# Talking to hire: How small firms pave their way to hire when large firms lay off

**Jung Min Kim** **Sugata Roychowdhury** **Siqi Zheng**

Kellogg School of Management, Northwestern University

June, 2024

**Abstract**

We study how firms change their hiring and disclosure strategies when they face greater hiring opportunities. In the setting of the technology industry's massive layoffs, we find evidence consistent with small firms increasing hiring and enhancing their information environment when large firms in the same industry engage in layoffs. Specifically, small firms increase their number of job postings following large firms' downsizing, and those firms that intend to hire further increase the length of their job postings to provide more information to their prospective employees. We find that small firms' hiring speed accelerates following large firms' downsizing, and that the improvement in hiring speed is driven by those firms that increase information disclosure through longer job postings. We also examine firms' use of other disclosure channels to find that small firms increase their media press releases, which helps accelerate their hiring speed when the information is carried by tech-oriented media sources. Furthermore, consistent with human capital being an important driver of growth, we find evidence of more innovation activities and improved financial performance for the small firms following the layoff shock. Overall, our paper suggests that small firms respond to the industry-wide layoffs as an opportunity to hire more talent, and that they increase disclosure to attract and inform prospective employees when there are greater hiring opportunities.

**Keywords**: Labor; Disclosure; Layoff; Hiring; Job Posting; Media

## 1 Introduction

The accounting literature on corporate disclosure has extensively studied how firms use disclosure to communicate with external stakeholders. Much of this literature focuses on disclosure's informational role in the capital market to find that firms adjust their disclosure strategies in response to the investors' information demand (see Beyer, Cohen, Lys, and Walther, 2010 for a review). However, recent studies suggest that disclosure is also an important mechanism through which firms communicate with other key stakeholders, such as customers, employees, and local communities (Chakravarthy, deHaan, and Rajgopal, 2014; Choi, Choi, and Malik, 2023a; Noh, So, and Zhu, 2023). In particular, studies that focus on firms' communication with their prospective employees find that prospective employees acquire information about a firm through various forms of disclosure including earnings announcements, 10-Ks, and job postings (Choi, Pacelli, Rennekamp, and Tomar, 2023b; deHaan, Li, and Zhou, 2023; Sran, 2021). And yet, there is limited evidence on how firms' hiring strategies and their accompanying disclosure strategies that target prospective employees vary cross-sectionally when labor market conditions change. Moreover, compared to the well-established literature that studies the role of disclosure in attracting *financial capital* (e.g., Lambert, Leuz, and Verrecchia, 2007), studies on disclosures targeted at hiring and attracting *human capital* and their effectiveness are still at an early stage.

In this paper, we fill this gap in the literature by examining how firms of different sizes change their hiring and disclosure strategies when a labor supply shock presents a new hiring opportunity. In addition, we also examine whether the disclosure strategies are effective in informing and attracting talent, providing evidence on the role of disclosure in the labor market. Specifically, we empirically examine whether extensive layoffs by large technology firms incentivize the small firms in the same industry to seize the hiring opportunity and increase hiring, and further enhance their information environment through disclosure for more successful and timely hiring outcomes.

We use the technology industry's series of layoffs during 2022-2023 led by large technology firms as an event that expanded labor supply for other firms. In 2022, the technology industry increased its layoff announcements by 649%, which marks the highest job cut since the dot-com crash more than 20 years ago.[1] This sequence of high-profile layoffs by major technology companies began with Meta's announcement of more than 11,000 layoffs in November 2022 and continued into the year 2023.[2] While the specific reasons for the layoffs likely vary across firms, a number of companies officially attributed their layoff decisions to over-hiring during the COVID economy.[3]

When large firms engage in layoffs, the strategic response from the small firms in the same industry is unclear ex-ante. On one hand, smaller firms, traditionally challenged at talent acquisition, may find an opportunity to hire quality employees when large firms start releasing talent and take advantage of it. In line with this prediction, a stream of research in labor economics suggests an inverse relation between the labor strategies of large and small firms within the same industry. For example, Moscarini and Postel-Vinay (2009, 2012) document that large and small employers' employment growth respond in opposite directions to the macroeconomic cycle. The key insight from the literature is that large firms, which are typically

[1] The number of workers that were laid off in the technology industry in 2022 and 2023 combined reached at least 400,000 (https://layoffs.fyi/). As a comparison, the number of workers that were laid off in the 2001 dot-com crash was around 200,000 (https://www.bls.gov/opub/reports/mass-layoffs/archive/extended_mass_layoffs2001.pdf). For more information, also see Bloomberg article "What Tech Job Cuts Say About Silicon Valley — and the Rest of the Economy": https://www.bloomberg.com/news/articles/2023-01-18/what-2022-tech-layoffs-say-about-silicon-valley-the-economy

[2] See Crunchbase layoff tracker: https://news.crunchbase.com/startups/tech-layoffs/

[3] For instance, Mark Zuckerberg, CEO of Meta, explained in the layoff announcement that the downsizing was due to an overly rapid growth during the pandemic and a surge in online commercial revenue, and a mistaken belief that this shift would be permanent (See New York Times article "Meta Lays Off More Than 11,000 Employees": https://www.nytimes.com/2022/11/09/technology/meta-layoffs-facebook.html). Similarly, several large technology companies expanded extensively during the pandemic, but the demand for online services waned as people returned to in-person activities post-pandemic. As a result, many large technology companies revised their labor strategies and announced substantial layoffs following Meta.

more productive and higher-paying, can attract talent more easily, making their hiring less dependent on the availability of unemployed workers.[4] As a result, large firms hire and grow when the economy expands, and they shed the accumulated employment when the economy enters a downturn. In contrast, small firms find it difficult to attract talent when the economy is expanding, but because they are more constrained by talent search and hiring frictions during normal times, they do not shrink as quickly during recessions. This variation in large and small firms' employment growth cycles at a *macro* level would lead us to expect that small firms strategically focus their hiring and disclosure efforts during periods of large firms' downsizing.

On the other hand, when it comes to the reallocation of human capital across firms, another possibility is that an industry-wide decrease in demand has a similar or even more severe negative effect on small firms' hiring capacity. In this case, small firms may also choose to mirror their larger counterparts and downsize. This prediction is in line with Lanteri (2018), who models the reallocation pattern of physical capital across firms under different macroeconomic conditions to find that reallocation is pro-cyclical. The paper posits that there is a lack of reallocation during recessions because there is little demand for capital from investing firms. This reasoning would predict that when large firms lay off personnel, small firms decelerate their hiring as well. Thus, it remains an empirical question how labor reallocation across firms takes place at the individual *firm* level when large-scale layoffs occur.

As smaller firms adjust their hiring strategies, disclosure likely plays a key strategic role. Prior literature finds that job seekers rely on corporate disclosure to inform their job search, highlighting the importance of prospective employees as one of the key audiences of corporate disclosure (Choi et al., 2023a; Choi et al., 2023b; Pacelli, Shi, and Zou, 2022; Sran, 2021).

[4] For instance, Dunn (1986) and Oi and Idson (1999) find that larger firms provide higher pay and greater job security. Bidwell, Won, Barbulescu, and Mollick (2015) find that high-status employers are better able to attract workers who value the signal of ability that employment at those firms provides. Bishop (2012) and Arellano-Bover (2024) find that large firms provide more opportunities for employee skill developments relative to small firms.

Therefore, if the layoffs by larger firms present smaller firms with access to high-quality labor previously out of reach, this will motivate the smaller firms to re-evaluate the costs and benefits of disclosure in the presence of greater hiring opportunities.

There are non-trivial costs associated with disclosure. Especially in the context of labor-oriented disclosure, recent studies find that managers trade off information provision for prospective employees and proprietary cost concerns for rivals in their job posting disclosure choices (Cao, Cheng, Tucker, and Wan, 2023; Sran, 2021). The extensive layoffs by large firms can reduce the incremental benefit of disclosure for the small firms that intend to hire because labor supply greatly exceeds labor demand to the point where smaller hiring firms' bargaining power is substantially stronger compared to the job seekers. The strong position in the labor market, in turn, can reduce the need for, and inclination towards, disclosure for small firms concerned about associated proprietary costs.

At the same time, improving information environment through disclosure helps increase the probability of filling the job vacancy with a better match. In particular, after large firms' layoffs, small firms' job postings and related disclosure have the potential to reach a broader audience of talented job seekers who may not have paid attention to small firms when large firms were hiring extensively. This expanded pool of labor supply and greater attention from the laid-off talent returning to the job market increase the labor market benefits to disclosure. Moreover, the information asymmetry between the employers and the job seekers may be the greatest for small firms due to the lack of information sources. This information asymmetry can introduce significant frictions to the job search process, especially if the job seekers are concerned about the robustness of their potential employers and have little information about the firm or the role they would play in the firm if they were to join. Therefore, small firms may seek to improve their information environment and increase their visibility and credibility through more disclosure as they prepare to take advantage of the new hiring opportunities.

In sum, whether and how firms change their hiring and disclosure strategies when a labor supply shock presents greater hiring opportunities remains an empirical question to be tested. Thus, in this paper, we study whether small firms change their hiring strategies when large firms are downsizing, and whether disclosure facilitates the labor reallocation process between large and small firms. We answer this question using empirical data on corporate job postings between January 2018 and August 2023.

We first identify the timing of the layoff shock based on the news articles from RavenPack that cover corporate layoff announcements. Figure 1 presents a time-series plot of the proportion of unique firms announcing layoffs within each size group, defined based on the employment size, from January 2021 to August 2023. The plot shows a rapid increase in the layoff announcements led by large firms which roughly begin around November of 2022 and persist until the end of our sample period. November 2022 also coincides with Meta's announcement of more than 11,000 layoffs which was followed by a sequence of high-profile layoffs by major technology companies. Thus, we create an indicator variable (*Layoff*) that equals one if the year-month is on or after November 2022, and zero before, to mark the period of labor supply shock. Figure 1 also highlights that the sudden increase in layoffs starting in November 2022 is most pronounced for large firms whereas the trends are not as striking for medium and small firms. In our empirical analyses, we compare the small and large firms' hiring and disclosure decisions using the medium firms as the benchmark to focus on the cross-sectional reallocation of labor.

Our empirical analysis first examines how firms change their hiring decisions in response to the layoff-induced labor supply shock. We use firms' job posting data from

Lightcast (formerly known as Emsi Burning Glass) to proxy for firms' hiring activities. In particular, we measure *JobPostingFreq* as the aggregate number of new jobs (logged) each firm posts in a given month. We find that small firms significantly increase new job creation relative to medium firms, unlike large firms that significantly reduce new job creation relative to medium firms. Moreover, we find that small firms' hiring becomes significantly more sensitive to their investment opportunities (proxied by Tobin's Q) following the layoff shock. This is consistent with small firms being previously constrained by a lack of labor supply, and the layoffs alleviating their hiring frictions, allowing them to acquire human capital more efficiently as needed. Overall, we document that small firms engage in more aggressive hiring activities when they face an abnormal increase in labor supply, providing evidence consistent with labor reallocation across firms of different sizes during times of extensive layoffs.

To further understand the role of disclosure as it relates to hiring decisions, we next examine whether and how firms change their job posting disclosures following the layoffs. We use average job posting length (logged) as a proxy for firms' disclosure through their job postings that target prospective employees (*PostingLength*). While disclosure literature has traditionally focused on disclosure through corporate filings or earnings announcements (Choi et al., 2023b; deHaan et al., 2023), recent studies posit that managers also treat job postings as disclosures (Cao et al., 2023; Sran, 2021). Consistent with managers providing information through job postings, we find that small hiring firms significantly increase the length of their job postings relative to the medium firms following the labor supply shock, whereas there is little change in large firms' job posting length relative to that of medium firms. This result suggests that small firms use disclosure to attract and inform prospective employees when there are greater hiring opportunities.

We then examine whether providing more disclosure is effective in facilitating the hiring process. In particular, we focus on the hiring speed measured as the average number of days it takes until the position is filled and the job posting is taken down (*TimeToHire*). We find that small firms' hiring speed relative to that of medium firms accelerates following the layoff shock, and that the improvement in hiring speed is driven by those firms that increase information disclosure through longer job postings. This finding is consistent with disclosure alleviating information asymmetry between job seekers and employers in the labor market and reducing hiring frictions.

