whether they should apply an opening or accept an offer. If the job advertisement does not deliver a clear message, resources invested in later stages of hiring as well as the hiring outcome may be discounted. As job advertisement is a formal and credible information source that candidates can rely on to mitigate the information asymmetry when applying (Rees 1966), studies show that information in job advertisements is crucial in influencing PO and PJ fit. Saks and Ashforth (1997) use a longitudinal field experiment to show that the quantity of information in the job search is positively associated with PO and PJ fit and that improved fit translates to higher job satisfaction. Roberson et al. (2005) conduct an experiment with college graduates and find recruiting-message specificity is particularly important for attracting candidates and improving their PO and PJ fit. Since higher job satisfaction leads to better job performance (Landy 1989), studies overall suggest that higher information quality in job advertisements improves employees' perceptions and, ultimately, job performance.

2.2.4 Human Resource Management and Organizational Performance

A large body of evidence demonstrates a positive relationship between human resource management and organizational performance (reviewed by Stiles and Kulvisaechana 2003). A number of studies establish the link between employees' emotional and psychological profiles and organizational performance. Arthur (1992, 1994) finds HRM that focuses on motivating employees' commitment helps improve firms' productivity. Jordan et al. (2002) find negative employee perceptions about jobs lead to lower individual and organizational commitment, and Patterson et al. (1997) report a positive relationship between employees' attitude toward the firm and organizational productivity.

2.2.5 Intangibles and Value-relevance

The accounting literature has documented that intangible investments are increasingly important (e.g., Zeghal and Maaloul 2011). However, intangibles are rarely recognized as assets. What's more, the timely expensing and untimely recognition of future cash flows generated by intangible investments creates distortions and thus reduces the usefulness of accounting numbers. (e.g., Lev and Zarowin 1999; Lev 2003). Especially when intangibles play a more important role in creating value

(Stewart 1997), the lack of recognition of intangibles could further hurt the value-relevance of financial information. Lev and Zarowin (1999) suggest the informativeness of financial information declines from 1977–1996, while Liang and Yao (2005) study a sample of high-tech firms in Taiwan and observe the same trend. Managers' response to the decreasing value-relevance of financial information is voluntary disclosure. Lang and Lundholm (1993) find that firms provide more voluntary disclosure when their accounting numbers are less value-relevant. And Lougee and Marquardt (2004) document that managers issue more press releases when their firms' accounting information is less useful. Complimenting these findings, the results of Amir and Lev (1996) suggest the non-financial information is useful when evaluate firms' fundamental economic values. Hirschey et al. (2001) further find that the data of R&D expenses is more useful when the investors have more information about the quality of the patents filed by the firm. Collectively, the literature indicates that non-financial information, especially information relating to intangibles, improves the value-relevance of financial data.

2.2.6 Proprietary Information, Competition and Disclosure

Research on disclosure theories has established that competition affects disclosure through proprietary cost. On one hand, managers are motivated to share information by various capital market benefits: lower cost of capital (Leuz and Verrecchia 2000), stock-based compensation incentives (Noe 1999), and lower litigation risk (Skinner 1994, 1997). On the other hand, disclosing too much may reveal information that could be used by product-market rivals (e.g., Verrecchia 1983; Darrough and Stoughton 1990). When competition is modeled as a post-entry game and uses the setting that firms are endowed with private information about future aggregated demand, Clinch and Verrecchia (1997) find existing competition deters firms from disclosing too much private information. Bamber and Cheon (1998) empirically confirm this prediction and find disclosure-related proprietary cost deters managerial forecasts. Case studies also suggest that firms designate specific departments to collect and analyze information from competitors and that this information is then passed around internally (e.g., Hamel, Doz, and Prahalad 1989). The relationship between disclosure and proprietary information leakage could also be observed in real life. In the introduction of this paper, I presented an example in which the media successfully inferred a Microsoft future product by digging through skill requirements in the company's job advertisements. If information in job advertisements points to future products or strategies, product market rivals are highly likely to try to capture it, and therefore disclosure through job advertisements may also entail proprietary costs.

2.3 Hypotheses Development

As discussed in section 2.2.2 and 2.2.3, information asymmetry creates labor market friction and reduce the efficiency of matching. Mortensen (1986) conceptually suggests that job advertisement information could reduce this search friction. If disclosure indeed enhances matching between firms and workers, I expect a higher level of disclosure to be associated with better human capital performance. As a result, I propose my first two hypotheses as follows.

H1a: Job advertisement specificity positively predicts employees' satisfaction.

H1b: Job advertisement specificity negatively predicts employees' turnover rate.

As discussed in section 2.2.4, the literature has established the link that human capital performance translates to organizational performance. Also, as suggested by Mortensen (1986) and Shimer and Wright (2004), information provided to candidates could lead to a more efficient social equilibrium. If job advertisement specificity promotes human capital performance, I expect the specificity could also predict firm productivity and financial performance. Thus I propose my next hypotheses as follows.

H2a: Job advertisement specificity positively predicts firms' productivity.

H2b: Job advertisement specificity positively predicts firms' financial performance.

As discussed in section 2.2.5, information about intangibles tends to enhance the usefulness of the financial information. If job advertisement specificity conveys information about future human capital performance, I expect the financial information of firms providing more specific job advertisements to be more value-relevant. As a result, I propose the following hypothesis.

H3: Job advertisement specificity increases the value-relevance of firms' accounting earnings.

As discussed in section 2.2.6, it is well documented that product market competition constrains disclosure. I argue that, when articulating information in job advertisements, managers are motivated by the employee performance benefit but also constrained by the potential proprietary information leakage. I thus propose my final hypothesis as follows.

H4: Job advertisement specificity is positively associated with firms' dependence on employee performance and negatively associated with product market competition.

Chapter 3: Measurements, Sample Selection and Research Design

3.1 Main Variables

3.1.1 Burning Glass Technology Data and Specificity

The main data used to measure job advertisement specificity is provided by Burning Glass Technology. BGT is a technology firm focused on job market data analytics, and the variables used in this research come from its real-time labor database. This dataset is compiled by bot-scanning and parsing 40,000 internet sources daily to find job advertisements. These sources include job boards, such as Glassdoor and Monster, as well as corporate websites. Because of the comprehensive data collection, BGT has astonishing coverage: the dataset includes job advertisement-level attributes such as title, estimated salary range, educational and skill requirements, and hiring location for over 8 million distinct job advertisements across a seven-year sample period. A Georgetown University study reports that BGT collection covered 60% to 70% of job advertisements in 2013[9], and, in more recent years, BGT estimates this number has risen to 85%. This study mainly uses the variation in the way companies describe individual skills to construct the job-advertisements specificity measure.

The main measure for disclosure quality—job advertisement specificity—is built upon the hierarchical structure of skill requirements in BGT data. BGT collects skill requirements for each job and classifies each skill into three groups of categorical variables representing a hierarchical parent-child relationship taxonomy tree—skill-

[9] Understanding Online Job Advertisements Data, by Georgetown University, Center on Education and the Workforce, April 2014

family, skill-cluster and skill. Skill-family is the most aggregated level, while skill-clusters are the "branches" of skill-family, and skills are at the most granular level of classification. These three levels are built based on the skill definition of Occupational Information Network (O*NET) data and BGT algorithms.[10] Some skills listed in the original job postings are very specific and could be classified at the most disaggregated level; however, some are vague and could only be classified at aggregated level. For example, the skill of "SAS programming" belongs to the "data analytics" skill-cluster and the "information system" skill-family. If a firm lists the requirement specifically as "SAS programming," then all three levels of classifications could be identified; but if the firm lists the requirement vaguely as "data analytics," only the aggregated level of classification—skill-cluster—could be identified. This intuitive logic is consistent with taxonomy theory (Rye and Choi 2005): term specificity could be measured by information quantity in given domain. When a term has more details about the domain, which means information is provided at more granular level on the taxonomy tree, the term is more specific. Following this theory, I use the unique skill taxonomy of BGT data and create my job-advertisement specificity measure by calculating the proportion of skill requirements that could be identified to the most granular level of classification, and I use this measure to proxy for the disclosure quality in job advertisements.

I use two Microsoft job advertisements to illustrate how the measure of specificity is built and how firms could vary their descriptions to obfuscate information in job advertisements. The Microsoft example in the introduction illustrates how media accurately forecasted a Microsoft product, making it an ideal candidate for a case study:

[10] O*NET is a free online occupational database which is sponsored by Department of Labor/Employment and Training Administration.

I could specifically study job advertisements related to the artificially intelligent assistant for the event period and examine whether managers attempt to describe skills in the way that avoids information leakage.

To briefly recap, on May 16, 2014, several news outlets reported an unusual job posting from Microsoft, which hinted the company was working on the desktop version of Microsoft's virtual assistant, Cortana. This news later proved to be true, as Microsoft made the product announcement of Cortana for Windows 10 in January 2015. Following the timeline of this example, I pick two job advertisements from the BGT data, which are posted by Microsoft at least 30 days before the media coverage to avoid change of disclosure caused by news reports. These two openings are both software developer positions posted around the same time. However, the first job, presented in Panel A of Appendix II, requires two key skills that are essential for development of virtual assistant—natural language processing (NLP) and machine learning—while the second job, presented in Panel B of Appendix II, does not require such skills.

Out of nine skill requirements in job posting of Panel A, four skills could not be clearly identified. Specifically, one could not get a clear picture which tools for NLP and machine learning Microsoft was requiring for the software developer. On the contrary, the job advertisement in Panel B required 16 skills, and only two of them were vaguely described. Overall, the measure of specificity in this example captures the variation in the ways a firm describes required skills. The specificity measure also seems to accurately reflect how firms obfuscate requirements when a position may be involved with the development of future products.

I next examine whether all Microsoft job advertisements related to virtual assistants are consistently more obfuscated. I use all job advertisements posted by Microsoft between January and April 2014 to conduct a t-test to compare the mean of specificity for openings requires NPL skill or machine learning skill with openings that do not require these skills. Results reported in Panel C of Appendix II suggest that skills in jobs that do not require NLP or machine learning skills are described more specifically than those that do. As NLP and machine learning would be recognized by industry practitioners as requirements for developing an artificially intelligent assistant,[11] this result is consistent with the conjecture that managers obfuscate skill requirements in job advertisements when the position relates to the development of products. To avoid the potential bias introduced by comparing technical positions and nontechnical ones, I compare the mean of specificity between jobs requiring NLP and machine learning and those requiring manufacturing-design skill. This ensures the comparison is between two technical positions that require approximately the same skill level but different types of technical skills. The results from the t-test still holds.

Overall, this example suggests that the specificity measure captures variation in the way firms describe required skills and that firms attempt to vaguely describe skill requirements when a position relates to product development.

3.1.2 Glassdoor Employees' Review

To directly examine the impact of job advertisement specificity on employees' perceptions, I collect employees' satisfaction over seven job-related dimensions

[11] What it takes to build artificial intelligence skills by Joe McKendrick, *ZDNet.com*, June 9, 2017.

through www.glassdoor.com. These reviews are based on ratings and approval rates from current or previous employees and thus serve as a proxy for employees' perception and satisfaction. The ratings focus on the overall view of the firm, corporate culture, work-life balance, senior management, and career opportunity. These ratings are scaled from 1 to 5, with increments of 0.1. Also, I collect three approval rates: overall percentage of participants who would recommend this company to friends, percentage of participants who approve of the CEO's performance, and percentage of participants who have a positive business outlook for the company. All ratings and approval rates are collected as of July 13, 2017.

3.1.3 Employee Turnover Rate

Observing and measuring turnover is difficult without firm-level collection of the information. The turnover rate fits the context of this study would be the replacement of departing employees with new ones, excluding the expansion or the contraction of the labor force due to strategic plans of the firm. To measure the turnover due to matching, I first select a subsample of firms whose net number of employees dropped, compared to their data of the prior year, based on Compustat's reported number of employees. Then I use the number of job advertisements posted during the fiscal quarter, scaled by last year's total number of employees, as the percentage of employees who left the company and need to be replaced. The reason I measure turnover this way is twofold. First, I assume a net positive number of job advertisements means the firm is expanding, former employees left and must be replaced, or both. As a result, when the net number of employees is increasing, it is difficult to identify which job advertisement stems from expansion and which from turnover. Dropping all the firms with a net increase in employees helps me narrow down to firms with a net decrease of employees that are still hiring. The hires, in this case, are much more likely to be replacements. Second, although there is no guarantee that, when a firm posts a job advertisement, the new hire would replace a departing employee because of the former employee found a new job, if on average all firms with a net decrease of labor force mostly are hiring for replacement, the number of vacancies should be closely related to the turnover. Consistent with this argument, I find the mean of the turnover rate captured in this study is 2.7%, which is close to the 3.3% posted by Bureau of Labor Statistics in 2008.[12] Without delving into the firm-level data collection, using the number of vacancies as the measure of turnover for a subsample seems approximately close to the national average.

3.1.4 Labor Contribution to Output Growth

I measure the industry dependence for labor performance using Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics (BLS) industry-level production account data. Specifically, I use the labor contribution to output growth to proxy for the industry-level demand for job performance. By BEA/BLS's definition (Lyndaker 2016), this data is constructed by pulling BEA's GDP by industry data and BLS's capital and labor hours' data to create a consistent decomposition of the sources of growth by factors such as multifactor productivity, labor, and capital. If labor contribution to output growth is relatively higher, it is then more necessary for firms in that industry to improve labor performance to sustain growth. Thus the labor

[12] "Job Openings and Labor Turnover Survey," Bureau of Labor Statistics, 2008

contribution to output growth serves as a proxy for industry demand for human capital.

3.1.5 Measures of Product Market Competition

Based on the literature, I employ industry concentration to proxy for competition from existing rivals. Industry concentration is the most commonly used measure for competition (e.g., Verrecchia and Weber 2006; Berger and Hann 2003; Li 2010). The brief sketch of the argument from the research is that the concentration of market share captures the extent to which firms compete with existing rivals. If the industry is highly concentrated (and thus dominated by a few firms), competition between existing rivals is lower. Following Verrecchia and Weber (2006), I measure industry concentration using the ranking of industry Herfindahl Index of market share, where higher industry concentration means lower competition.

3.1.6 Other Variables

In addition to the skill description, this study also uses several other pieces of information from job advertisements: specialization of the skill, experience required, and salary estimation made by the posting websites (e.g., Glassdoor.com salary estimation). The specialization of the skill is defined by BGT as whether a skill is specifically used by a certain occupation or used by many occupations. Required experience is defined as required number of years of work experience in a similar job. The salary estimation is an estimated range of salary made by a recruiting website such as Glassdoor.com,[13] and I take an average for the estimated minimum and maximum

[13] "What are Salary Estimates in Job Listings?" Sep. 25, 2017, Glassdoor.com.

of the salary as the estimated average salary for the job opening. Because salary estimation requires historical data, the salary variable only covers about 30% of the sample.

The main outcome variables reported in Tables 3 to 5 are operating outcome variables: total factor productivity (TFP), standardized unexpected earnings (SUE), and three-day cumulative abnormal return over the earnings announcement (CAR3). The TFP data entails a firm-level estimation of productivity from 2010–2013, which is obtained from the website of Selale Tuzel, based on the work of Imrohoroglu and Tuzel (2014). The measurements of SUE and CAR3 are defined in Appendix I.

The literature (e.g., Li 2008; Tetlock 2008) suggests firm size, market-to-book, and leverage should be taken into account when explaining earnings surprise. I use the end-of-quarter logarithm of market capitalization and the logarithm of market capitalization to book value of assets to measure size and market to book. Also, I use the sum of short-term and long-term debt to measure leverage. Additionally, as firms' disclosures may be consistent across the board, I use readability of the 10-K (Bonsall, Leone and Miller, 2015) to control for financial disclosure quality. Verrechia and Weber (2006) suggest financing decisions may affect managers' incentive for disclosure. Thus I control for the debt issuance by adding indicator variables that equal to one if the firm issued debt in the fiscal quarter of the job advertisement disclosure. When examining the relationship between specificity and earnings surprise, I also use variables from Compustat to control for firm age; investment in property, plant, and equipment; total accruals; dividend payment; special items recognized as line items in the income statement; volatility and complexity of firms' operations; and the total number of segments. I also include analyst forecast-related variables from I/B/E/S to control for other omitted factors that are not reflected through the accounting numbers. These variables include analyst forecast errors, dispersion, and revisions as well as analyst coverage of the firms. All variables are further defined in appendix I.

3.2 Sample Selection and Descriptive Statistics

Panel A of Table 1 describes sample selection. I start with the BGT sample and merge it with quarterly Compustat dataset. As all BGT job advertisements are recorded daily, I define the job advertisements between the two consecutive fiscal quarters *t-1* and *t* as the disclosure captured for fiscal quarter *t*, and I calculate the average of specificity of all job advertisements posted between these consecutive earnings announcements as the proxy for disclosure quality observed at *t+1*. I use several other firm and industry variables from Compustat, CRSP, and I/B/E/S as well as data published by researchers discussed in Section 3.1. The final sample of this study includes 2,832 firms over the period of January 2010–December 2016

Panel B of Table 1 compares the sample used in this study with the universe of firms in the Compustat data. As BGT data collects job advertisement attributes online, the sample firms in this study are relatively large: their average market value is almost 40% greater than the average of the Compustat universe. Also, on average, the firms in my sample operate with less debt, smaller market-to-book values, and greater profitability.

Panel C of Table 1 presents the descriptive statistics of major variables in this study. On average, 82.5% percent of skills in the job advertisements are described specifically. This number seems sufficiently high, given firms need a certain level of detail to attract good candidates. Also, the standard deviation (0.09) is relatively high, compared to the mean (0.825), and the spread of specificity (0.513) indicates the measure provides substantial variation. This variation is also reflected in Figure 1: specificity differs in a significant manner by skill-family. It also worth noting that, the between-industry variation of specificity is relatively small (Panel D of Table 1), however the between-firm variation is much more pronounced (Panel E of Table 1). It appears that firms within an industry demonstrate significant differences in the way they describe skills in job advertisements. The specificity measure thus seems to be a valid proxy for information quality in job advertisements. Also, it worth noting that more than half of the sample firms operate in relatively high competition industries. I will discuss details of the variation in specificity below.

3.3 Research Design

3.3.1 Test of H1a: Specificity and Employees' Satisfaction

To investigate the relationship between job advertisement information and future employee satisfaction, I use a cross-sectional data of future employees' reviews of their employers collected from Glassdoor.com. I start my analysis by estimating the following specification:

$$Satisfaction_{t+n} = f(\alpha + \beta_1 Specificity_t + \beta_2 Controls_t), \tag{1}$$

where $Satisfaction_{t+n}$ represents eight different dimensions of employee reviews collected on July 13, 2017 (discussed in section 3.1.2). Because the first five dimensions collected from Glassdoor are in the form of ratings, from 1 to 5, I use an ordinal logistic regression to estimate equation (1) for these five variables (i.e., overall, corporate culture, work-life balance, senior management, and career opportunity). The other three dimensions of employee satisfaction are continuous percentage approval rates, and thus I use a linear regression to estimate equation (1) for them (i.e., recommend job to friends, CEO approval, and business outlook). Coefficient β_1 in equation (1) reflects the relationship between information specificity in job advertisements and future employee satisfaction and thus provides the evidence for H1a. If disclosure through job advertisements enhances employees' perceptions of their job and company, I expect β_1 to be significantly positive. When estimating equation (1), I control for firm size, market-to-book ratio, leverage, profitability, the number of employees who participate in the review, and stock volatility over the fiscal quarter as a proxy for the operational volatility.