In a series of additional analyses, we further explore the implications of the layoff shock on various aspects of corporate hiring and disclosure strategies as well as future growth. First, we narrow down job postings to those seeking experienced workers with at least one year of previous work experience. Consistent with small firms leveraging the labor supply shock as an opportunity to attract talent previously out of reach, we find a significant increase in the number of job postings for experienced workers as well as a significant increase in the length of the job postings for experienced workers for small firms relative to medium firms following the layoff shock. We also find that small firms take fewer days to hire a position for experienced workers relative to medium firms following the layoff-induced labor supply shock, especially if they provide more information through longer job postings.

Secondly, we examine whether firms use other disclosure channels in addition to job postings to reach a broader group of prospective employees. While job posting is the most direct and guaranteed way of providing information to job seekers, its scope may be limited if it only reaches the job seekers who are already somewhat interested in the firm. Therefore, firms might also adopt other disclosure avenues to provide information about the firm to a broader base of prospective employees and expand its labor pool at the external margin. Specifically, we focus on corporate disclosure through media press releases (*Media_PR*, *Media_PRTech*) to find that small firms compared to medium firms provide more media press releases following the labor supply shock. We also find that the increase in press releases is primarily driven by firms with a stronger need to hire that have posted more jobs and have historically taken longer to hire. Looking at the consequences, we find that more press releases through media help accelerate the hiring speed, but only if the information is carried by tech-oriented media sources like TechCrunch.

In our third set of additional analyses, we examine the future growth outcomes of small and large firms following the layoffs to understand the importance of human capital acquisition in promoting growth. We focus on announcements about product development activities (*ProductAnn*) and patent applications (*Patent*) in the subsequent periods, and future *ROA* as measures of future growth. Consistent with human capital being an important driver of growth, we find evidence of more active product developments, increased patent applications, and improved financial performance for small firms relative to the medium firms following the layoff shock.

Finally, we conduct an exploratory analysis that examines labor reallocation patterns outside of the technology industry during the same time period. Using Hoberg-Phillips product market similarity score to identify whether firms are more or less similar to large technology firms, we find a similar labor reallocation pattern of increased hiring by smaller firms that are more similar to large technology firms (Hoberg and Phillips, 2010, 2016). However, we do not find such results for small firms that are dissimilar to the large technology firms, suggesting broader labor market implications of the technology industry's layoff shock across other industries that share similarities in the product market space.

Overall, our findings are consistent with the idea that small firms increase hiring and enhance their information environment for better hiring outcomes when large firms in the same industry downsize. These findings make several contributions to the accounting and labor economics literature. First, our findings show that small firms strategically focus their hiring and disclosure efforts during periods of increased labor supply when they are most likely to achieve success, and the labor market decisions and disclosure decisions are not made in isolation but rather inform and affect each other. This finding is in contrast to the notion that greater labor supply enhances the employers' bargaining power in the labor market and lowers the need for hiring efforts across all employers. Instead, the finding implies that small firms use disclosure strategically to overcome hiring frictions and to attract talent when such talent becomes available, but small firms need to compete to access it. For example, employees laid from large firms may decide to wait for large firms to begin hiring again, or they may look for jobs at other large firms from outside the industry. At the very least, small firms have to compete with one another to attract well-qualified laid-off employees to themselves. In this regard, we provide firm-level evidence that corporate disclosure can facilitate the labor reallocation across firms when large firms downsize.

Second, we broaden the scope of the disclosure literature by providing evidence that firms make disclosure decisions with other stakeholders, and in particular, prospective employees in mind. This finding also has implications for the SEC's recent introduction of mandatory disclosure requirements for firms' human capital practices, which can provide a more direct disclosure avenue for firms that wish to communicate to their prospective employees in a credible manner.[5]

Third, we contribute to the literature that examines various consequences of disclosure. Much of the early research on disclosure consequences centers around capital market outcomes such as stock price and firm value implications (Ball and Brown,1968; Beaver, 1968), while more recent stream of work examines the real effects of disclosure regarding financial investment decisions (see Roychowdhury, Shroff, and Verdi, 2019 for a review). Our findings add to this literature by showing that disclosure can help alleviate information asymmetry

[5] See SEC press release: https://www.sec.gov/news/press-release/2020-192

between job seekers and employers and thereby facilitate a timelier hiring process, which has important implications on human capital investments as key drivers of future growth.

The paper proceeds as follows. Section 2 discusses the relevant literature. Section 3 describes the institutional details of the technology industry layoff setting. Section 4 develops hypotheses. Section 5 describes the data, and Section 6 presents the empirical analyses. Section 7 concludes the paper.

## 2 Literature Review

### 2.1 Disclosure to investors and other stakeholders

The accounting literature on corporate disclosure has extensively studied how firms use disclosure to communicate with external stakeholders. Much of this literature focuses on the disclosure's informational role in the capital market to find that firms adjust their disclosure strategies in response to the investors' information demand (see Beyer et al., 2010 for a review). Relatedly, in a comprehensive review paper, Healy and Palepu (2001) discuss the six forces that affect managers' disclosure decisions for capital market reasons as follows: capital market transactions, corporate control contests, stock compensation, litigation, proprietary costs, and management talent signaling.

Despite the literature's primary focus on the capital market and equity investors as the key audience of corporate disclosure, more recent papers suggest that disclosure is also an important mechanism through which firms communicate with other stakeholders. For instance, Chakravarthy et al. (2014) document that following a major accounting restatement event, firms disclose to repair their reputation with different groups of stakeholders including capital providers, customers, employees, and local communities. Moreover, existing studies show that various stakeholders respond to firms' disclosures. For example, analyzing large-scale GPS data, Noh et al. (2023) document that consumers react to firms' earnings announcements by paying more visits to their physical stores.

Particularly relevant to our study, several papers examine whether existing and potential employees rely on corporate disclosure to inform their decision making. For instance, Choi et al. (2023a) and deHaan et al. (2023) find that job seekers and existing employees rely on earnings announcements to initiate and inform their job search. Apart from disclosure of financial information, research also documents that job seekers value non-financial information such as diversity information (Choi et al., 2023b). Focusing on job postings as a disclosure avenue to potential employees, Pacelli et al. (2022) find that information on corporate culture in job postings helps firms better attract job seekers. In addition, Sran (2021) and Cao et al. (2023) find that firms treat job postings as disclosures and trade off labor market benefits and proprietary costs in deciding how much information to include in job postings. More recently, the SEC mandated human capital disclosure in firms' Form 10-Ks, giving rise to a stream of research that studies the disclosure content and the value implications of human capital disclosures. For example, Batish et al. (2021) document that after the human capital disclosure mandate, firms increase their disclosures about diversity, equity, and inclusion (DEI) as well as employee turnover. Overall, a growing stream of literature documents that employees and prospective employees are important stakeholders and relevant audiences to corporate disclosure.

## 2.2 Labor competition and reallocation

Our work is also closely related to the literature on firms' competition for labor and the reallocation of labor resources. Human capital is a key production input for firms that enables high-quality output, fosters innovation, fuels growth, and enhances competitive advantage. Recognizing the importance of securing a high-quality workforce, firms compete for talent in the labor market. Prior research documents that large and established firms generally have certain hiring advantages as they have more extensive resources, higher pay, established brand recognition, formal training programs, and more comprehensive benefits packages that are valued by potential employees (Dunn, 1986; Oi and Idson, 1999; Bishop, 2012; Bidwell et al., 2015; Arellano-Bover, 2024). Given this hiring advantage large firms generally have in the labor market, small firms in the same industry may find their hiring opportunities limited when large firms are hiring aggressively and expanding.

On a macro level, Moscarini and Postel-Vinay (2009) and Moscarini and Postel-Vinay (2012) find that large firms' employment growth is more sensitive to business cycle conditions than small firms because large employers shed more jobs during recessions and create more new jobs during expansions, as compared to small employers. This variation in large and small firms' employment growth cycles at a *macro* level, combined with the small firms' relative hiring disadvantage in the labor market, raises the possibility that small firms strategically focus their hiring efforts during periods of large firms' downsizing to hire away the laid-off workers.

Apart from the macro-level labor cycle association, research also studies the labor reallocation effects related to more specific corporate events. Focusing on corporate distress, Brown and Matsa (2016) document that job seekers accurately perceive firms' financial conditions, and employers' financial distress results in fewer and lower quality applicants. In a similar manner, Babina (2020) finds that employees of firms currently subject to financial distress tend to depart to entrepreneurship. Interestingly, Babina, Ouimet, and Zarutskie (2022) document that a successful IPO increases departures of high-wage employees to startups and triggers industrial diversification through employment growth in non-core industries. In another stream of work, Graham, Kim, Li, and Qiu (2015) find that when an employer files for bankruptcy, the majority of employees leave the firm, the industry, and the local labor market.

In a related work, vom Berge and Schmillen (2023) focus on a mass layoff event and find that local spillovers significantly attenuate the direct impact of mass layoffs on municipal-level employment, and about a quarter of the 1-year direct employment loss due to a mass layoff event is absorbed within the same municipality.

At a broader level, there are also studies that focus on the reallocation of physical capital across firms under different macroeconomic conditions. For instance, Lanteri (2018) studies the business-cycle dynamics of the reallocation pattern of physical capital across firms to find that reallocation is pro-cyclical. The paper explains that there is a lack of reallocation during recessions because there is little demand for capital from investing firms despite more firms wanting to disinvest capital.

Overall, prior studies suggest that human capital reallocation can happen following either changes in macroeconomic trends or certain idiosyncratic corporate events. However, little is known about what facilitates the matching process between potential employers and job seekers when labor reallocations occur. That is, how do individual job seekers find their way to their next employers, and what strategies do small firms rely on to pave their ways to expansion when the labor market condition changes. We answer this question by studying whether small firms change their hiring strategies when large firms are downsizing, and whether a disclosure channel plays a role in the labor reallocation process between large and small firms.

## 3 Institutional Background

In 2022, the technology industry increased its job cuts by 649%, which marks the highest job cut since the dot-com crash more than 20 years ago.[6] The announcement of Meta's

[6] See Bloomberg article "What Tech Job Cuts Say About Silicon Valley—and the Rest of the Economy": https://www.bloomberg.com/news/articles/2023-01-18/what-2022-tech-layoffs-say-about-silicon-valley-the-economy

layoff of 11,000 employees on November 9, 2022, constituting 13% of its workforce, marked the start of a series of high-profile layoffs across major technology firms.[7] In the following months, Amazon, Alphabet, and other tech giants also announced workforce reductions of approximately 10% of their current workforce.[8] Consequently, the technology labor market saw a rapid increase in labor supply, unmatched by the number of available job positions, reflecting the industry's shifting dynamics in the post-pandemic landscape.

While the specific reasons for the layoffs likely differ across firms, a number of companies officially attributed their layoff decisions to over-hiring during the COVID economy. For instance, Mark Zuckerberg, CEO of Meta, attributed their downsizing to an overly rapid growth during the pandemic, when a surge in online commerce led to a big spike in revenue, and a mistaken belief that this shift would be permanent.[9] Similarly, many big technology companies that expanded extensively during the pandemic had to revise their labor strategies and announce substantial layoffs as the demand for online services began to wane post-pandemic. In fact, when large technology companies started to announce layoffs and let go a substantial portion of their new hires from the pandemic, the media in hindsight pointed out their 'over-hiring' strategies during the pandemic as the culprit underlying the post-pandemic layoffs.[10]

Interestingly, while large technology firms' layoff news dominated the headlines, smaller players in the industry seemingly started to expand. Several media articles have reported that smaller firms increased their job postings and acquired more office spaces during large technology firms' layoffs. Bloomberg, for instance, reports that the recent downturn in

[7] See tech layoff timeline in 2022: https://www.computerworld.com/article/3679733/tech-layoffs-in-2022-a-timeline.html?page=1
[8] See CNBC article: https://www.cnbc.com/2023/01/18/tech-layoffs-microsoft-amazon-meta-others-have-cut-more-than-60000.html
[9] See New York Times article "Meta Lays Off More Than 11,000 Employees": https://www.nytimes.com/2022/11/09/technology/meta-layoffs-facebook.html
[10] See Medium article as an example: https://steve-taplin.medium.com/big-tech-employee-numbers-before-and-after-the-pandemic-tells-the-real-story-bc67779c3cc8

the technology industry has provided an opportunity for tech startups to finally attract and hire top talents. According to their report, tech startups posted 15% more positions than big technology firms in the wave of layoffs among the tech giants.[11] In a similar manner, a recent article from CNN shows that smaller firms are growing their footprints while larger companies are pruning office spaces.[12]

In light of this preliminary evidence, we focus in this paper on the technology industry's large-scale layoffs during 2022-2023 led by large technology firms as a setting that expanded high-quality labor supply for the rest of the firms. The series of layoffs in the technology industry in 2022-2023 potentially provides an ideal setting to study labor reallocation across different cross-sections of firms. First, human capital is the key asset in the technology industry, which makes labor market strategies and human capital management particularly important in this setting (Bapna, Langer, Mehra, Gopal, and Gupta, 2013). Second, large and small firms in the technology industry adopted different hiring strategies during the pandemic, leading to differences in their labor market positions during the time of layoffs led by large technology firms. Third, in contrast to a situation where a single large firm downsizes due to an idiosyncratic negative event, multiple major firms are moving in unison in this setting, strengthening the magnitude of the layoff shock throughout the industry, and limiting the possibility of labor reallocation merely within the group of large firms. Thus, we use this setting to study how firms change their hiring and disclosure strategies when a labor supply shock presents a new hiring opportunity, and whether such strategies are effective in talent attraction.