3.3.2 Test of H1b: Specificity and Employee Turnover

To further support the argument that information disclosed to candidates would improve human capital performance, I examine the relationship between job advertisement specificity and subsequent employee turnover by estimating the following specification:

$$Turnover_{t+n} = f(\alpha + \beta_1 Specificity_t + \beta_2 Controls_t), \tag{2}$$

where $Turnover_{t+n}$ is the number of job advertisements posted for the firm-quarters that have a net loss of employees (the measurement has been discussed in section 3.1.3.). In this regression, I test the relationship between specificity and future turnover of one to four quarters ahead, and coefficient β_1 provides the empirical test for H1b. When estimating equation (2) and using specificity of period t to predict the turnover rate of period *t+n*, I control for turnover rate of period *t*, net change of employees for the fiscal year, earnings surprise, proportion of specialized skills among all skills used by the firm, average years of experience required by the firm, a fourth-quarter indicator, a firm-level beta estimated from a market model, firm size, market-to-book ratio, leverage, and return-on-assets of period *t.*

3.3.3 Test of H2a: Specificity and Total Factor Productivity

To test whether disclosure to applicants improves firms' productivity, I examine the relationship between specificity and TFP by estimating the following specification:

$$TFP_{t+n} = f(\alpha + \beta_1 Specificity_t + \beta_2 Controls_t), \quad (3)$$

where TFP_{t+n} is firm-year total factor productivity provided by Selale Tuzel. Coefficient β_1 provides the evidence for H2a. I control for the R&D investment; property, plant, and equipment investment; number of employees; product market competition; product similarity; quarterly sales; overall employee review from Glassdoor.com; firm size; market-to-book ratio; and leverage when estimating equation (3).

3.3.4 Test of H2b: Specificity and Earnings Surprise

H1a, H1b, and H2a attempt to establish the link between information specificity in job advertisements and human capital performance. H2b aims to examine whether improvements in human capital performance would translate into future financial performance. To examine the relationship between specificity and future earnings, I estimate below specification:

$$SUE_{t+n} = f(\alpha + \beta_1 Specificity_t + \beta_2 Controls_t), \qquad (4)$$

where SUE is the earnings surprise in subsequent *n* quarters and coefficient β_1 provides evidence on the relationship between specificity and future financial performance. Because SUE measures the earnings surprises, I also estimate equation (4) using the change of specificity between quarter *t-1* and *t* as the main independent variable. I follow Li (2008) and Tetlock (2008) and control for a group of firm characteristics as well as analysts' forecast features. The firm characteristics included in the estimation are size, market-to-book ratio, leverage, beta, proportion of specialized skills, average requirement for related experience, total accruals, dividend payments, firm age, operating volatility and complexity, number of segments, and ROA. I also include the readability of the 10-K to control for the common elements of disclosure. The analyst forecast-related variables are forecast errors, forecast dispersion, revision, and analyst coverage.

3.3.5 Test of H3: Specificity and Value-relevance of Accounting Numbers

To test the third hypothesis and examine whether information in job advertisements enhances the usefulness of accounting numbers, I estimate the following equation:

$$CAR3_t = f(\alpha + \beta_1 Specificity_t \times SUE_t + \beta_2 Controls_t), \qquad (5)$$

where CAR3 is the three-day cumulative abnormal return around the earnings announcement and coefficient β_1 provides evidence on whether job advertisement specificity enhances the value-relevance of accounting information by increasing the earnings response coefficient (ERC). I control for firm size, market-to-book, analyst coverage, overall employee review of the firm, readability of the annual filings, and the interaction of SUE with these control variables. I further control forecast dispersion, forecast error, and beta.

3.3.6 Test of H4: Specificity and Product Market Competition

To test the disclosure constraint and provide empirical evidence for H4, I estimate the following equations:

$$Specificity = f(\alpha + \beta_1 Hindex + \beta_2 Lb_{contr} + \beta_3 Controls + \varepsilon), \quad (6)$$

$$Specificity = f(\alpha + \beta_1 Hindex \times Lb_{contr} + \beta_2 Controls + \varepsilon), \quad (7)$$

where coefficient β_1 in both equations provide evidence for H4. Equation (6) examines whether specificity is negatively associated with competition (while higher *Hindex* means lower competition, a positive β_1 represents this relationship), and equation (7) investigates whether the dependence on labor performance could offset managers' concerns about proprietary costs (which indicates a positive β_1). I control for firm characteristics, such as readability of the annual filings, debt issuance, whether the firm had a loss for the fiscal quarter, size, market-to-book ratio, leverage, ROA, and change in number of employees.

Chapter 4: Empirical Results

4.1 Specificity and Human Capital Performance

Panel A of Table 2 reports the test for the relationship between job advertisement specificity and employees' satisfaction, which is reflected in equation (1). The coefficients on *Spec* are all positive and statistically significant, and all results remain when year-quarter fixed effects and industry fixed effects are included. This finding indicates more detailed job advertisements positively predict employees' view of the firm, including their view of their job and senior management team. The coefficient on *Spec* is higher when employee satisfaction is measured as the approval of the corporate culture and optimism about the firm's business outlook, with values of 0.689 and 0.066, respectively. These results serve as direct evidence of a job advertisement disclosure benefit: more information provided to job applicants enhances future employees' perceptions of the firm. Additionally, this evidence is consistent with prior experimental and field studies and suggests information disclosure to job candidates can benefit employees in both entry and experienced positions in different occupations.

Panel B of Table 2 shows the results of estimating equation (2), which examines the relationship between job advertisement specificity and future turnover. The coefficient on *Spec* for column one is negative and significant, which suggests that specificity of job postings between quarter t and $t-1$ negatively predicts the turnover occurring from quarter t to $t+1$. I also test whether specificity predicts turnover rates of quarter $t+2$, $t+3$, and $t+4$. The negative and significant coefficient on *Spec* in columns

(2) and (4) indicates that the empirical evidence is consistent with the argument that more specific advertisements reduce the turnover of future employees.

4.2 Specificity and Organizational Performance

Table 3 reports the results when estimating equation (3) and provides evidence for the test of H2a. The positive and significant coefficients on *Spec* in both columns of Table 3 suggest that more specific job advertisements indicate improvements in future productivity. Table 4 also reports the results of estimating equation (4) and demonstrates the relationship between specificity and future earnings surprise, providing evidence for H2b. Coefficients on *Spec* are all positive and significant, indicating that job advertisement specificity positively predicts earnings. In particular, since SUE is measured as earnings innovation, column (3) of Table 4 reports the relationship between the change of specificity and earnings innovation. The positive coefficient is still consistent with prior findings. Combining the results of Tables 3 and 4, the evidence is consistent with the hypothesis that job advertisement specificity positively predicts productivity and ultimately financial performance.

4.3 Specificity and Value-Relevance of Earnings

As reported in Tables 1 and 2, job advertisement specificity indicates the performance of an important intangible assets—human capital. Table 5 presents the evidence for the test of H3, where I test whether this forward-looking information about intangibles could enrich the company's information environment and enhance the value-relevance of its accounting numbers. The coefficients on the interaction term of *SUE* and *Spec* in both columns (1) and (2) are significantly positive, indicating that, when the firm provides more specific job advertisements during the fiscal quarter, the earnings announcement at the quarter-end are more informative. This further suggests that job advertisements convey forward-looking information on the performance of intangibles and that this information is useful when the market evaluates accounting earnings.

4.4 Disclosure Constraint—Specificity and Product Market Competition

Table 6 reports the results of estimating equation (6) and (7), where I test whether product market competition inhibits disclosure through job advertisements. The coefficient on *Hindex* in column (2) is significantly positive, indicating that, when a firm faces less competition, its managers would provide more specific job advertisements. This finding is consistent with the proprietary cost hypothesis. Additionally, the coefficient on *Lb_contr* is also significantly positive, which further supports H1a and H1b, that is, that human-capital performance benefits motivate managers to commit to a higher level of disclosure.

The coefficient on the interaction of *Lb_contr* and *Hindex* is positive and significant, which further suggests that concerns about human capital performance and proprietary costs work together to determine managers' disclosure decisions: when a firm depends more on labor performance, managers' concerns over proprietary costs are alleviated.

Chapter 5: Additional Analysis

5.1 Endogeneity

The test of equations (6) and (7) indicates that specificity is determined by both firm-level and industry-level characteristics. To address this endogeneity issue, I use the BGT data and decompose the specificity into an exogenously determined component and a residual component, to test whether the findings still hold using exogenously determined specificity as the independent variable.

As discussed in section 3.1.1, BGT collects skills data and classifies each skill into a taxonomy, where the most aggregated level of classification is skill-family. This skill-family includes 28 distinct categories or skills. Figure 1 shows the specificity averaged by each skill in skill-family. Because of the innate features of different skills, the variation in specificity would be partially determined by the nature of the type of the skill, thus managers must describe some skills specifically in job advertisements due to their nature. However, for other skills, they prefer not to go into details. For example, if a company plans to hire someone with a specific background in religious studies, it is natural for the job description to be very detailed. On the other hand, if a company aims to hire a security adviser, the advertisement probably should be vague to protect the firm's security protocols. Different industries hire and use human capital in distinct ways, and I exploit the exogenous variation in how an industry uses skills and how specificity exogenously varies with different skills to decompose the specificity.

In particular, I use the industry average of each skill's proportion in all the skills the industry acquires during the fiscal quarter to proxy for the exogenous human capital formation for the industry. For each fiscal quarter, I first calculate the number of times each skill in the skill-family appeared, divided by the total number of skills required in the firm's job advertisements, as the firm-level proportion of skills. I then take an industry-quarter average of the firm-level proportion of skills. This industry-quarter proportion of each skill-family variable represents industry-level skill utilization and formation. I assume how industry uses skills is exogenously given, and I estimate the following equation:

$$Specificity = f\big(\alpha + \beta_1 skill_{family} + \beta_2 Hindex + \beta_3 Lb_{contr} + Control + \varepsilon\big). \tag{8}$$

When estimating equation (8), I also control for industry-quarter average of experience, specialized skills, number of employees, its quarterly change, and salary. I assume the industry requirements for its labor force as well as the way the industry uses human capital are exogenously given. Thus the predicted specificity minus the bias serves as the exogenously determined specificity, *Pspec*. Naturally, the residual specificity is *Rspec.* I then use this exogenously determined specificity to examine whether the main results hold.

Table 7 reports the results of estimating equation (3) while replacing *Spec* with *Pspec* and *Rspec.* The significantly positive coefficient on *Pspec* and the insignificant one on *Rspec* indicate that the exogenous component of job advertisement specificity consistently indicates improvement of future productivity. Table 8 repeats the estimation of equation (4) using *Pspec* and *Rspec*. The positive and significant coefficient on *Pspec* and the insignificant one on *Rspec* provide corroborative evidence that exogenously determined specificity positively predicts earnings. Moreover, I repeat this test using the earnings of the next one to four quarters as the dependent variables and find that *Pspec* positively predicts earnings for three of the four quarters. These results alleviate concerns over endogeneity and support the robustness of the main findings.

5.2 Diff-in-Diff Test Based on the American with Disabilities Act Amendments Act (ADAAA)

To further address the potential endogeneity issue and ensure the financial performance implications documented in this paper are mainly driven by the information content of job advertisements, I utilize an exogenous policy change on how firms prepare job descriptions as a natural experiment, to test whether the change in job descriptions affects performance.

The ADAAA is an amendment to the original Americans with Disability Act of 1990 (ADA) and other civil right laws governs the disability nondiscrimination issues. The original ADA has strict definition of disability and the standard for determining whether an individual is protected by the law is demanding. The enactment of the amendment is a direct response to such limitations in protecting the rights of persons with disabilities, and the major change of the ADAAA is in the expansion of the definition of disability. Especially, the Title I of the ADAAA governs the disputes in an employment relationship, and the U.S. Equal Employment Opportunity Commission (EEOC) is the agency to regulate and enforce ADAAA and its related complaints.

After the enactment of ADAAA in 2009, EEOC published the final rules to implement the ADAAA on March 25, 2011 and these rules became effective on May 24, 2011. The policy implications of ADA and ADAAA have been studied by scholars and practitioners since the enactments. Particularly, both academic findings (e.g. Stone and Colella, 1996) and HR consultants (e.g. Bridget Miller, 2014) suggest that job descriptions are critical in the compliance of ADA: the law requires the qualification of an individual with a disability should be evaluated solely based on the essential functions of the job[14], and based on EEOC's regulation, a written job description is one of the most important evidence to show such essential function (EEOC, 1992). Specifically, Bridget (2014) suggests that job descriptions could show the detailed requirements for the job, at the same time identify the essential requirements that have to be met by the candidates' qualifications. In other word, if a candidate with disability could meet all requirements of the job, then the candidate is protected by the ADAAA. However, if a candidate with disability could not meet the essential requirements, then he/she is not protected by the ADAAA thus the firm could reduce its litigation risk from potential ADA complaints. As a result, after the enforcement of the ADAAA, firms would naturally post more specific job requirements, to comply with the regulation at the same time use the job requirements as an evidence and justification for their hiring decisions, to protect them from potential labor disputes.

Although the ADAAA is a federal law and governs all private firms with more than 15 employees, it's impact still varies state-by-state. As indicated by Rosenbaum et al. (2011), many states have their own disability rights laws and some of them even exceed the standards and scopes of ADAAA, while other states have weaker disability protection regulations. This difference in state-level disability protection makes some firms more prone to ADA disputes when the state-level protection before ADAAA is

[14] HR Daily Advisor, "How Do Job Descriptions Relate to the ADA", https://hrdailyadvisor.blr.com/2014/04/07/how-do-job-descriptions-relate-to-the-ada/

weak. Thus for firms hire differently among different states, the imposed legal risk and the responsive change in the job descriptions vary by both the state level ADAAA complaint threat, and the proportion of employees hired within the state. To further identify the treated firms (firms that have a higher risk imposed by ADAAA) and the control firms (firms that are less affected by ADAAA), I use the BGT data and EEOC complaint data, to create a proxy to measure the firm-year ADAAA exposure.

For each state-year, EEOC publishes the data of the complaints received from the residents, as a percentage of the total annual complaints. I compare this percentage with the state's population. If the proportion of the state-year EEOC complaints exceed that of the state's population, I create a dummy variable *high_eeoc_state* equals to 1 (0 otherwise) to identify this state as high EEOC risk state.

Next, I use the BGT data to compute the number of firm-year job advertisements by states. This firm-year hiring ratio for each state is calculated as the number of distinct job advertisement posted by offices in the particular state, divided by the firm-year total hiring of the year. I multiply this firm-year-state hiring ratio with the *high_eeoc_state* indicator, then aggregate the firm-year-state ratio by each firm. The end result of this exercise is a proportion of the firm-year hiring that is exposed to higher risk of EEOC complaint. I interpret this ratio as the measure for the exposure to ADAAA litigation risk, as when this ratio is higher, the firm would have a larger proportion of employees hired from the states where the residents are more likely to file an EEOC complaint. I set the *ada_risk* indicator equals to 1 if this firm-year ratio is greater than the sample median, and 0 otherwise.

Table 10 reports the result of the Diff-in-Diff test based on a propensity-score matched sample. The entire sample in this study covers period from 2010 to 2016, I first constrain the sample to cover just one year before and one year after the enactment of ADAAA (2010 – 2012), then create a propensity score matched sample using the *ada_risk* as the treatment variable, and match on firm size, market-to-book ratio, leverage, earnings surprises, the total number of employee, the change of employee number, industry, fiscal year and quarter. I drop all observations that are off-support and keep the nearest neighbor, and run below regression:

$$Performance = f(\alpha + \beta_1 ada\_risk + \beta_2 postada + \beta_3 ada\_risk * postada + Control). \quad (9)$$

The first column of Table 10 reports the change of specificity for the high ADA risk firms after the enforcement of ADAAA. This result supports the view that ADAAA is an exogenous shock on how detail firms draft the job requirements, as I find job advertisement specificity significantly increased for the high ADA risk firms after the ADAAA. Consistent with the argument that more specific job advertisements improve the matching between the companies and the employees, I find a significantly negative coefficient on the interaction of *ada_risk* and *postada* when turnover rate is the dependent variable in equation (9). This finding indicates that after the enforcement of ADAAA, the human resource managements of the firms that are more exposed to the ADAAA are significantly improved. Moreover, I find significantly positive coefficients on the interaction terms when the dependent variables are the quarterly sales, or the earnings surprises. Collectively, the findings in this additional test further confirm the main findings of this paper, that job advertisement information affects firms' human capital management as well as financial performances.

5.3 Cross-Sectional Test of Specificity-Earnings Relationship

The analysis of disclosure through job advertisements relies on the argument that managers are motivated to provide more information to applicants for the sake of future firm performance. To further explore how specificity influences future performance, I test the cross-sectional variation in the specificity-earnings relationship. Specifically, I test how labor-performance dependence, number of job advertisements, and the average requirement of experience in job advertisements affect the positive relationship between specificity and future earnings.

H1 suggests that job advertisement specificity could indicate future financial performance because of its human capital implications. As a result, it is natural to argue that the relationship between specificity and future earnings would be stronger if the growth of the firm is more dependent on labor performance, if the number of job advertisements is greater or the open positions more senior. Table 9 provides the results for these conjectures. Consistent with H1 and H2b, the coefficients on the interaction term of *Chg_spec* and all three partition variables are significantly positive. This additional evidence adds to the argument that job advertisements contain forward-looking information about human capital performance and that this performance implication is jointly determined by the job advertisement information and the attributes of the recruitment.

Chapter 6: Conclusion

Answering the call for a study of the “process by which firms recruit and specifically how they advertise their openings” (Mortensen 1986), this paper empirically examines the benefits and the constraints of disclosure through job advertisements. Using attributes of millions of corporate job advertisements, I provide consistent evidence documenting that, as a special form of voluntary disclosure, job advertisements help improve firms’ hiring outcomes, thus enhancing overall organizational productivity and financial performance, and adding to the value-relevance of accounting numbers. These results augment the understanding of voluntary disclosure mechanisms by suggesting that labor performance implications could effectively substitute capital market benefits, and motivate managers’ disclosure through job advertisements.

This paper also adds to the ongoing debate over human capital disclosure, by pointing to an alternative source of information for investors and other corporate stakeholders. Additionally, the findings imply that, although created specifically for job applicants, labor market information could also be used by product market competitors and that the potential proprietary costs prevent managers from disclosing too much to labor market candidates. The empirical evidence presented here suggests multiple groups of audiences may actively monitor human capital related disclosure, and the findings could give policymakers a clearer picture of managerial incentives and constraints for disclosures related to corporate human capital. Taken together, this paper shows that job advertisement is an important voluntary disclosure channel, and its content is informative not only to job candidates, but also to capital- and product-market participants.

Appendices

Appendix I: Variable Definitions
Main Variables:

Spec: measure of specificity, calculated as quarterly average of the number of specific skills in the job posting divided by total number of skills requirement in the job posting

Pspec: predicted specificity, calculated as a linear prediction of firm-quarter Spec based on equation (8).