## 4 Hypothesis Development

[11] See Bloomberg article: https://www.bloomberg.com/news/articles/2023-04-25/small-us-firms-recruit-big-tech-layoffs-with-surge-in-openings?leadSource=uverify\%20wall
[12] See CNN article: https://www.cnn.com/2023/06/06/business/global-companies-office-space-cuts/index.html

When large firms engage in layoffs, the strategic response from the small firms in the same industry is unclear ex-ante. On one hand, research in labor economics documents an inverse relation between the labor strategies of large and small firms within the same industry at a macro level in response to market-wide economic cycles (Moscarini and Postel-Vinay, 2009, 2012). We might expect a similar negative relation at the individual firm level if smaller firms, traditionally challenged in talent acquisition, find an opportunity to hire quality employees when large firms start releasing talent. On the other hand, smaller firms may choose to mirror their larger counterparts and downsize if their hiring capacity is similarly or even more severely hampered due to an industry-wide decline in demand (Lanteri, 2018).

Therefore, we first examine how small firms' hiring strategies change in response to the layoff-induced labor supply shock, and state our first hypothesis in the null form as follows:

**Hypothesis 1:** *When large firms lay off, small firms in the same industry do not change their hiring strategies.*

As smaller firms adjust their hiring strategies, disclosure likely plays a key strategic role. Prior literature finds that job seekers rely on corporate disclosure to inform their job search, highlighting the importance of prospective employees as one of the key audiences of corporate disclosure (Choi et al., 2023a; Choi et al., 2023b; Pacelli et al., 2022; Sran, 2021). Therefore, if the layoffs by larger firms present smaller firms with access to high-quality labor previously out of reach, this will motivate the smaller firms to re-evaluate the costs and benefits of disclosure in light of the greater hiring opportunities.

In the context of labor-oriented disclosure, recent studies find that managers trade off information provision for prospective employees and proprietary cost concerns for rivals in their job posting disclosure choices (Cao et al., 2023; Sran, 2021). When large firms in the same industry lay off a number of their employees, small firms that intend to hire may find it worthwhile to provide more information to the expanded group of high-quality prospective employees as their perceived benefits to disclosure increase. First, after large firms' layoffs, small firms' job postings and related disclosure have the potential to reach a broader audience of talented job seekers who may not have paid attention to small firms when large firms were hiring extensively. This expanded pool of labor supply and greater attention from the laid-off talent returning to the job market increase the labor market benefits to disclosure as it helps increase the probability of filling the job vacancy with a better match. Moreover, the information asymmetry between employers and job seekers may be the greatest for small firms due to the lack of information sources. This information asymmetry can introduce significant frictions to the job search process, motivating small firms to improve their information environment and increase their visibility and credibility through more disclosure as they prepare to take advantage of the greater hiring opportunities.

That said, another possibility is that the layoffs by large firms reduce the incremental benefit of disclosure for the small firms that intend to hire because labor supply greatly exceeds labor demand to the point where smaller hiring firms' bargaining power is substantially stronger compared to the job seekers. The strong position in the labor market, in turn, can reduce the need for disclosure for the small firms.

Thus, our second hypothesis examines how small firms change their disclosure strategies to align with their hiring strategies in response to the layoff-induced labor supply shock. We state the hypothesis in the null form as follows:

**Hypothesis 2:** *When large firms lay off, small firms in the same industry that intend to hire do not change their disclosure strategies.*

To the extent disclosure helps attract and inform prospective employees by alleviating information asymmetry between job seekers and employers, we expect the hiring process to be more seamless and timely for those firms that provide more disclosure.

Thus, our final hypothesis examines whether disclosure is effective in facilitating the hiring process. In particular, we focus on the hiring speed defined as the number of days it takes to fill the position, and state our third hypothesis in the null form as follows:

**Hypothesis 3:** *Disclosure by the small firms that intend to hire in response to large firms' layoffs does not affect their hiring speed.*

## 5 Data

Our sample for the analysis consists of 31,916 firm-months between January 2018 and August 2023 that operate in the technology industry. We define technology industry as the ones with the following 2017 NAICS codes: 511200 - 512000 (Software publishers), 518000 - 520000 (Data processing, Other information services), 541500 - 541600 (Computer systems design and related services), and 334000 - 334600 (Computer and electronic product manufacturing). Within the sample of technology firms, we classify the sample observations into small, medium, and large firms based on their employment size. Specifically, small firms are defined as firms with 200 employees or fewer, medium firms are defined as firms with greater than 200 and fewer than 5000 employees, and large firms are defined as firms with 5000 employees or greater. The number of employees is from Compustat and is based on the first year the firm enters our sample to avoid reclassification error. Of the 31,916 firm-months, 4,699, 17,496, and 9,721 firm-months are from small, medium, and large firms, respectively.[13]

[13] We conduct robustness tests using alternative thresholds to define small, medium, and large firms and find similar results (Table 7).

We measure firms' labor market activities using data on job postings from Lightcast. This dataset provides detailed information about firms' job postings, including the number of job postings, the application requirements, and the dates on which the firm posted the job and took it down, which collectively allows us to measure firms' hiring activities. Moreover, the dataset contains information about the content of the postings, which allows us to measure the amount of information firms provide through their job postings. We first match the firms on Lightcast with Compustat firms by conducting exact name matching. For those firms that could not be matched using the exact name matching process, we perform an additional matching process where we manually compare the names and the website addresses of the firms on Lightcast and match them with Compustat firms. The series of process matches 691 out of the 1,520 unique firms in the technology industry from the Compustat sample.

For further analysis, we also obtain data on media articles and press releases from RavenPack. RavenPack dataset allows us to identify the articles that specifically pertain to 'layoffs', thereby enabling us to validate our measure and timing of the layoff shock variable *Layoff*. Furthermore, using RavenPack dataset, we are able to narrow down on corporate press releases that are originated by the firm, and in particular, on the ones that are distributed via news providers that may be more relevant for workers in the technology industry, such as TechCrunch or The Verge. Thus, we use this dataset to understand firms' use of media press releases as another channel through which they communicate with their prospective employees. We also obtain data on product-related announcements from Capital IQ Key Developments and data on patent applications from United States Patent and Trademark Office (USPTO) to create proxies for future innovation and growth.[14] Throughout all our analyses, we also use

[14] USPTO dataset is manually matched to our sample firms based on company names following the approach in Cetin (2023). We thank Furkan Cetin for sharing the matched dataset with us.

firm fundamentals data obtained from Compustat to create various firm characteristics variables.

Table 1 presents summary statistics for the key variables used in the analyses. Panel A, panel B, and panel C present summary statistics for the small, medium, and large firms, respectively. Our key outcome variables of interest are *JobPostingFreq* defined as the natural logarithm of one plus the total number of jobs posted in a given month, *PostingLength* defined as the natural logarithm of one plus the average number of words contained in the job postings posted in a given month, and *TimeToHire* defined as the number of days it takes until the firm takes down the job posting. An average small firm in the sample posts 1.4 jobs in a month, the postings on average contain 453 words, and the postings stay on the platform for 59 days. An average medium firm in the sample posts 11 jobs in a month, the postings on average contain 577 words, and the postings stay on the platform for 60 days. An average large firm in the sample posts 85 jobs in a month, the postings on average contain 588 words, and the postings stay on the platform for 61 days. The summary statistics highlight the importance of accounting for cross-sectional differences in the labor market landscape across firms.

## 6 Empirical Results

### 6.1 Main Results

We begin our empirical analyses by first examining whether small firms adjust their hiring plans when large firms lay off (Hypothesis 1). To focus on the labor reallocation pattern across firms of different sizes, we conduct difference-in-differences analyses that compare small and large firms' job posting frequencies using the medium-sized firms as the benchmark. Specifically, we estimate regression equation (1) on the sample of small and medium firms to examine how small firms change their job posting frequency relative to the medium firms. And then for comparison, we re-estimate the regression equation (1) on the sample of large and medium firms to examine how large firms change their job posting frequency relative to the medium firms.

$$JobPostingFreq_{i,m} = \beta_0 + \beta_1\, Layoff_m \times\ Small_i(Large_i) + \Gamma\, Controls\ +\ Firm\, FE + Month\, FE + \varepsilon_{i,m}. \tag{1}$$

Throughout our analyses, $i$ indicates firm and $m$ indicates year-month. The dependent variable, $JobPostingFreq_{i,m}$, is the natural logarithm of one plus the number of new jobs firm $i$ posts in month $m$. $Layoff_m$ is an indicator variable that equals one if the year-month is on or after November 2022, and zero before, to mark the period of labor supply shock. In Figure 1, we plot the proportion of unique firms announcing layoffs within each size group from January 2021 to August 2023 to corroborate November 2022 as the beginning of the layoff shock. The figure shows a rapid increase in the layoff announcements led by large firms that begin around November 2022 and persist until the end of our sample period. Note that the period also coincides with Meta's major layoff announcement which was followed by a sequence of high-profile layoffs by major technology companies. $Small_i(Large_i)$ is an indicator variable that equals 1 if the firm is identified as a small (large) firm based on the employment size. Our coefficient of interest is $\beta_1$ which captures the change in small (large) firms' job posting frequencies relative to the medium firms.

To account for the differences in the hiring capacity across firms, we control for the firms' market value of equity ($logMVE$) and financial performance ($ROA$). In addition, we control for the risk and uncertainty underlying the firms' performance using measures of earnings volatility ($EarnVol$) and financial leverage ($Leverage$). Particularly relevant to the technology industry, we also control for several measures of growth and investment, including capital investments ($Investment$), R&D expenditures ($R\&D$), and sales growth ($Growth$).[15] We further allow the effects of the control variables to vary across firms that belong to different size groups by additionally including the set of control variables interacted with $Small_i(Large_i)$. We also include firm fixed effects to control for unobservable firm-specific differences in hiring strategies, and month fixed effects to control for the common time trends. Note that the coefficients on the main effects ($Layoff_m$ and $Small_i(Large_i)$) are subsumed by the inclusion of firm and month fixed effects throughout the analyses. Standard errors are clustered by firm and month to account for within-firm and within-month residual dependence. Detailed variable definitions are presented in Appendix A.

Table 2 presents the estimation results. The coefficient on $Layoff \times Small$ is positive and significant, and roughly suggests a 24 percent increase in the number of jobs posted by the small firms relative to the medium firms following the layoff shock. In comparison, the coefficient on $Layoff \times Large$ is negative and significant, and roughly suggests a 15 percent decrease in the number of jobs posted by the large firms relative to the medium firms. To further examine the trends in the hiring activities across firms following the layoff shock, in Figure 2, we plot the job posting frequencies over time for small and large firms compared to the medium firms. We find no visible trends prior to the layoff shock in November 2022 ($t$), followed by a diverging pattern where small firms increase their job postings while large firms decrease theirs. Collectively, the job posting frequency analysis suggests that small firms adopt more aggressive hiring strategies when they face an abnormal increase in labor supply.