Respec: residual specificity, calculated as the firm-quarter actual specificity minus predicted specificity

Turnover: employee turnover rate, calculated as the firm-quarter number of job advertisements posted divided by the total number of employees for firm-year that have a net decrease of employee

Overall: the overall employees' rating (1–5) for the company, posted on www.glassdoor.com as of July 13, 2017

Culture: the employees' rating (1–5) for corporate culture of the company, posted on www.glassdoor.com as of July 13, 2017

Worklife: the employees' rating (1–5) for work-life balance of the company, posted on www.glassdoor.com as of July 13, 2017

Sr_mgt: the employees' rating (1–5) for senior management of the company, posted on www.glassdoor.com as of July 13, 2017

Career: the employees' rating (1–5) for career opportunity of the company, posted on www.glassdoor.com as of July 13, 2017

Recom: percentage of participating employees who would recommend the company to their friends, posted on www.glassdoor.com as of July 13, 2017

CEO: percentage of participating employees who approve the performance of CEO, posted on www.glassdoor.com as of July 13, 2017

Outlook: percentage of participating employees who hold a positive view of the company's business outlook, posted on www.glassdoor.com as of July 13, 2017

CAR3: cumulative abnormal return for -1 to 1 trading days around quarterly earnings announcement, scaled by standard deviation of abnormal returns for (-7, -1) trading days before quarterly earnings announcement, the earnings announcement day is set as day 0.

Revision: revision of analysts' forecasts consensus, calculated as median of forecasts in quarter t minus median of forecasts in quarter $t-1$ for quarter t using I/B/E/S data

SUE: standardized unexpected earnings, calculated as seasonal earnings difference minus the average earnings of past 10 quarters, divided by the standard deviation of the past 10 quarters' earnings

Specialized: percentage of skills that are specialized among all skill requirements in a job advertisement. The BGT data identifies a skill as specialized when it is only used in fewer than five occupations

Exp: the number of years of relative experience required by the position

Salary: the average of minimum salary and maximum salary. The minimum and maximum salary is estimated by a job search website such as Glassdoor or Monster and thus the coverage of salary data is constrained by the coverage of the job search websites

Control Variables:

Hindex: Rank of Herfindalh index of market share by industry. The Herfindalh index is calculated as sum of the squared market share of each publicly traded firm in a particular two-digit NAICS code. Market share is calculated as the sales of a particular firm divided by total sales of the NAICS industry

Rd_int: quarterly R&D intensity, calculated as R&D expense of current quarter scaled by total asset for each two-digit SIC industry

Bogindex: 10-k readability measure provided by Bonsall, Leone, and Miller (2015). This measure is the sum of three readability dimensions: sentence readability, word readability, and writing style. A higher Bog index indicates lower readability.

Debtiss: indicator variable equal to one if a company issued long-term debt in the current quarter, zero otherwise

Loss: indicator variable equal to one if firm is taking a loss in current quarter, zero otherwise

Size: logarithm of market capitalization

MtoB: logarithm of market value to book value

Lev: leverage, calculated as short-term plus long-term debt divided by market value of equity

ROA: return on assets, calculated as earnings divided by lagged total assets

Chg_emp: annual change of employee number calculated divided by lagged employee number

Lb_contr: industry level labor contribution to output growth based on Bureau of Labor Statistics's (BLS) and Bureau of Economic Analysis's (BEA) data

Simm: total similarity based on Hoberg and Phillips (2014), measured as the average of all pair-wise product similarity based on 10-K product description of firm *i* with all other *j* firms in product market

Review_ct: number of participating employees for the Glassdoor review

Stdret: standard deviation of daily stock returns between last and current earnings announcement

CAR27: cumulative abnormal return for -30 to -3 trading days before quarterly earnings announcement, scaled by standard deviation of abnormal returns for (-30, -3) trading days before quarterly earnings announcement, the earnings announcement day is set as day 0.

Vol: average shares traded between last and current quarterly earnings announcement

Spread: average bid-ask spread between last and current quarterly earnings announcement

Numest: number of analysts following based on I/B/E/S data

Disp: analysts' forecast dispersion, calculated as the standard deviation of analysts' quarterly earnings forecasts in the most recent period before the announcement date, scaled by earnings volatility of the past 10 quarters

FE: analysts' forecast errors, calculated as the consensus of analysts' forecasts minus the actual value of the EPS, scaled by earnings' volatility of past 10 quarters

Appendix II: Examples of Job Advertisements Specificity

Panels A and B of Appendix II provide the data structure of two examples of job advertisements posted by Microsoft in BGT data and the calculation of the specificity measure. See Appendix I for variable definitions.

Panel A: Example Job Advertisement 1

Job ID: 432000163 Company: Microsoft Corp. Post Date: March 7, 2014

Skill Family	*Skill Cluster*	*Skill*	Identifiability	Total Skill Requirement	Identifiable Skills	Specificity
Information Technology	*C and C++*	*C++*	1	9	4	0.556
Analysis	*Data Mining*	*Data Mining*	0	9	4	0.556
Sales	*General Sales Practices*	*Description and Demonstration of Products*	1	9	4	0.556
Analysis	*Machine Learning*	*Machine Learning*	0	9	4	0.556
Information Technology	*Microsoft Development Tools*	*Microsoft C#*	1	9	4	0.556
Analysis	*Natural Language Processing (NLP)*	*Natural Language Processing*	0	9	4	0.556
Manufacturing and Production	*Product Development*	*Product Development*	0	9	4	0.556
Information Technology	*Software Development Principles*	*Software Engineering*	1	9	4	0.556
Information Technology	*Software Development Principles*	*Software Development*	1	9	4	0.556

Panel B: Example Job Advertisement 2

Job ID: 432067138 Company: Microsoft Corp. Post Date: March 13, 2014

Skill Family	*Skill Cluster*	*Skill*	Identifiability	Total Skill Requirement	Identifiable Skills	Specificity
Information Technology	*C and C++*	*C++*	1	16	14	0.875
Information Technology	*Data Warehousing*	*Data Modeling*	1	16	14	0.875
Information Technology	*Database Administration*	*Relational Databases*	1	16	14	0.875
Information Technology	*Database Administration*	*Relational Database Design*	1	16	14	0.875
Information Technology	*Enterprise Resource Planning*	*Enterprise Resource Planning*	0	16	14	0.875
Architecture and Construction	*General Architecture*	*Architectural Design*	1	16	14	0.875
Information Technology	*Java*	*JAVA*	1	16	14	0.875
Information Technology	*Microsoft Development Tools*	*ASP*	1	16	14	0.875
Information Technology	*Microsoft Development Tools*	*.NET Programming*	1	16	14	0.875
Information Technology	*Microsoft Development Tools*	*Microsoft C#*	1	16	14	0.875
Manufacturing and Production	*Product Development*	*Prototyping*	1	16	14	0.875
Information Technology	*Programming Principles*	*Object-Oriented Analysis and Design (OOAD)*	1	16	14	0.875
Business	*Project Management*	*Project Management*	0	16	14	0.875
Information Technology	*Software Development Principles*	*Service-Oriented Architecture (SOA)*	1	16	14	0.875
Information Technology	*Software Development Principles*	*Software Architecture*	1	16	14	0.875
Information Technology	*Software Development Principles*	*Software Development*	1	16	14	0.875

Panel C: Difference of Specificity Between Artificial Intelligence Jobs and Other Jobs of Microsoft

This table provides a t-test of the average specificity between job advertisements that require skills for artificial intelligence and jobs that do not. All job advertisements are posted by Microsoft between January and April 2014. See Appendix I for variable definitions.

Mean of Specificity	
Postings without Machine Learning Skills	0.768
Postings with Machine Learning Skills	0.659
Difference	0.109***
	(123.36)

Mean of Specificity	
Postings without NPL Skills	0.761
Postings with NPL Skills	0.655
Difference	0.106***
	(39.31)

Mean of Specificity	
Postings without Machine Learning or NPL Skills	0.761
Postings with Machine Learning and NPL Skills	0.646
Difference	0.115***
	(34.37)

Mean of Specificity	
Postings with Manufacturing Design Skills	0.737
Postings with Machine Learning and NPL Skills	0.646
Difference	0.092***
	(17.94)

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Table 1: Sample Description

Table 1, Panel A, presents the sample selection criteria. Panel B presents the key statistics comparison between sample used by this study and the universe of Compustat quarterly data over the sample period between January 2010 and December 2016. Panel C presents the descriptive statistics of the sample used by this study. Panel D presents job advertisement specificity and number of job advertisements by industry. All variables are defined in Appendix I.

Panel A: Sample Selection

	Number of Firms
BGT and Compustat Firms	4511
Less Firms with less than 10 quarters of earnings or no I/B/E/S data	(1087)
Less Firms with no CRSP abnormal return data	(592)
Firms in Final Sample	2832

Panel B: Comparison Between Current Sample and Compustat Quarterly Data

Compustat

Variable	N	Mean	Std.	Min	25%	50%	75%	Max
Size	229,599	5.254	2.661	-12.72	3.389	5.242	7.148	13.48
Leverage	198,693	0.815	2.222	0	0.00130	0.166	0.621	16.73
Market-to-Book	208,703	2.827	6.945	0.0242	0.374	0.856	1.913	40.01
ROA	218,680	-0.077	0.276	-1.509	-0.030	0.002	0.013	0.138

Sample of this Study

Variable	N	Mean	Std.	Min	25%	50%	75%	Max
Size	33,131	7.394	1.767	1.245	6.144	7.322	8.518	13.483
Leverage	30,865	0.487	1.119	0.000	0.030	0.200	0.516	16.729
Market-to-Book	33,129	1.417	1.593	0.024	0.513	0.974	1.744	40.005
ROA	33,139	0.006	0.046	-1.509	0.002	0.009	0.020	0.138

Panel C: Descriptive Statistics of Job Advertisement Attributes

VARIABLES	(1) N	(2) Mean	(3) Std.	(4) 25%	(5) 50%	(6) 75%
Spec	33,139	0.825	0.086	0.789	0.831	0.871
Chg_spec	27,696	0.007	0.121	-0.036	0	0.038
Pspec	23,632	-0.070	0.103	-0.147	-0.104	0.028
Respec	22,071	0	0.074	-0.030	0.005	0.039
Specialized	33,139	0.722	0.120	0.656	0.722	0.788
Exp	31,138	4.477	1.642	3.448	4.400	5.312
Salary	12,290	11.042	0.626	10.631	11.041	11.428
Num_jobs	32,111	0.026	0.038	0.004	0.013	0.033
Turnover	11,647	-4.65	1.661	-5.570	-4.397	-3.514
Size	33,131	7.394	1.767	6.144	7.322	8.518
Lev	30,865	0.487	1.119	0.030	0.200	0.516
MtoB	33,129	1.417	1.593	0.513	0.974	1.744
PP&E	19,533	5,700	21,066	148.304	671.697	2,811
Sales	33,136	1,505	5,595	81.537	251.902	862.753
Age	33,139	92.201	47.869	54.000	81.000	123.000
Opt_std	33,139	52.554	103.147	4.275	13.026	44.204
Opt_comp	33,139	326.621	46.297	293	333	360
SI	32,769	-0.003	0.013	-0.001	0	0
Acc	32,860	-0.002	0.059	-0.022	0	0.021
Div	33,139	0.083	0.275	0	0	0
CAR3	33,139	0.007	2.610	-1.564	0.039	1.598
CAR27	33,139	0.005	0.107	-0.049	0.004	0.057
Beta	33,138	1.187	1.000	0.605	1.118	1.705
SUE	33,139	-0.013	0.991	-0.630	-0.003	0.618
ROA	33,139	0.006	0.046	0.002	0.009	0.020
Hindex	26,958	2.432	1.942	1	1	3
RD	33,139	9.165	19.021	0	0	7.288
RD_int	33,139	0.003	0.003	0	0.001	0.005
Numest	33,139	9.867	7.556	4	8	14
Revision	33,139	-0.023	0.100	-0.040	-0.010	0.010
Disp	30,942	0.043	0.069	0.010	0.020	0.050
FE	33,023	-0.000	0.013	-0.001	0.000	0.002
Lb_contr	33,070	0.066	0.576	-0.217	-0.046	0.230
Stdret	32,862	-4.001	0.483	-4.337	-4.034	-3.692
Emp	32,317	16.745	71.455	0.901	3.079	10.206
Chg_emp	32,075	0.067	0.240	-0.019	0.032	0.104
Review_ct	28,587	3,649	10,640	43	144	502
Overall	29,091	3.272	0.490	3	3.300	3.600
Culture	29,091	3.214	0.601	2.800	3.200	3.600
Worklife	29,091	2.870	0.523	2.500	2.900	3.200
Senior_mgt	29,091	2.870	0.523	2.500	2.900	3.200
Career_oppo	29,091	2.985	0.484	2.700	3.000	3.300
CEO_app	28,529	0.713	0.213	0.580	0.750	0.880
Bus_out	28,222	0.462	0.185	0.320	0.460	0.590

Panel D: Job Advertisements and Specificity by Industry

This table provides the distribution of job advertisements, number of firms, average specificity by industry, the counts of job advertisements and industry definitions based on BGT data.

1 Digit SIC	Industry	Specificity	# of Job Advertisements	# of Firms
0	Agriculture, Forestry, and Fishing	0.825	15,435	5
1	Mining	0.821	144,963	135
2	Manufacturing	0.813	672,330	422
3	Manufacturing	0.810	1,258,186	678
4	Transportation, Communication, Electric	0.828	900,269	239
5	Wholesale and Retail	0.839	2,034,972	253
6	Finance, Insurance, and Real Estate	0.843	1,719,805	600
7	Services	0.830	1,242,052	378
8	Services	0.824	541,838	109
9	Nonclassifiable	0.793	106,732	8

Penal E: Summary Statistics of Specificity by Industry

This table provides the summary statistics of the job-advertisement specificity distribution within each one-digit SIC industry.

1 Digit SIC	Mean	Std.	Min	25%	50%	75%	Max
0	0.825	0.097	0.550	0.794	0.809	0.817	1
1	0.821	0.100	0.488	0.774	0.827	0.879	1
2	0.813	0.082	0.488	0.778	0.818	0.855	1
3	0.810	0.081	0.488	0.778	0.817	0.852	1
4	0.828	0.088	0.488	0.791	0.833	0.873	1
5	0.840	0.088	0.488	0.800	0.843	0.890	1
6	0.844	0.090	0.488	0.810	0.854	0.895	1
7	0.829	0.078	0.488	0.804	0.837	0.870	1
8	0.824	0.083	0.488	0.781	0.833	0.872	1
9	0.793	0.076	0.488	0.784	0.800	0.827	1

Figure 1: Job Advertisement Specificity by Skill-family

Figure 1 presents the job advertisement specificity by each skill-family. For every job advertisement in BGT data, each required skill is described by three categorical variables in the dataset: skill-family, skill-cluster, and skill. The skill-family variable is the most aggregated level.

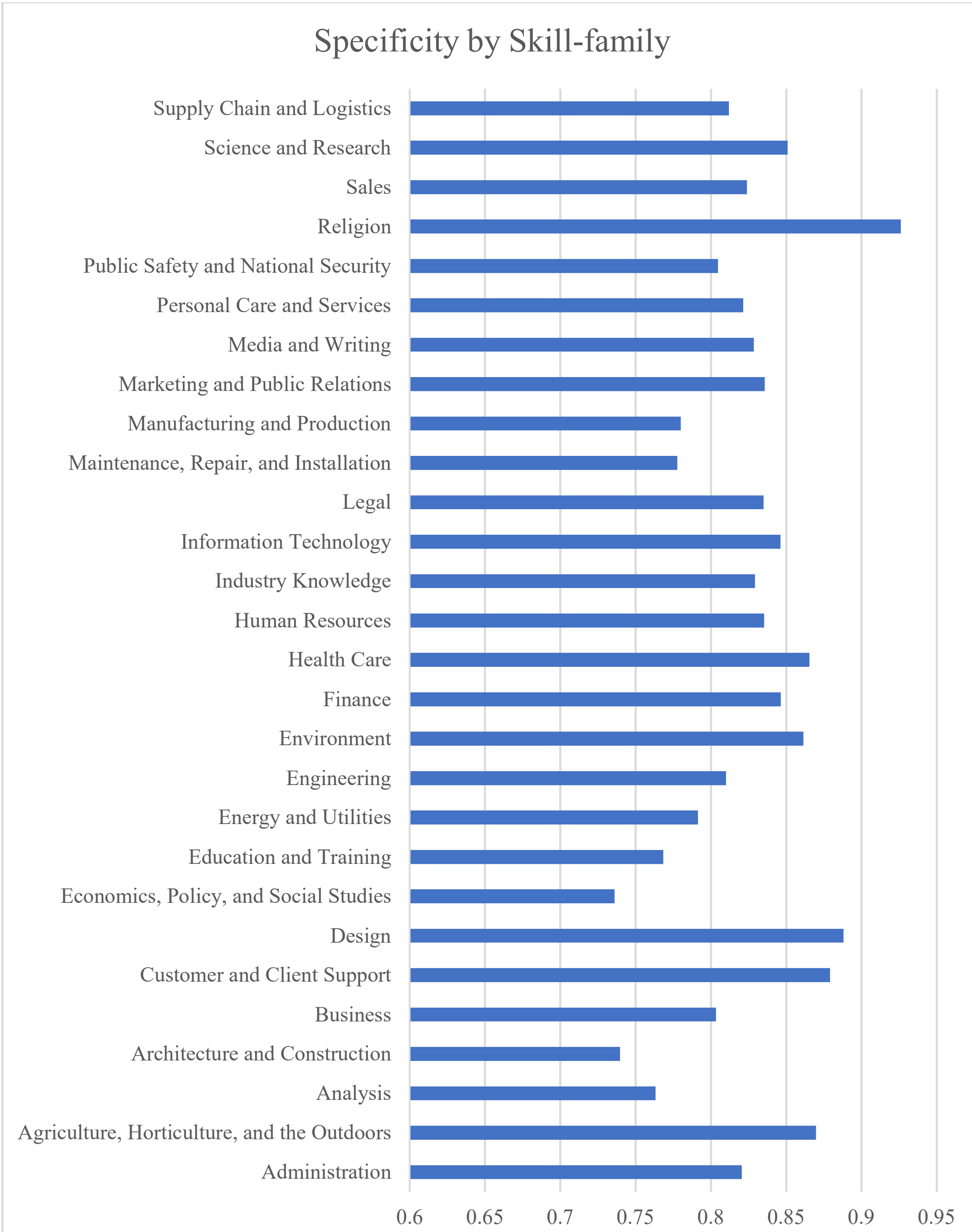

Table 2: Specificity and Human Capital Performance

Panel A: Job Advertisement Specificity and Employees' Satisfaction

This table presents the relationship between job advertisement specificity and employees' satisfaction. Columns 1–5 report results from an ordinal logistic regression to estimate the rating improvements by higher specificity; columns 6–8 report results from an OLS regression to estimate the percentage approval improvements by higher specificity. All Glassdoor data is collected on July 13, 2017. See Appendix I for variable definitions.