To better understand the significance of the increased labor supply, we next investigate whether the layoff shock affected firms' hiring sensitivity to investment opportunities. If small firms' hiring had previously been constrained by a lack of labor supply, the series of layoffs

[15] All stock variables are measured at the beginning of the quarter, and all flow variables are measured during the quarter.

and the resulting increase in labor supply would alleviate their hiring frictions. This, in turn, would allow them to attract and hire talent more efficiently as needed. To analyze the effects of the layoffs on firms' hiring sensitivity, we estimate a modified version of regression equation (1) that additionally interacts $Layoff \times Small(Large)$ with a measure of investment opportunities. Following Verdi (2006) and McNichols and Stubben (2008), we measure investment opportunities using Tobin's Q, calculated as the ratio of the market value of total assets to the book value of total assets.

Table 3 reports the estimation results. Column (1) ((2)) presents how small (large) firms change their hiring sensitivity to the investment opportunities following the layoff shock relative to the medium firms. We find that small firms' hiring becomes significantly more sensitive to their investment opportunities following the layoff shock ($t$-stat on $Layoff \times Small \times Tobin'sQ$ is 2.02). However, we do not find a significant change in large firms' hiring sensitivity ($t$-stat on $Layoff \times\ Large \times Tobin'sQ$ is 1.17). This finding is consistent with small firms' hiring traditionally being more constrained by a lack of labor supply. Consequently, when the layoffs created an abnormal increase in labor supply, this alleviated their hiring frictions, allowing them to acquire human capital more efficiently as needed. In columns (3) and (4), we repeat the estimation after excluding control variables that are potentially correlated with growth and investment to find similar results. Overall, our evidence suggests that small firms engage in more aggressive hiring activities when they face an abnormal increase in labor supply, which drives labor reallocation across firms of different sizes during times of layoffs.

If extensive layoffs by larger firms motivate smaller firms to hire more aggressively, this will also motivate them to update their disclosure strategies as they re-evaluate the costs and benefits of disclosure in light of the greater hiring opportunities. Thus, in our next analysis, we examine whether small firms change their disclosure strategies when large firms lay off

(Hypothesis 2). Similar to our previous analysis, we first estimate regression equation (2) on the sample of small and medium firms to study how small firms adjust their disclosure strategies relative to the medium firms, and then re-estimate the regression equation (2) on the sample of large and medium firms for comparison.

$$PostingLength_{i,m} = \beta_0 + \beta_1\, Layoff_m \times\, Small_i(Large_i) + \Gamma\, Controls\; +\; Firm\, FE \\ +\, Month\, FE + \varepsilon_{i,m}. \quad (2)$$

$PostingLength_{i,m}$ is the natural logarithm of one plus the average number of words contained in the job postings that firm $i$ posts in month $m$. All other variables are as previously defined. We continue to include firm fixed effects to control for unobservable differences in the disclosure strategies across firms, and month fixed effects to control for the common time trends, and cluster standard errors at the firm and month level. Our coefficient of interest is $\beta_1$ which captures the change in small (large) firms' disclosure through job postings relative to the medium firms.

The estimation results are reported in Table 4. Note that the number of observations is smaller than in Table 2 because this sample is restricted to the firm-months during which the firm intends to hire (i.e., have posted at least one job posting). The coefficient on $Layoff\, \times\, Small$ is positive and significant, and roughly suggests an 8 percent increase in the length of the job postings posted by the small firms relative to the medium firms following the layoff shock. In comparison, the coefficient on $Layoff\, \times\, Large$ is insignificant, suggesting that large firms relative to the medium firms do not change the length of their job postings following the layoff shock. Overall, the results suggest that small firms increase disclosure and provide more information through job postings in order to attract and inform prospective employees when there are greater hiring opportunities.

A natural follow-up question to these results is whether providing more information through job postings is effective in facilitating the hiring process (Hypothesis 3). In particular, we focus on hiring speed as a key metric because a quick filling time benefits the firm by lowering the recruitment costs and minimizing the productivity loss associated with unfilled job positions. As a benchmark, we first estimate whether the hiring speed changes for the small and large firms relative to the medium firms following the layoff shock by estimating regression equation (3). Then, we examine whether disclosure helps accelerate the hiring speed by estimating regression equation (4) as follows.

$$TimeToHire_{i,m} = \beta_0 + \beta_1\, Layoff_m \times Small_i(Large_i) + \Gamma Controls + Firm\,FE + Month\,FE + \varepsilon_{i,m}. \tag{3}$$

$$\begin{aligned} TimeToHire_{i,m} = {} & \beta_0 + \beta_1\, Layoff_m \times Small_i \times HighLength_{i,m} + \beta_2\, Layoff_m \times Small_i \\ & + \beta_3\, Layoff_m \times HighLength_{i,m} + \beta_4\, Small_i \times HighLength_{i,m} \\ & + \beta_5\, HighLength_{i,m} + \Gamma Controls + Firm\,FE + Month\,FE \\ & + \varepsilon_{i,m}. \end{aligned} \tag{4}$$

$TimeToHire_{i,m}$ is the average number of days it takes for firm $i$ to fill in the job positions and take down the job postings posted in month $m$. In order to allow sufficient time for us to observe whether the job postings are subsequently taken down, we require at least 3 months of lead time for this variable. Consequently, the sample period for this analysis stops in May 2023. We also define $HighLength_{i,m}$ as an indicator variable that equals one if $PostingLength_{i,m}$ is above median within each size group, and zero otherwise, to estimate the incremental effect of disclosure on hiring speed. All other variables are as previously defined. We continue to include firm fixed effects and month fixed effects, and cluster standard errors at the firm and month level. Our coefficient of interest in regression equation (3) is $\beta_1$, which captures the change in small (large) firms' hiring speed relative to the medium firms following the layoff shock. In comparison, our coefficient of interest in regression equation (4), $\beta_1$, captures whether the change in the small firms' hiring speed relative to the medium firms following the layoff shock is primarily driven by those firms that provide more information through longer job postings.

The estimation results of equations (3) and (4) are reported in Table 5. Note that the number of observations is smaller than in Table 2 or Table 4 because the sample is restricted to the firm-months during which the firm intends to hire (i.e., have posted at least one job posting), and have at least 3 months of lead time. In column (1) of Table 5, the coefficient on $Layoff \times Small$ is negative and significant, and roughly suggests that the amount of time it takes to hire a position decreases by 2 days for the small firms relative to the medium firms following the layoff shock. In comparison, in column (2) of Table 5, the coefficient on $Layoff \times Large$ is insignificant, suggesting that large firms relative to the medium firms do not experience a meaningful change in their hiring speed following the layoff shock. In column (3) of Table 5, we further explore the role of disclosure through job postings in accelerating the hiring speed. We find a negative and significant coefficient estimate on $Layoff \times Small \times HighLength$, which suggests that longer job postings that contain more information help firms hire faster by alleviating hiring frictions in the job market. In particular, smaller firms with longer job postings are able to hire faster roughly by 4 days compared to the medium firms following the shock, but those with shorter job postings do not experience a meaningful improvement in their hiring speed. Overall, the results suggest that small firms that provide more disclosure for their prospective employees in their job postings are able to hire faster after the large firms lay off.

## 6.2 Additional Tests

### 6.2.1 Job Postings for Experienced Workers

In our main analysis, we find that small firms increase hiring and enhance their information environment when large firms in the same industry engage in layoffs. This finding is consistent with the explanation that small firms face difficulty attracting high-quality labor during normal times, and consequently take advantage of the industry-wide layoff as an opportunity to attract and hire high-quality labor previously out of reach.[16] In our additional analysis, we further corroborate this explanation by narrowing down on job postings for high-quality experienced workers. We define job postings for high-quality experienced workers as those that impose at least one year of work experience as an application requirement.

In Table 6, we repeat the earlier analyses after conditioning on job postings for experienced workers. Panel A of Table 6 re-estimates regression equation (1) using $ExperJobPostingFreq_{i,m}$ as the dependent variable. Panel B of Table 5 re-estimates regression equation (2) using $ExperJobPostingFreq_{i,m}$ as the dependent variable. Panel C of Table 6 re-estimates regression equations (3) and (4) using $ExperTimeToHire_{i,m}$ as the dependent variable. We find evidence consistent with small firms hiring experienced workers more aggressively and providing longer job postings for experienced workers relative to the medium firms subsequent to the layoff shock. Moreover, small firms are able to fill in the positions for experienced workers faster, especially if they provide more information in their job postings. These results collectively support the explanation that the extensive layoffs

[16] In line with this explanation, a recent research project led by 365 Data Science, an educational institution that focuses on data analysis skills, reveals that the laid-off workers from the technology industry are "qualified individuals with solid education and experience" (https://365datascience.com/trending/who-was-affected-by-the-2022-2023-tech-layoffs/). Specifically, they analyze 1,157 LinkedIn profiles of people laid off in between November 2022 and January 2023 by large technology firms to understand the characteristics of those who were laid off. They find that the laid-off workers had been working for the firm for 2.5 years on average, have work experience of 11.9 years on average, and more than 59% (30%) of them hold a bachelor's (master's) degree. They conclude that "experience and qualifications weren't key criteria for selecting laid-off employees", and that over-hiring during the pandemic is likely responsible for the extensive layoffs.

initiated by large technology firms provided smaller firms with increased hiring opportunities for high-quality experienced labor.

### 6.2.2 Disclosure through Media Press Release

In our next additional analysis, we examine whether firms use other disclosure channels in addition to the job postings to reach a broader group of prospective employees. While job posting is the most direct and guaranteed way of providing information to the job seekers, its scope may be limited if it only reaches those job seekers who are already somewhat interested in the firm. Therefore, firms might also adopt other disclosure avenues to reach a broader base of prospective employees and expand its labor pool at the external margin.[17] To explore this possibility, we focus on media press release as an alternative disclosure avenue and study whether small firms provide more media press releases when large firms downsize, and whether press releases are effective in facilitating the hiring process.

In Panel A of Table 7, we estimate a modified version of regression equation (2) where we replace $PostingLength_{i,m}$ with two measures of media press releases as alternative measures of information disclosure. Our first measure of media press release is $Media\_PR$ defined as the natural logarithm of one plus the number of press releases issued by the firm in a given month that are carried by a news provider on RavenPack. Our second measure of media press release, $Media\_PRTech$, narrows down on tech-oriented news sources such as TechCrunch which might be more relevant for job seekers in the technology industry. Specifically, $Media\_PRTech$ is defined as the natural logarithm of one plus the number of press releases issued by the firm in a given month that are carried by any one of the following

[17] Further supporting this conjecture, our anecdotal evidence based on conversations with executives at small technology companies reveal that they increase media disclosures under three specific circumstances: (i) when they have new product releases, (ii) when they intend to hire, and (iii) when they intend to attract funding. Consistent with media being an important information source for job seekers, current employees at technology firms we interviewed also mention that they often search their prospective employers through credible media sources to acquire relevant information in the job search process.

"tech news sources" on RavenPack: TechCrunch, The Verge, Ars Technica, Wired, CNET, Mashable, Engadget, TechRader, ZDNet, VentureBeat, Gizmodo, Recode, Tom's Hardware, PCMag, Android Authority, MIT Technology Review, and Digital Trends.

Columns (1) through (4) present the estimation results using the full sample of firm-months, including the months in which a firm does not post a job. Columns (5) through (8) repeat this estimation using the sample firm-months during which the firm intends to hire (i.e., have posted at least one job posting). Consistent with Table 2, we first estimate this relation using the sample of small and medium firms (odd-numbered columns report the results), and then re-estimate this relation using the sample of large and medium firms for comparison (even-numbered columns report the results). Using different samples and multiple measures of media press releases, we find that small firms increase the frequency of their media press releases compared to the medium firms following the layoffs. The coefficient estimates roughly suggest a 16-17 percent increase in the overall media press releases and a 2 percent increase in the ones that are featured in tech-oriented news sources. In comparison, media press releases by the large firms compared to the medium firms do not change significantly, and their press releases on tech-oriented news sources decrease roughly by 6 percent. Overall, this result provides preliminary evidence that small firms provide more press releases through media to communicate with their prospective employees and enhance their visibility, in line with their more aggressive hiring strategies following the layoffs.