	Overall	Culture	Worklife	Sr_mgt	Career	Recom	CEO	Outlook
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Spec	**0.515*** **	**0.689*** **	**0.571*** **	**0.571*** **	**0.501*** **	**0.057*** **	**0.051*** **	**0.066*** **
	(3.513)	(4.654)	(3.875)	(3.875)	(3.375)	(4.412)	(3.125)	(4.679)
Size	0.323***	0.205***	0.218***	0.218***	0.282***	0.027***	0.029***	0.024***
	(27.008)	(17.814)	(18.913)	(18.913)	(23.746)	(26.553)	(23.181)	(20.770)
MtoB	0.085***	0.129***	0.120***	0.120***	0.117***	0.009***	0.010***	0.013***
	(8.825)	(12.193)	(11.219)	(11.219)	(12.066)	(11.292)	(11.113)	(13.704)
Lev	-0.017	-0.031**	-0.002	-0.002	-0.010	-0.001	0.000	-0.002**
	(-1.513)	(-2.353)	(-0.153)	(-0.153)	(-0.863)	(-1.241)	(0.273)	(-2.434)
ROA	1.796***	1.809***	2.236***	2.236***	0.396	0.226***	0.201***	0.337***
	(5.042)	(5.325)	(5.870)	(5.870)	(1.201)	(7.087)	(4.894)	(9.167)
Review_ct	0.019**	0.045***	-0.045***	-0.045***	0.120***	0.000	-0.007***	-0.006***
	(2.426)	(5.757)	(-5.770)	(-5.770)	(15.230)	(0.466)	(-8.251)	(-7.043)
Stdret	0.203***	0.151***	0.053*	0.053*	0.200***	0.006**	0.005	-0.009***
	(6.598)	(4.931)	(1.760)	(1.760)	(6.503)	(2.338)	(1.561)	(-3.174)
Num_jobs	0.002***	0.002***	0.003***	0.003***	0.004***	0.000***	0.000**	0.000
	(6.243)	(6.117)	(6.791)	(6.791)	(9.982)	(6.181)	(2.522)	(1.073)
Constant						0.462***	0.667***	0.173***
						(31.225)	(35.725)	(10.560)
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,526	26,526	26,526	26,526	26,526	26,329	26,014	25,752
R-squared						0.163	0.128	0.150

Robust z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Panel B: Specificity and Future Turnover Rate

This table presents the relationship between job advertisement specificity and future turnover. This test is conducted on a subsample where all firms' number of employees fell from last year. $Turnover_{t+n}$ is the number of job advertisements posted during the *n*th quarter in the future, scaled by the total number of employees. See Appendix I for variable definitions.

	Dependent variable: $Turnover_{t+n}$			
VARIABLES	(1)	(2)	(3)	(4)
	$Turnover_{t+1}$	$Turnover_{t+2}$	$Turnover_{t+3}$	$Turnover_{t+4}$
Spec	**-0.377****	**-0.446****	-0.165	**-0.498***
	(-2.123)	(-2.032)	(-0.679)	(-1.857)
Chg_emp	-0.243*	-0.136	-0.145	-0.167
	(-1.649)	(-0.768)	(-0.739)	(-0.708)
Turnover	0.341***	0.139***	0.050***	-0.009
	(29.432)	(10.171)	(3.287)	(-0.519)
SUE	0.013	0.030**	0.031**	0.030*
	(1.141)	(2.292)	(2.125)	(1.885)
Specialized	-0.017	-0.037	0.175	-0.068
	(-0.121)	(-0.215)	(0.903)	(-0.315)
Qtr4	1.151***	3.167***	-2.320**	2.814***
	(3.625)	(14.682)	(-2.476)	(3.168)
Beta	0.001	0.005	0.001	0.002
	(0.085)	(0.318)	(0.060)	(0.074)
Experience	0.002	0.016	0.019	-0.008
	(0.232)	(1.429)	(1.501)	(-0.567)
Size	-0.016	-0.059	-0.070	-0.006
	(-0.288)	(-0.839)	(-0.849)	(-0.066)
MtoB	0.015	0.070*	0.121***	0.056
	(0.441)	(1.717)	(2.651)	(1.121)
Lev	-0.031	-0.022	-0.030	-0.041
	(-1.533)	(-0.835)	(-0.952)	(-1.224)
ROA	0.423	0.172	-0.328	-0.433
	(0.970)	(0.339)	(-0.616)	(-0.806)
Constant	-3.306***	-6.082***	-3.267***	-6.688***
	(-7.011)	(-10.122)	(-4.159)	(-5.294)
Observations	7,420	5,915	4,644	3,554
Adj. R-squared	0.156	0.085	0.048	0.050
Yr.-Qtr. Fixed Eff.	Yes	Yes	Yes	Yes
Firm Fixed Eff.	Yes	Yes	Yes	Yes

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

Table 3: Specificity and Future Productivity

This table presents the relationship between job advertisement specificity and next-year's total-factor productivity (TFP). The firm-year TFP measure is provided by Selale Tuzel, based on Imrohoroglu and Tuzel (2014). *Chg_spec* is the difference of $Spec_t$ and $Spec_{t-1}$ scaled by $Spec_{t-1}$. This test is conducted on a subsample with the period between 2010–2013, due to TFP data availability. See Appendix I for variable definitions.

	Dependent variable: TFP_{t+1}	
VARIABLES	(1)	(2)
Spec	**0.137*****	**0.173****
	(2.688)	(2.013)
Size	0.155***	0.190***
	(66.599)	(31.468)
MtoB	0.031***	0.033***
	(9.681)	(5.509)
Lev	0.012***	0.025***
	(2.791)	(3.492)
R&D		-0.001**
		(-2.154)
Emp		-0.001***
		(-9.385)
Overall		0.001
		(0.083)
Simm		0.032***
		(2.913)
Hindex		0.055**
		(2.289)
PP&E		-0.000***
		(-7.223)
Sales		0.000***
		(8.025)
Constant	-1.564***	-2.060***
	(-34.247)	(-7.817)
Observations	11,601	4,929
R-squared	0.296	0.421
Glassdoor Review Ctrl.	No	Yes

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

Table 4: Specificity and Future Earnings' Surprise

This table presents the relationship between job advertisement specificity and future earnings. *Chg_spec* is the difference of $Spec_t$ and $Spec_{t-1}$ scaled by $Spec_{t-1}$. See Appendix I for variable definitions.

	Dependent variable: SUE_{t+1}		
VARIABLES	(1)	(2)	(3)
Spec	**0.131***	**0.300*****	
	(1.776)	(3.115)	
Chg_spec			**0.188*****
			(2.733)
SUE	0.291***	0.297***	0.296***
	(49.204)	(16.439)	(15.955)
Size	-0.007**	0.018*	0.016
	(-2.198)	(1.702)	(1.617)
MtoB	0.003	-0.000	-0.001
	(0.659)	(-0.028)	(-0.133)
Lev	0.010*	0.002	0.007
	(1.683)	(0.285)	(0.835)
Beta		-0.017***	-0.017**
		(-3.014)	(-2.470)
Specialized		0.104	0.058
		(1.581)	(0.723)
Experience		-0.003	-0.003
		(-0.644)	(-0.567)
Acc		-0.627***	-0.551***
		(-4.277)	(-3.184)
Div		0.009	0.008
		(0.381)	(0.223)
Age		0.000	0.000
		(0.428)	(0.142)
SI		-7.643***	-7.651***
		(-11.618)	(-10.943)
Opt_Std		-0.000*	-0.000
		(-1.809)	(-1.442)
Seg		-0.001	-0.003**
		(-1.187)	(-1.967)
Opt_comp		0.000	0.000*
		(1.370)	(1.947)
Numest		-0.002	-0.002
		(-0.878)	(-0.976)
FE		0.793	0.661
		(0.841)	(0.750)
Disp		0.086	0.056
		(0.930)	(0.518)
Revision		0.337***	0.326***
		(3.800)	(3.946)
Bogindex		-0.001	-0.001
		(-1.055)	(-0.964)
ROA		-1.505**	-1.480**
		(-2.522)	(-2.333)
Observations	25,816	18,102	16,353
Adj. R-squared	0.086	0.119	0.112
Yr-Qtr Fixed Eff.	No	Yes	Yes
Ind. Fixed Eff.	No	Yes	Yes
Glassdoor Review Ctrl.	No	Yes	Yes

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

Table 5: Specificity and Value-relevance of Earnings

This table presents the relationship between job advertisement specificity and future total-factor productivity (TFP). This test is conducted on a subsample with the period between 2010–2013. $Turnover_{t+n}$ is the number of job advertisements posted of the *n*th quarter in the future, scaled by the total number of employees. See Appendix I for variable definitions.

	Dependent variable: CAR3	
VARIABLES	(1)	(2)
SUE×Spec	**0.439*****	**0.361****
	(2.790)	(2.138)
SUE×Size	-0.003	0.025**
	(-0.361)	(2.332)
SUE×MtoB	-0.003	0.002
	(-0.358)	(0.183)
SUE×Overall		0.028
		(1.139)
SUE×Numest		-0.002
		(-0.544)
SUE×Bogindex		-0.002
		(-1.031)
SUE	-0.027	-0.173
	(-0.182)	(-0.733)
Spec	0.236	0.296**
	(1.371)	(1.984)
Lev	-0.004	0.063***
	(-0.348)	(3.939)
Size	0.006	-0.016
	(0.401)	(-0.827)
MtoB	-0.013	-0.013
	(-1.351)	(-1.576)
CAR27		3.654***
		(11.842)
Overall		0.084***
		(3.402)
Bogindex		0.000
		(0.051)
Numest		0.002
		(0.626)
Disp		-0.542*
		(-1.877)
Revision		-0.256
		(-1.162)
FE		25.179***
		(14.057)
Beta		-0.036**
		(-2.215)
Constant	-8.729***	-8.575***
	(-41.817)	(-34.269)
Observations	30,865	24,273
Adj. R-squared	0.020	0.057
Yr.-Qtr. Fixed Eff.	Yes	Yes
Ind. Fixed Eff.	Yes	Yes
Glassdoor Review Ctrl.	No	Yes

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

Table 6: Specificity and Product Market Competition

This table presents the test on the incentive and constraint of job advertisement specificity. See Appendix I for variable definitions.

	Dependent variable: Spec			
VARIABLES	(1)	(2)	(3)	(4)
Lb_contr	**0.007*****			
	(4.505)			
Hindex		**0.003*****		-0.010**
		(4.129)		(-2.077)
Simm			**0.003*****	
			(3.822)	
Lb_contr				-0.013
				(-1.338)
Lb_contr×Hindex				**0.006*****
				(2.623)
Rd_int	0.494	0.472	-0.173	0.458
	(1.309)	(1.272)	(-0.482)	(1.195)
RD	0.000***	0.000***	0.000***	0.000***
	(4.790)	(4.287)	(4.177)	(4.280)
Debt_iss	-0.002	-0.001	-0.001	-0.001
	(-0.977)	(-0.921)	(-0.627)	(-0.911)
Loss	-0.003	-0.004	-0.003	-0.004*
	(-1.487)	(-1.617)	(-1.429)	(-1.651)
Chg_emp	-0.006**	-0.006**	-0.006**	-0.007***
	(-2.220)	(-2.424)	(-2.205)	(-2.601)
Size	-0.002***	-0.002***	-0.002***	-0.002***
	(-4.163)	(-4.159)	(-4.360)	(-4.115)
MtoB	0.002***	0.002**	0.001**	0.002**
	(2.864)	(2.309)	(2.207)	(2.333)
Lev	0.002***	0.002***	0.002***	0.002***
	(4.802)	(4.544)	(4.287)	(4.755)
Bogindex	-0.000	0.000	-0.000	0.000
	(-0.536)	(0.122)	(-1.144)	(0.139)
Specialized	-0.182***	-0.181***	-0.181***	-0.181***
	(-20.611)	(-19.476)	(-20.449)	(-19.468)
Software	0.030**	0.018	0.033***	0.017
	(2.440)	(1.379)	(2.677)	(1.336)
Exp	-0.003***	-0.003***	-0.003***	-0.003***
	(-4.525)	(-4.082)	(-4.482)	(-4.048)
Salary	0.002*	0.003***	0.002*	0.003***
	(1.699)	(2.842)	(1.787)	(2.853)
ROA	-0.073***	-0.066**	-0.067**	-0.063**
	(-2.596)	(-2.160)	(-2.367)	(-2.079)
Constant	0.920***	0.885***	0.932***	0.912***
	(59.129)	(51.141)	(58.558)	(39.756)
Yr-Qtr Fixed Eff.	Yes	Yes	Yes	Yes
Ind. Fixed Eff.	Yes	Yes	Yes	Yes
Observations	10,653	8,783	10,453	8,750
R-squared	0.217	0.227	0.219	0.227

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

Table 7: Expected Specificity, Residual Specificity and Future Productivity

This table presents the relationship between expected specificity, residual specificity and one-year-ahead total-factor productivity (TFP). The firm-year TFP measure is provided by Selale Tuzel, based on Imrohoroglu and Tuzel (2014). This test is conducted on a subsample with the period between 2010–2013, due to TFP data availability. Pspec is the exogenously determined job advertisement specificity. Rspec is the residual specificity. See Appendix I for variable definitions.

	Dependent variable: TFP_{t+1}	
VARIABLES	(1)	(2)
Pspec	**0.117*****	
	(2.832)	
Rspec		0.005
		(0.092)
Size	0.152***	0.148***
	(16.468)	(16.229)
MtoB	0.012*	0.013**
	(1.834)	(1.985)
Lev	0.026***	0.024***
	(3.045)	(2.873)
R&D	-0.000	-0.000
	(-0.135)	(-0.142)
Emp	-0.001***	-0.001***
	(-3.255)	(-3.201)
Overall	0.050	0.053
	(1.519)	(1.611)
Simm	0.008	0.010
	(0.635)	(0.767)
Hindex	0.011	0.010
	(1.008)	(0.871)
PP&E	-0.000***	-0.000***
	(-2.808)	(-2.939)
Sales	0.000*	0.000*
	(1.730)	(1.792)
Constant	-1.565***	-1.541***
	(-3.477)	(-3.422)
Observations	4,237	4,237
R-squared	0.330	0.330
Glassdoor Review Ctrl.	Yes	Yes

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

Table 8: Expected Specificity, Residual Specificity and Future Earnings' Surprise

Panel A: Exogenously Determined Specificity and Next Quarter Earnings' Surprise

This table presents the results of how specificity predicts earnings' surprise. Pspec is the exogenously determined job advertisement specificity. Rspec is the residual specificity.

	Dependent variable: SUE_{t+1}	
VARIABLES	(1)	(2)
Pspec	**0.579***	
	(1.749)	
Rspec		0.185
		(1.152)
SUE	0.281***	0.281***
	(14.317)	(14.287)
Beta	-0.020***	-0.020***
	(-2.590)	(-2.631)
Specialized	0.060	0.075
	(0.750)	(0.963)
Experience	-0.009*	-0.008
	(-1.689)	(-1.495)
Overall	-0.001	-0.001
	(-0.027)	(-0.012)
Acc	-0.594***	-0.601***
	(-3.345)	(-3.395)
Div	0.010	0.008
	(0.216)	(0.190)
Size	-0.002	-0.003
	(-0.226)	(-0.255)
MtoB	0.003	0.004
	(0.652)	(0.826)
Lev	0.008	0.008
	(0.940)	(0.949)
Age	0.000	0.000
	(0.788)	(0.791)
Si	-7.418***	-7.412***
	(-10.919)	(-10.802)
Opt_std	0.000	0.000
	(0.677)	(0.659)
Seg	-0.003**	-0.003**
	(-1.999)	(-2.073)
Opt_comp	0.000	0.000
	(1.488)	(1.529)
Numest	-0.001	-0.001
	(-0.339)	(-0.297)
FE	1.310	1.330
	(1.291)	(1.309)
Disp	0.149	0.153
	(1.270)	(1.321)
Revision	0.370***	0.370***
	(3.835)	(3.816)
Bogindex	-0.001	-0.001
	(-0.708)	(-0.541)
ROA	-1.287**	-1.285**
	(-2.192)	(-2.185)
Observations	12,989	12,989
Adj. R-squared	0.104	0.103
Yr-Qtr Fixed Eff.	Yes	Yes
Ind. Fixed Eff.	Yes	Yes

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

Panel B: Expected Specificity, Residual Specificity and Subsequent Earnings' Surprises

This table presents the relationship between job advertisement specificity and subsequent one to four quarters' earnings' surprises. SUE_{t+n} is the standardized unexpected earnings of the *n*th quarter in the future. Pspec is the exogenously determined job advertisement specificity. Rspec is the residual specificity. See Appendix I for variable definitions.

	Dependent variable: SUE_{t+n}			
	(1)	(2)	(3)	(4)
VARIABLES	Q1	Q2	Q3	Q4
Spec	**0.300*** **	0.003	0.045	0.030
	(3.115)	(0.035)	(0.437)	(0.281)
Pspec	**0.579***	0.211	**0.908****	**0.863****
	(1.749)	(0.556)	(2.432)	(2.075)
Rspec	0.185	-0.113	-0.126	-0.099
	(1.152)	(-0.831)	(-0.905)	(-0.452)
Ctrl. Var.	Yes	Yes	Yes	Yes
Yr.-Qtr. Fixed Eff.	Yes	Yes	Yes	Yes
Ind. Fixed Eff.	Yes	Yes	Yes	Yes

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

Table 9: Cross-Sectional Test of Specificity-Earnings Relationship

This table presents the cross-sectional variation of the relationship between job advertisement specificity and future earnings. *Chg_spec* is the difference of $Spec_t$ and $Spec_{t-1}$ scaled by $Spec_{t-1}$. See Appendix I for variable definitions.

	Dependent variable: SUE_{t+1}		
VARIABLES	(1)	(2)	(3)
Chg_spec×Lb_contr	**0.145****		
	(2.389)		
Chg_spec×Num_jobs		**3.320****	
		(2.072)	
Chg_spec×Experience			**0.384*****
			(3.077)
Lb_contr	-0.030		
	(-1.219)		
Num_jobs		-0.455***	
		(-3.187)	
Experience			-0.021
			(-1.099)
Chg_spec	0.188***	0.126	-0.393*
	(2.724)	(1.580)	(-1.861)
SUE	0.295***	0.294***	0.296***
	(15.948)	(13.639)	(13.949)
Constant	1.118**	1.095**	1.118**
	(2.488)	(2.199)	(2.287)
Observations	16,322	16,235	16,353
Adj. R-squared	0.103	0.118	0.104
Ctrl. Variables	Yes	Yes	Yes
Yr.-Qtr. Fixed Eff.	Yes	Yes	Yes
Ind. Fixed Eff.	Yes	Yes	Yes
Glassdoor Review Ctrl.	Yes	Yes	Yes

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

Table 10: Diff-in-Diff Test Based on the Enforcement of ADAAA
This table reports the results for the diff-in-diff test using ADAAA as natural experiment. The design and variables are defined in Section 5.2

VARIABLES	(1) Specificity	(2) Sales	(3) SUE	(4) Turnover
ada_risk	-0.013	-0.012	-0.088	0.522
	(-0.422)	(-0.779)	(-0.753)	(1.501)
postada	-0.058	-0.014	-0.162*	0.306**
	(-1.356)	(-0.803)	(-1.876)	(2.007)
ada_risk×postada	**0.049***	**0.027*****	**0.111***	**-0.275****
	(1.791)	(2.703)	(1.686)	(-2.375)
Specialized	-0.821***	-0.017	-0.193	-0.031
	(-7.843)	(-0.586)	(-1.125)	(-0.058)
Exp	-0.008	0.001	0.002	0.021
	(-1.270)	(0.314)	(0.131)	(0.705)
Size	-0.064*	0.226***	-0.459***	0.341*
	(-1.915)	(8.991)	(-4.438)	(1.848)
MtoB	0.016	-0.101***	0.241***	-0.053
	(0.680)	(-5.934)	(4.036)	(-0.491)
Lev	-0.018	0.067***	-0.034	0.034
	(-1.128)	(4.685)	(-1.216)	(0.783)
ROA	-0.083	2.130***	16.848***	-0.348
	(-0.228)	(5.112)	(11.941)	(-0.614)
R&D	0.000	0.001**	0.001	0.002
	(0.688)	(2.462)	(0.679)	(0.433)
Constant	2.582***	3.079***	3.387***	-6.582***
	(10.072)	(10.676)	(4.665)	(-5.081)
Observations	6,198	6,198	6,198	1,916
R-squared	0.026	0.319	0.199	0.084
Year-Quarter Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes

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

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