To better understand the underlying motives for increasing press releases, we next explore whether some firms are more likely to increase media press releases than others. Focusing on the firms' need to hire, we create a $HiringNeed$ variable which takes into account both the firm's demand for labor and the hiring difficulty the firm was previously facing. In particular, $HiringNeed$ equals two if the number of job postings and the average number of days it takes to fill a position from the past two months are both above median within each size group (i.e., want to hire but cannot hire in a timely manner), one if only one of the two is above median, and zero otherwise. To examine whether firms' hiring need motivates them to provide more press releases, we regress the two measures of media press releases on the triple-interaction term $Layoff \times Small \times HiringNeed$ as well as the interaction terms, the main effects, the set of control variables including their interactions with employment size group indicators, and fixed effects. Panel B of Table 7 presents the estimation results. Focusing on the small firms' disclosure behavior relative to the medium firms, we find that the increase in press releases is primarily driven by those firms with a stronger need to hire that post more jobs and have historically taken longer to hire.

Finally, we investigate whether providing more press releases helps firms fill their positions faster. To the extent that firms' enhanced media presence reduces search frictions in the job market by alleviating information asymmetry against their prospective employees, we expect providing more press releases will help expedite the hiring process. In Panel C of Table 7, we re-estimate a modified version of regression equation (4) using $HighMedia\_PR$ and $HighMedia\_PRTech$ as the moderating variables. $HighMedia\_PR$ ($HighMedia\_PRTech$) is an indicator variable that equals one if $Media\_PR$ ($Media\_PRTech$) is above median within each size group, and zero otherwise. Interestingly, we find that providing more press releases helps accelerate the hiring speed, but only if the information is carried by tech-oriented media sources. This finding suggests that certain tech-oriented media outlets serve as a crucial information source for the job seekers in the technology industry.

### 6.2.3 Future Growth Outcomes

In our third set of additional analyses, we examine the future growth outcomes of small and large firms following the layoffs. Prior literature finds that investment in human capital facilitates high-quality output, fosters innovation, and stimulates growth (Acharya, Baghai, and

Subramanian, 2014; Chang, Fu, Low, and Zhang, 2015; Derrien, Kecskés, and Nguyen, 2023; Edmans, 2011). To the extent the series of layoffs in the technology industry provided small firms with a unique opportunity to attract and hire talent, we would expect this investment in human capital at these firms to translate to stronger future growth. We analyze the changes to future growth outcomes by estimating a modified version of regression equation (1) that replaces the dependent variable with measures of future growth. In particular, we focus on product-related announcements $ProductAnn$ and patent application $Patent$ in the subsequent periods as well as future $ROA$ as measures of future growth.

Panel A of Table 8 presents how new product development activities change following the layoff events.[18] Consistent with human capital being an important driver of innovation, we find evidence of more product-related announcements for the small firms relative to the medium firms following the layoff shock. The coefficient on $Layoff \times Small$ is significantly positive and roughly suggests a 4 (9) percent increase in product-related announcements in the subsequent month (quarter). On the contrary, the coefficient on $Layoff \times Large$ is negative and significant in the subsequent month and insignificant over the subsequent quarter. Similarly, in Panel B of Table 8, we examine whether there are any changes to firms' patenting activities following the layoff shock.[19] We find a significant increase in patent applications at small firms compared to medium firms subsequent to the layoffs ($t$-stats are 5.19 and 4.70), suggesting that the improvement in human capital acquisition leads to more innovation. In contrast, patent applications at large firms decrease significantly relative to the medium firms ($t$-stats are –5.53 and –5.28). In Panel C of Table 8, we further focus on future $ROA$ as a measure of financial performance to find that financial performance significantly improves for the small firms

[18] The number of observations is smaller than what is reported in Table 2 because we require firms to have made at least one product-related announcement during our sample period, and to have a non-missing match with Capital IQ firm identifiers.

[19] The number of observations is smaller than what is reported in Table 2 because we require firms to have applied for at least one patent during our sample period.

relative to the medium firms following the layoff shock ($t$-stat 2.37). However, the changes in future $ROA$ remains insignificant for the large firms relative to the medium firms ($t$-stat 0.07). Collectively, these findings suggest that human capital is an important driver of growth and the labor reallocation subsequent to the layoffs has important implications for future innovation and growth.

#### 6.2.4 Labor Reallocation Outside of Technology Industry

Finally, we conduct an exploratory analysis that examines labor reallocation patterns outside of the technology industry during the same time period. For this analysis, we focus on the sample of firms that are *not* in the technology industry as per our definition based on the 4-digit NAICS codes.[20] Within this sample of non-IT firm-months, we use the Hoberg-Phillips product market similarity score to identify firms that are more or less similar to large technology firms (Hoberg and Phillips, 2010, 2016). The Hoberg-Phillips score is measured as of the year 2021, which is the latest year for which the data is available. Panel A of Table 9 presents the sample distribution across industries at the 3-digit NAICS code level. The distribution table suggests that not only those firms that are dissimilar to technology firms but also the ones that are similar to them are distributed across several industry groups, highlighting the overarching influence of the technology firms on the broader economy.

We then examine the labor reallocation pattern within these two samples of firms by re-estimating regression equation (1). Panel B of Table 9 presents the estimation results. We find a similar labor reallocation pattern of increased hiring by smaller firms that are similar to large technology firms. However, we do not find such results for the firms that are dissimilar to large technology firms. Collectively, these findings suggest that the layoffs in the technology

[20] Technology industry is defined as ones with the following 2017 NAICS codes: 511200 - 512000 (Software publishers), 518000 - 520000 (Data processing, Other information services), 541500 - 541600 (Computer systems design and related services), and 334000 - 334600 (Computer and electronic product manufacturing).

industry have broader labor market implications across other industries that share similarities in the product market space.

### 6.3 Robustness Tests

In this section, we describe our robustness tests which are reported in the internet appendix. The purpose of these analyses is to test whether our inferences are robust to alternative research design choices. We first examine whether our results are robust to using alternative definitions of small, medium, and large firms. In particular, we employ four sets of alternative cutoffs of small, medium, and large firms and re-estimate our main results. First, we re-define small firms as the ones with 200 employees or fewer, medium firms as the ones with greater than 200 and fewer than 3,000 employees, and large firms as the ones with 3,000 employees or greater. Second, we re-define small firms as the ones with 300 employees or fewer, medium firms as the ones with greater than 300 and fewer than 5,000 employees, and large firms as the ones with 5,000 employees or greater and re-estimate these relations. Our third alternative thresholds define small firms as the ones with 300 employees or fewer, medium firms as the ones with greater than 300 and fewer than 3,000 employees, and large firms as the ones with 3,000 employees or greater. Finally, we again re-estimate these relations with small firms defined as the ones with 150 employees or fewer, medium firms as the ones with greater than 150 and fewer than 5,000 employees, and large firms as the ones with 5,000 employees or greater. Using these alternative cutoffs to define small, medium, and large firms, we continue to find similar results.

Next, we consider the possibility that the labor market uncertainty during the early days of COVID might have influenced our findings by introducing extreme observations. To rule out this concern, we re-estimate our main results after excluding the first three months of COVID during which the uncertainty was the highest (Mar 2020, Apr 2020, and May 2020) from the sample. Our findings remain robust to this exclusion, suggesting that the market-wide uncertainty during COVID is unlikely to explain our results.

## 7 Conclusion

This paper studies how small firms change their hiring strategies and disclosure strategies when large firms in the same industry lay off talent. Using the technology industry's extensive layoffs in late 2022 as the setting, we find that small firms increase hiring and improve their information environment when large firms downsize. Specifically, small firms increase their number of job postings following large firms' downsizing, and those firms that intend to hire further increase the length of their job postings to provide more information for their prospective employees. We find that small firms' hiring speed accelerates following the layoff events, and that the improvement in hiring speed is driven by those firms that increase information disclosure through longer job postings. Overall, our findings suggest that small firms that face difficulty attracting talent during normal times leverage the industry-wide layoffs as an opportunity to attract and hire more employees, and that they use disclosure to facilitate the hiring process.

Collectively, this paper brings disclosure literature and labor economics literature together to study the labor market strategies at small and large firms during times of layoffs, and the role of corporate disclosure in this labor reallocation process. We extend the disclosure literature by providing evidence that firms make disclosure decisions with prospective employees in mind. Furthermore, we find that firms use disclosure to attract and inform prospective employees when there are greater hiring opportunities, suggesting that labor market decisions and disclosure decisions are interconnected and influence each other. Our findings show that disclosure targeted towards prospective employees can help alleviate information asymmetry between job seekers and employers, highlighting a labor market consequence of disclosure. Given the importance of human capital as a key driver of growth, our findings should be of interest to firms, employees, and policy makers in the labor market space and disclosure regulation space.

**Figure 1:** Layoff Announcements by Size Groups (2021-01 to 2023-08)

This figure plots the proportion of unique firms announcing layoffs in a given month within each size group between January 2021 and August 2023 in the technology industry sector. Small firms are defined as firms with 200 employees or fewer. Medium firms are defined as firms with greater than 200 and fewer than 5,000 employees. Large firms are defined as firms with 5,000 employees or greater. The number of employees is from Compustat and is based on the first year the firm enters our sample.

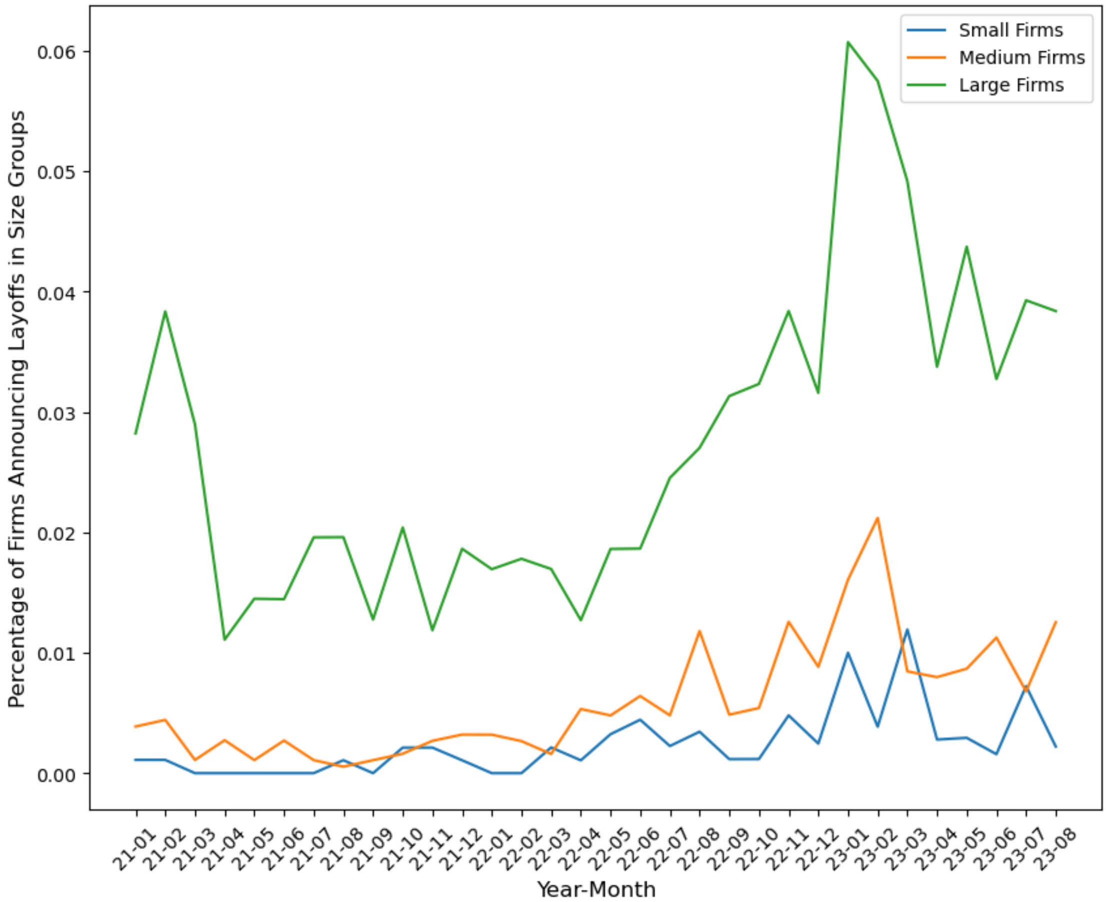
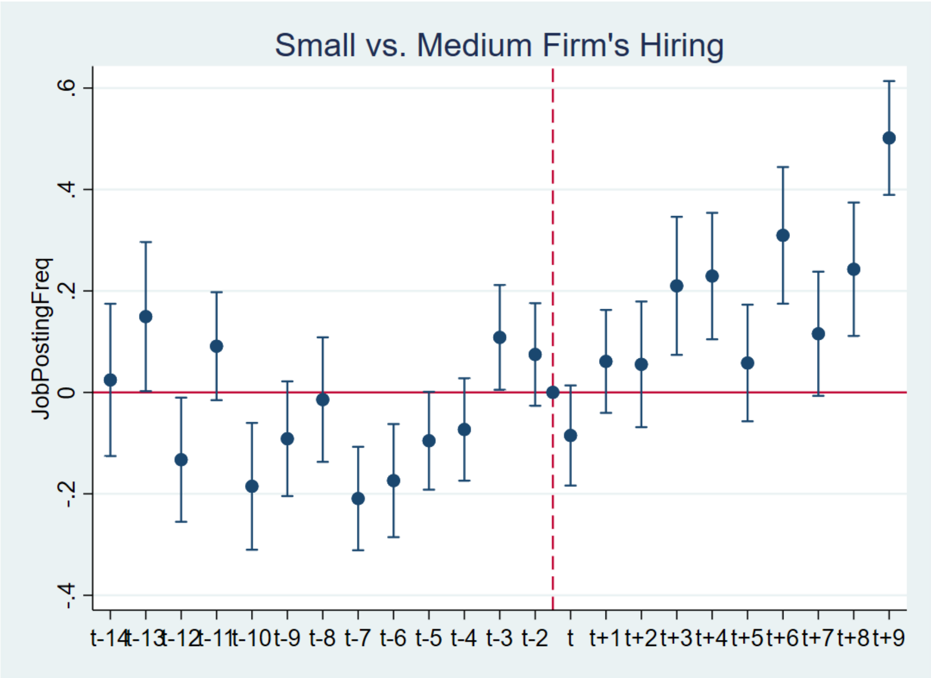


**Figure 2:** Trends in Job Postings

**Panel A:** Small vs. Medium Firm's Hiring




**Panel B:** Large vs. Medium Firm's Hiring

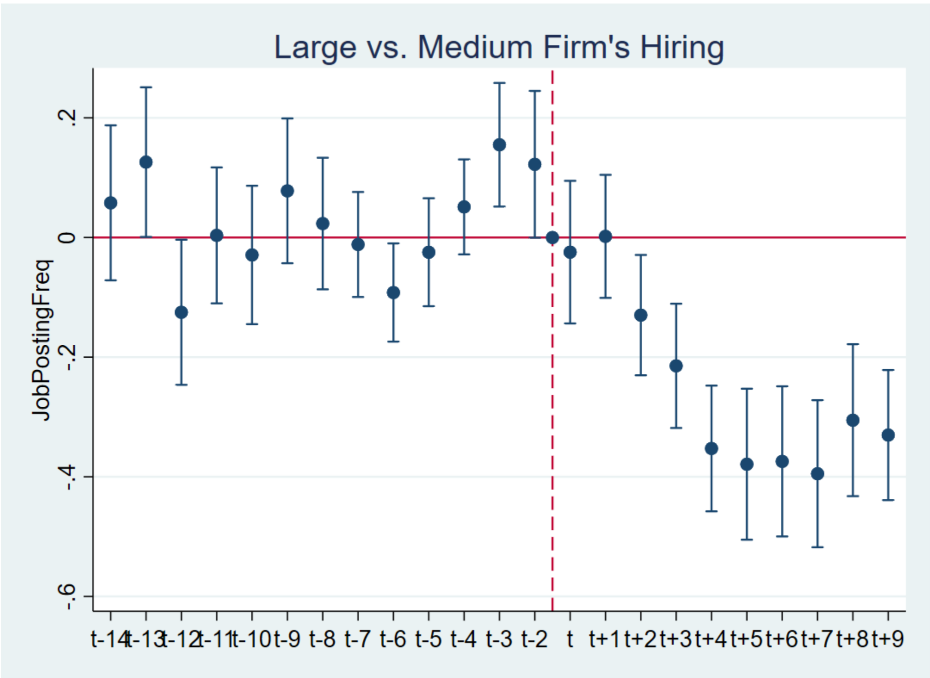


**Table 1:** Summary Statistics

**Panel A:** Small Firm Sample

| | Obs. | Mean | Std.Dev. | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| Layoff | 4,699 | 0.156 | 0.363 | 0.000 | 0.000 | 0.000 |
| JobPostingFreq | 4,699 | 0.879 | 1.091 | 0.000 | 0.693 | 1.386 |
| PostingLength | 2,579 | 6.117 | 0.457 | 5.855 | 6.146 | 6.385 |
| TimeToHire | 2,427 | 58.539 | 16.653 | 51.625 | 61.000 | 64.571 |
| Tobin'sQ | 4,699 | 3.106 | 2.932 | 1.340 | 2.106 | 3.725 |
| ExperJobPostingFreq | 4,699 | 0.691 | 0.981 | 0.000 | 0.000 | 1.099 |
| ExperPostingLength | 2,185 | 6.208 | 0.409 | 5.953 | 6.215 | 6.440 |
| ExperTimeToHire | 2,054 | 58.665 | 17.808 | 52.000 | 61.000 | 65.000 |
| Media_PR | 4,699 | 1.059 | 0.867 | 0.000 | 1.099 | 1.792 |
| Media_PRTech | 4,699 | 0.005 | 0.066 | 0.000 | 0.000 | 0.000 |
| $ProductAnn_{m+1}$ | 4,137 | 0.150 | 0.321 | 0.000 | 0.000 | 0.000 |
| $ProductAnn_{q+1}$ | 4,137 | 0.386 | 0.504 | 0.000 | 0.000 | 0.693 |
| $Patent_{m+1}$ | 1,337 | 0.177 | 0.419 | 0.000 | 0.000 | 0.000 |
| $Patent_{q+1}$ | 1,322 | 0.374 | 0.628 | 0.000 | 0.000 | 0.693 |
| $ROA_{q+1}$ | 4,619 | –0.077 | 0.196 | –0.104 | –0.036 | 0.003 |
| logMVE | 4,699 | 4.568 | 1.423 | 3.566 | 4.417 | 5.537 |
| ROA | 4,699 | –0.067 | 0.108 | –0.104 | –0.036 | 0.003 |
| EarnVol | 4,699 | 0.056 | 0.066 | 0.014 | 0.031 | 0.067 |
| Leverage | 4,699 | 0.142 | 0.200 | 0.013 | 0.071 | 0.183 |
| Investment | 4,699 | 1.193 | 2.240 | 0.098 | 0.410 | 1.333 |
| R&D | 4,699 | 0.032 | 0.030 | 0.008 | 0.026 | 0.047 |
| Growth | 4,699 | 0.070 | 0.365 | –0.115 | 0.022 | 0.195 |

**Table 1:** Summary Statistics (Cont'd)

**Panel B:** Medium Firm Sample

| | Obs. | Mean | Std.Dev. | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| Layoff | 17,496 | 0.177 | 0.381 | 0.000 | 0.000 | 0.000 |
| JobPostingFreq | 17,496 | 2.479 | 1.487 | 1.386 | 2.565 | 3.584 |
| PostingLength | 15,413 | 6.359 | 0.369 | 6.168 | 6.385 | 6.590 |
| TimeToHire | 14,617 | 59.911 | 13.357 | 53.000 | 61.000 | 67.311 |
| Tobin'sQ | 17,496 | 3.876 | 3.480 | 1.585 | 2.569 | 4.867 |
| ExperJobPostingFreq | 17,496 | 2.113 | 1.420 | 1.099 | 2.197 | 3.178 |
| ExperPostingLength | 14,682 | 6.419 | 0.341 | 6.233 | 6.439 | 6.634 |
| ExperTimeToHire | 13,935 | 60.176 | 14.008 | 53.154 | 61.000 | 67.679 |
| Media_PR | 17,496 | 1.566 | 0.896 | 1.099 | 1.609 | 2.197 |
| Media_PRTech | 17,496 | 0.042 | 0.238 | 0.000 | 0.000 | 0.000 |
| $\text{ProductAnn}_{\mathbf{m+1}}$ | 16,480 | 0.188 | 0.362 | 0.000 | 0.000 | 0.000 |
| $\text{ProductAnn}_{\mathbf{q+1}}$ | 16,480 | 0.460 | 0.552 | 0.000 | 0.000 | 0.693 |
| $\text{Patent}_{\mathbf{m+1}}$ | 6,447 | 0.401 | 0.635 | 0.000 | 0.000 | 0.693 |
| $\text{Patent}_{\mathbf{q+1}}$ | 6,289 | 0.783 | 0.927 | 0.000 | 0.693 | 1.386 |
| $\text{ROA}_{\mathbf{q+1}}$ | 17,302 | –0.014 | 0.061 | –0.030 | –0.004 | 0.012 |
| logMVE | 17,496 | 7.263 | 1.741 | 6.167 | 7.412 | 8.426 |
| ROA | 17,496 | –0.014 | 0.050 | –0.030 | –0.004 | 0.011 |
| EarnVol | 17,496 | 0.022 | 0.035 | 0.006 | 0.011 | 0.022 |
| Leverage | 17,496 | 0.244 | 0.222 | 0.050 | 0.202 | 0.374 |
| Investment | 17,496 | 1.474 | 1.938 | 0.357 | 0.835 | 1.823 |
| R&D | 17,496 | 0.026 | 0.021 | 0.010 | 0.022 | 0.037 |
| Growth | 17,496 | 0.042 | 0.163 | –0.022 | 0.039 | 0.095 |

**Table 1:** Summary Statistics (Cont'd)

**Panel C:** Large Firm Sample

| | Obs. | Mean | Std.Dev. | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| Layoff | 9,721 | 0.142 | 0.349 | 0.000 | 0.000 | 0.000 |
| JobPostingFreq | 9,721 | 4.455 | 1.875 | 3.555 | 4.595 | 5.714 |
| PostingLength | 9,271 | 6.378 | 0.308 | 6.238 | 6.397 | 6.561 |
| TimeToHire | 8,884 | 61.277 | 11.923 | 55.114 | 62.114 | 68.497 |
| Tobin'sQ | 9,721 | 2.777 | 1.986 | 1.484 | 2.194 | 3.279 |
| ExperJobPostingFreq | 9,721 | 3.998 | 1.868 | 2.996 | 4.111 | 5.247 |
| ExperPostingLength | 9,101 | 6.458 | 0.273 | 6.311 | 6.463 | 6.624 |
| ExperTimeToHire | 8,717 | 61.636 | 12.280 | 55.282 | 62.331 | 68.889 |
| Media_PR | 9,721 | 2.207 | 0.973 | 1.609 | 2.303 | 2.890 |
| Media_PRTech | 9,721 | 0.235 | 0.621 | 0.000 | 0.000 | 0.000 |
| $ProductAnn_{m+1}$ | 8,960 | 0.328 | 0.501 | 0.000 | 0.000 | 0.693 |
| $ProductAnn_{q+1}$ | 8,960 | 0.711 | 0.734 | 0.000 | 0.693 | 1.386 |
| $Patent_{m+1}$ | 7,158 | 1.465 | 1.577 | 0.000 | 1.099 | 2.485 |
| $Patent_{q+1}$ | 6,974 | 2.094 | 1.902 | 0.000 | 1.792 | 3.466 |
| $ROA_{q+1}$ | 9,644 | 0.015 | 0.038 | 0.005 | 0.015 | 0.027 |
| logMVE | 9,721 | 9.491 | 1.559 | 8.454 | 9.572 | 10.559 |
| ROA | 9,721 | 0.015 | 0.030 | 0.005 | 0.015 | 0.027 |
| EarnVol | 9,721 | 0.013 | 0.022 | 0.003 | 0.007 | 0.014 |
| Leverage | 9,721 | 0.294 | 0.171 | 0.173 | 0.280 | 0.390 |
| Investment | 9,721 | 1.956 | 2.489 | 0.578 | 1.138 | 2.254 |
| R&D | 9,721 | 0.013 | 0.014 | 0.000 | 0.009 | 0.019 |
| Growth | 9,721 | 0.022 | 0.145 | –0.030 | 0.020 | 0.066 |

This table presents summary statistics of the variables used in our analysis. Our sample consists of 31,916 firm-months from January 2018 to August 2023 in the technology industry. Technology industry is defined as firms that have 2017 NAICS codes: 511200 - 512000 (Software publishers), 518000 - 520000 (Data processing, Other information services), 541500 - 541600 (Computer systems design and related services), and 334000 - 334600 (Computer and electronic product manufacturing). Of the 31,916 firm-months, 4,699, 17,496, and 9,721 firm-months are from small, medium, and large firms, respectively, defined based on employment size. Small firms are defined as firms with 200 employees or fewer. Medium firms are defined as firms with greater than 200 and fewer than 5,000 employees. Large firms are defined as firms with 5,000 employees or greater. The number of employees is from Compustat and is based on the first year the firm enters our sample. Panel A, panel B, and panel C present summary statistics for small, medium, and large firms, respectively.

**Table 2:** Labor Supply Shock and Hiring

| | *JobPostingFreq* (1) | *JobPostingFreq* (2) |
|---|---|---|
| *Layoff X Small* | 0.244*** | |
| | (2.78) | |
| *Layoff X Large* | | –0.152* |
| | | (–1.86) |
| *LogMVE* | 0.203*** | 0.193*** |
| | (5.20) | (5.08) |
| *ROA* | –0.337 | –0.340 |
| | (–1.03) | (–1.04) |
| *EarnVol* | –0.443 | –0.436 |
| | (–0.95) | (–0.94) |
| *Leverage* | –0.255 | –0.261 |
| | (–1.51) | (–1.56) |
| *Investment* | 0.025** | 0.024** |
| | (2.37) | (2.31) |
| *R&D* | –2.113 | –2.359 |
| | (–1.37) | (–1.51) |
| *Growth* | 0.084 | 0.091 |
| | (1.43) | (1.61) |
| Observations | 22,195 | 27,217 |
| Adjusted $R^2$ | 0.778 | 0.854 |
| Sample | Small & Medium | Large & Medium |
| Firm FE | Yes | Yes |
| Month FE | Yes | Yes |
| Small(Large)XControl | Yes | Yes |

This table examines how the job posting frequency changes in response to the layoff-induced labor supply shock. Column (1) presents how the small firms change their job posting frequency using the medium firms as the benchmark. Column (2) presents how the large firms change their job posting frequency using the medium firms as the benchmark for comparison. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered at Firm and Month level are presented in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

**Table 3:** Labor Supply Shock and Hiring Sensitivity to Investment Opportunities

| | *JobPostingFreq* (1) | *JobPostingFreq* (2) | *JobPostingFreq* (3) | *JobPostingFreq* (4) |
|---|---|---|---|---|
| *Layoff X Small X Tobin'sQ* | 0.042** | | 0.042** | |
| | (2.02) | | (2.01) | |
| *Layoff X Small* | 0.143 | | 0.149 | |
| | (1.46) | | (1.52) | |
| *Layoff X Large X Tobin'sQ* | | 0.028 | | 0.031 |
| | | (1.17) | | (1.27) |
| *Layoff X Large* | | –0.214* | | –0.213* |
| | | (–1.86) | | (–1.83) |
| *LogMVE* | 0.240*** | 0.223*** | 0.246*** | 0.231*** |
| | (4.88) | (4.60) | (4.96) | (4.72) |
| *ROA* | –0.278 | –0.291 | –0.203 | –0.199 |
| | (–0.86) | (–0.90) | (–0.65) | (–0.63) |
| *EarnVol* | –0.403 | –0.403 | –0.417 | –0.415 |
| | (–0.86) | (–0.86) | (–0.89) | (–0.89) |
| *Leverage* | –0.254 | –0.263 | –0.254 | –0.258 |
| | (–1.53) | (–1.59) | (–1.52) | (–1.55) |
| *Investment* | 0.025** | 0.024** | | |
| | (2.35) | (2.29) | | |
| *R&D* | –1.486 | –1.850 | | |
| | (–1.01) | (–1.24) | | |
| *Growth* | 0.087 | 0.093 | | |
| | (1.47) | (1.64) | | |
| Observations | 22,195 | 27,217 | 22,195 | 27,217 |
| Adjusted $R^2$ | 0.778 | 0.854 | 0.778 | 0.854 |
| Sample | Small & Medium | Large & Medium | Small & Medium | Large & Medium |
| Firm FE | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes | Yes |
| Main Effects | Yes | Yes | Yes | Yes |
| Interacted Effects | Yes | Yes | Yes | Yes |

This table examines how hiring sensitivity to investment opportunities changes in response to the layoff-induced labor supply shock. Column (1) presents how the small firms change their hiring sensitivity to investment opportunities using the medium firms as the benchmark. Column (2) presents how the large firms change their hiring sensitivity to investment opportunities using the medium firms as the benchmark for comparison. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered at Firm and Month level are presented in parentheses. Levels of significance are presented as follows: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

**Table 4:** Labor Supply Shock and Disclosure through Job Postings

| | *PostingLength* (1) | *PostingLength* (2) |
|---|---|---|
| *Layoff X Small* | 0.082** | |
| | (2.60) | |
| *Layoff X Large* | | –0.014 |
| | | (–0.67) |
| *LogMVE* | 0.011 | 0.015* |
| | (1.23) | (1.70) |
| *ROA* | –0.106 | –0.113 |
| | (–1.17) | (–1.27) |
| *EarnVol* | –0.227 | –0.234 |
| | (–1.48) | (–1.53) |
| *Leverage* | 0.066 | 0.070 |
| | (1.43) | (1.57) |
| *Investment* | 0.001 | –0.001 |
| | (0.39) | (–0.22) |
| *R&D* | 0.177 | 0.183 |
| | (0.33) | (0.34) |
| *Growth* | –0.011 | –0.015 |
| | (–0.63) | (–0.82) |
| Observations | 17,992 | 24,684 |
| Adjusted $R^2$ | 0.585 | 0.585 |
| Sample | Small & Medium | Large & Medium |
| Firm FE | Yes | Yes |
| Month FE | Yes | Yes |
| Small(Large)XControl | Yes | Yes |

This table examines how the job posting length changes in response to the layoff-induced labor supply shock. The sample for this analysis is conditional on the firm having posted at least one job posting in a given month. Column (1) presents how the small firms change their job posting length using the medium firms as the benchmark. Column (2) presents how the large firms change their job posting length using the medium firms as the benchmark for comparison. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered at Firm and Month level are presented in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

**Table 5:** Labor Supply Shock and Time to Hire

| | *TimeToHire* (1) | *TimeToHire* (2) | *TimeToHire* (3) |
|---|---|---|---|
| *Layoff X Small X HighLength* | | | –4.262** |
| | | | (–2.07) |
| *Layoff X Small* | –2.111* | | 0.688 |
| | (–1.88) | | (0.37) |
| *Layoff X Large* | | –0.277 | |
| | | (–0.29) | |
| *LogMVE* | –0.786* | –0.876* | –0.767* |
| | (–1.79) | (–1.99) | (–1.76) |
| *ROA* | 1.511 | 1.177 | 1.414 |
| | (0.41) | (0.32) | (0.39) |
| *EarnVol* | 9.778* | 9.292* | 9.817* |
| | (1.76) | (1.68) | (1.77) |
| *Leverage* | –3.424** | –3.292* | –3.416* |
| | (–2.03) | (–1.97) | (–2.04) |
| *Investment* | 0.097 | 0.097 | 0.095 |
| | (0.94) | (0.88) | (0.92) |
| *R&D* | –0.426 | –7.596 | –1.393 |
| | (–0.02) | (–0.35) | (–0.06) |
| *Growth* | –0.439 | –0.539 | –0.444 |
| | (–0.60) | (–0.72) | (–0.60) |
| Observations | 17,044 | 23,501 | 17,044 |
| Adjusted $R^2$ | 0.261 | 0.308 | 0.261 |
| Sample | Small & Medium | Large & Medium | Small & Medium |
| Firm FE | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes |
| Main Effects | N/A | N/A | Yes |
| Interacted Effects | N/A | N/A | Yes |

This table examines how the number of days firms take to hire a position changes in response to the layoff-induced labor supply shock. The sample is conditional on the firm having posted at least one job in a given month. We require at least 3 months of lead time for the *TimeToHire* variable and hence the sample period stops in May of 2023 for this analysis. Column (1) presents how the small firms' hiring speed changes using the medium firms as the benchmark. Column (2) presents how the large firms' hiring speed changes using the medium firms as the benchmark for comparison. Column (3) presents whether the small firms' disclosures through job postings contribute to the hiring speed. *HighLength* indicates above median job posting length within each size group. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered at Firm and Month level are presented in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

**Table 6:** Labor Supply Shock and Job Postings for Experienced Workers

**Panel A:** Experienced Hiring

| | *ExperJobPostingFreq* (1) | *ExperJobPostingFreq* (2) |
|---|---|---|
| *Layoff X Small* | 0.223*** | |
| | (2.92) | |
| *Layoff X Large* | | –0.147* |
| | | (–1.83) |
| *LogMVE* | 0.202*** | 0.189*** |
| | (5.63) | (5.35) |
| *ROA* | –0.443 | –0.444 |
| | (–1.30) | (–1.32) |
| *EarnVol* | –0.414 | –0.413 |
| | (–0.92) | (–0.92) |
| *Leverage* | –0.200 | –0.210 |
| | (–1.26) | (–1.33) |
| *Investment* | 0.026** | 0.025** |
| | (2.51) | (2.49) |
| *R&D* | –1.663 | –1.891 |
| | (–1.10) | (–1.24) |
| *Growth* | 0.097* | 0.104* |
| | (1.76) | (1.96) |
| Observations | 22,195 | 27,217 |
| Adjusted $R^2$ | 0.764 | 0.848 |
| Sample | Small & Medium | Large & Medium |
| Firm FE | Yes | Yes |
| Month FE | Yes | Yes |
| Small(Large)XControl | Yes | Yes |

**Table 6:** Labor Supply Shock and Job Postings for Experienced Workers (Cont'd)

**Panel B:** Experienced Job Posting Length

| | *ExperPostingLength* | *ExperPostingLength* |
|---|---|---|
| | (1) | (2) |
| *Layoff X Small* | 0.070** | |
| | (2.10) | |
| *Layoff X Large* | | −0.020 |
| | | (−1.03) |
| *LogMVE* | 0.012 | 0.014* |
| | (1.46) | (1.68) |
| *ROA* | −0.015 | −0.021 |
| | (−0.18) | (−0.27) |
| *EarnVol* | −0.187 | −0.191 |
| | (−1.31) | (−1.34) |
| *Leverage* | 0.123*** | 0.124*** |
| | (3.03) | (3.20) |
| *Investment* | 0.001 | −0.001 |
| | (0.34) | (−0.44) |
| *R&D* | 0.172 | 0.157 |
| | (0.32) | (0.29) |
| *Growth* | −0.016 | −0.017 |
| | (−0.87) | (−0.97) |
| Observations | 16,867 | 23,783 |
| Adjusted $R^2$ | 0.599 | 0.603 |
| Sample | Small & Medium | Large & Medium |
| Firm FE | Yes | Yes |
| Month FE | Yes | Yes |
| Small(Large)XControl | Yes | Yes |

**Table 6:** Labor Supply Shock and Job Postings for Experienced Workers (Cont'd)

**Panel C:** Experienced Time to Hire

| | *ExperTimeToHire* (1) | *ExperTimeToHire* (2) | *ExperTimeToHire* (3) |
|---|---|---|---|
| *Layoff X Small X HighLength* | | | –5.422** |
| | | | (–2.17) |
| *Layoff X Small* | –2.719* | | 0.764 |
| | (–1.97) | | (0.34) |
| *Layoff X Large* | | –0.016 | |
| | | (–0.02) | |
| *LogMVE* | –0.463 | –0.726 | –0.441 |
| | (–1.03) | (–1.59) | (–0.98) |
| *ROA* | 3.325 | 3.077 | 3.251 |
| | (0.86) | (0.78) | (0.84) |
| *EarnVol* | 11.487* | 11.047* | 11.532* |
| | (1.75) | (1.69) | (1.76) |
| *Leverage* | –1.808 | –2.030 | –1.786 |
| | (–0.97) | (–1.08) | (–0.95) |
| *Investment* | 0.105 | 0.138 | 0.103 |
| | (0.94) | (1.10) | (0.93) |
| *R&D* | 3.893 | –3.448 | 2.983 |
| | (0.17) | (–0.15) | (0.13) |
| *Growth* | –0.235 | –0.424 | –0.246 |
| | (–0.26) | (–0.47) | (–0.28) |
| Observations | 15,989 | 22,652 | 15,989 |
| Adjusted $R^2$ | 0.240 | 0.280 | 0.240 |
| Sample | Small & Medium | Large & Medium | Small & Medium |
| Firm FE | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes |
| Main Effects | N/A | N/A | Yes |
| Interacted Effects | N/A | N/A | Yes |

This table examines how the job posting frequency (Panel A), job posting length (Panel B), and the number of days firms take to hire a position (Panel C) change in response to the layoff-induced labor supply shock, focusing on the job postings for experienced workers. We define job postings for experienced workers as those that impose at least one year of work experience as an application requirement. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered at Firm and Month level are presented in parentheses. Levels of significance are presented as follows: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

**Table 7:** Labor Supply Shock and Disclosure through Media

**Panel A:** Disclosure through Media

| | *Full Sample* | | | | *JobPostingFreq>0 Sample* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Media_PR* | | *Media_PRTech* | | *Media_PR* | | *Media_PRTech* | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Layoff X Small* | 0.156* | | 0.018* | | 0.173** | | 0.022* | |
| | (1.93) | | (1.85) | | (2.16) | | (1.74) | |
| *Layoff X Large* | | –0.104 | | –0.060*** | | –0.107 | | –0.060*** |
| | | (–1.47) | | (–3.21) | | (–1.53) | | (–3.18) |
| *LogMVE* | 0.022 | 0.043** | 0.014** | 0.023*** | 0.033 | 0.048** | 0.015** | 0.024*** |
| | (1.02) | (2.02) | (2.08) | (3.28) | (1.47) | (2.17) | (2.11) | (3.30) |
| *ROA* | –0.241 | –0.275 | –0.001 | –0.015 | –0.313 | –0.329 | 0.005 | –0.012 |
| | (–1.07) | (–1.18) | (–0.03) | (–0.34) | (–1.41) | (–1.47) | (0.09) | (–0.22) |
| *EarnVol* | 0.169 | 0.129 | –0.005 | –0.017 | –0.045 | –0.078 | –0.003 | –0.021 |
| | (0.53) | (0.38) | (–0.09) | (–0.31) | (–0.14) | (–0.23) | (–0.05) | (–0.35) |
| *Leverage* | –0.178* | –0.051 | –0.020 | 0.018 | –0.142 | –0.049 | –0.024 | 0.015 |
| | (–1.71) | (–0.50) | (–0.60) | (0.52) | (–1.36) | (–0.48) | (–0.65) | (0.39) |
| *Investment* | 0.006 | 0.007 | 0.002 | –0.000 | 0.003 | 0.004 | 0.002 | –0.000 |
| | (0.81) | (0.92) | (1.59) | (–0.06) | (0.34) | (0.53) | (1.62) | (–0.02) |
| *R&D* | 0.050 | –0.458 | 0.107 | 0.049 | 0.067 | –0.450 | 0.131 | 0.070 |
| | (0.05) | (–0.43) | (0.63) | (0.27) | (0.05) | (–0.32) | (0.59) | (0.29) |
| *Growth* | –0.000 | 0.019 | –0.001 | –0.001 | –0.030 | –0.005 | 0.001 | 0.001 |
| | (–0.01) | (0.66) | (–0.14) | (–0.11) | (–0.83) | (–0.14) | (0.13) | (0.13) |
| Observations | 22,195 | 27,217 | 22,195 | 27,217 | 17,992 | 24,684 | 17,992 | 24,684 |
| Adjusted $R^2$ | 0.483 | 0.567 | 0.599 | 0.785 | 0.470 | 0.567 | 0.610 | 0.791 |
| Sample | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium | Large & Medium |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 7:** Labor Supply Shock and Disclosure through Media (Cont'd)

**Panel B:** Why Disclose through Media

| | *Media_PR* (1) | *Media_PRTech* (2) |
|---|---|---|
| *Layoff X Small X HiringNeed* | 0.130** | 0.018* |
| | (2.40) | (1.70) |
| *Layoff X Small* | 0.074 | 0.004 |
| | (0.95) | (0.65) |
| *LogMVE* | 0.023 | 0.014** |
| | (1.05) | (2.09) |
| *ROA* | –0.238 | 0.002 |
| | (–1.05) | (0.04) |
| *EarnVol* | 0.171 | –0.005 |
| | (0.54) | (–0.10) |
| *Leverage* | –0.178* | –0.018 |
| | (–1.71) | (–0.56) |
| *Investment* | 0.006 | 0.002 |
| | (0.80) | (1.52) |
| *R&D* | 0.063 | 0.123 |
| | (0.06) | (0.72) |
| *Growth* | –0.000 | –0.001 |
| | (–0.01) | (–0.17) |
| Observations | 22,195 | 22,195 |
| Adjusted $R^2$ | 0.483 | 0.599 |
| Sample | Small & Medium | Small & Medium |
| Firm FE | Yes | Yes |
| Month FE | Yes | Yes |
| SmallXControl | Yes | Yes |
| Main Effects | Yes | Yes |
| Interacted Effects | Yes | Yes |

**Table 7:** Labor Supply Shock and Disclosure through Media (Cont'd)

**Panel C:** Effectiveness of Disclosure through Media

| | *TimeToHire* (1) | *TimeToHire* (2) |
|---|---|---|
| *Layoff X Small X HighMedia_PR* | 2.362 | |
| | (1.24) | |
| *Layoff X Small X HighMedia_PRTech* | | $-9.590^{**}$ |
| | | (−2.13) |
| *Layoff X Small* | $-3.372^{**}$ | $-1.972^{*}$ |
| | (−2.28) | (−1.73) |
| *LogMVE* | $-0.784^{*}$ | $-0.790^{*}$ |
| | (−1.79) | (−1.80) |
| *ROA* | 1.510 | 1.536 |
| | (0.41) | (0.42) |
| *EarnVol* | $9.797^{*}$ | $9.869^{*}$ |
| | (1.77) | (1.78) |
| *Leverage* | $-3.429^{**}$ | $-3.398^{**}$ |
| | (−2.03) | (−2.02) |
| *Investment* | 0.097 | 0.096 |
| | (0.94) | (0.93) |
| *R&D* | −0.391 | −1.218 |
| | (−0.02) | (−0.05) |
| *Growth* | −0.437 | −0.425 |
| | (−0.60) | (−0.58) |
| Observations | 17,044 | 17,044 |
| Adjusted $R^2$ | 0.261 | 0.261 |
| Sample | Small & Medium | Small & Medium |
| Firm FE | Yes | Yes |
| Month FE | Yes | Yes |
| SmallXControl | Yes | Yes |
| Main Effects | Yes | Yes |
| Interacted Effects | Yes | Yes |

This table examines how disclosure through media press releases changes in response to the layoff-induced labor supply shock. Panel A studies how the frequency of press releases changes in response to the layoff-induced labor supply shock. Columns (1) - (4) estimate the relation using the full sample of observations, and columns (5) - (8) estimate the relation within the sample observations that have posted at least one job posting in a given month. Columns (1), (3), (5), and (7) present how the small firms' frequency of media press releases changes using the medium firms as the benchmark. Columns (2), (4), (6), and (8) present how the large firms' frequency of media press releases changes using the medium firms as the benchmark for comparison. Panel B studies whether strong hiring need motivates firms to issue more press releases through media. *HiringNeed* is a variable that equals two if the number of job postings *JobPostingFreq* in a given month and the average number of days it takes to fill a position *TimeToHire* from the past two months are both above median within each size group (i.e., want to hire but cannot hire in a timely manner), one if only one of the two is above median, and zero otherwise. Panel C studies whether more disclosure through media is effective in accelerating the hiring speed. *HighMedia_PR* (*HighMedia_PRTech*) is an indicator variable that equals one if *Media_PR* (*Media_PRTech*) is above median within each size group, and zero otherwise. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered at Firm and Month level are presented in parentheses. Levels of significance are presented as follows: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table 8:** Labor Supply Shock and Future Growth Outcomes

**Panel A:** Product-related Announcements

| | $ProductAnn_{m+1}$ (1) | $ProductAnn_{m+1}$ (2) | $ProductAnn_{q+1}$ (3) | $ProductAnn_{q+1}$ (4) |
|---|---|---|---|---|
| *Layoff X Small* | 0.035** | | 0.089** | |
| | (2.01) | | (2.15) | |
| *Layoff X Large* | | –0.053*** | | –0.042 |
| | | (–2.77) | | (–1.29) |
| *LogMVE* | 0.016*** | 0.022*** | 0.022 | 0.032** |
| | (2.66) | (3.65) | (1.64) | (2.51) |
| *ROA* | 0.057 | 0.050 | –0.078 | –0.078 |
| | (0.71) | (0.62) | (–0.53) | (–0.54) |
| *EarnVol* | –0.168 | –0.172 | –0.104 | –0.094 |
| | (–1.51) | (–1.56) | (–0.37) | (–0.34) |
| *Leverage* | –0.002 | 0.012 | –0.049 | –0.020 |
| | (–0.05) | (0.41) | (–0.81) | (–0.33) |
| *Investment* | 0.275 | 0.327 | –1.859** | –1.828** |
| | (0.53) | (0.62) | (–2.54) | (–2.46) |
| *R&D* | –0.002 | –0.003 | 0.004 | 0.002 |
| | (–0.88) | (–1.19) | (0.67) | (0.45) |
| *Growth* | –0.005 | –0.007 | –0.011 | –0.017 |
| | (–0.27) | (–0.44) | (–0.44) | (–0.70) |
| Observations | 20,617 | 25,440 | 20,617 | 25,440 |
| Adjusted $R^2$ | 0.183 | 0.317 | 0.401 | 0.533 |
| Sample | Small & Medium | Large & Medium | Small & Medium | Large & Medium |
| Firm FE | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes | Yes |

**Table 8:** Labor Supply Shock and Future Growth Outcomes (Cont'd)

**Panel B:** Patent Applications

| | $Patent_{m+1}$ | $Patent_{m+1}$ | $Patent_{q+1}$ | $Patent_{q+1}$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Layoff X Small* | 0.224*** | | 0.417*** | |
| | (5.19) | | (4.70) | |
| *Layoff X Large* | | –0.564*** | | –0.794*** |
| | | (–5.53) | | (–5.28) |
| *LogMVE* | 0.011 | 0.060*** | 0.043 | 0.100*** |
| | (0.60) | (2.66) | (1.23) | (2.72) |
| *ROA* | 0.010 | –0.027 | 0.204 | 0.091 |
| | (0.04) | (–0.10) | (0.51) | (0.23) |
| *EarnVol* | –0.236 | –0.333 | 0.236 | 0.090 |
| | (–0.77) | (–1.02) | (0.44) | (0.16) |
| *Leverage* | –0.087 | 0.067 | –0.180 | –0.005 |
| | (–0.73) | (0.51) | (–0.72) | (–0.02) |
| *Investment* | 0.014** | 0.012* | 0.014 | 0.009 |
| | (2.36) | (1.72) | (1.39) | (0.93) |
| *R&D* | –1.015 | –0.984 | 0.588 | 0.616 |
| | (–0.79) | (–0.76) | (0.32) | (0.33) |
| *Growth* | –0.092* | –0.083 | –0.061 | –0.033 |
| | (–1.86) | (–1.64) | (–0.94) | (–0.48) |
| Observations | 7,784 | 13,605 | 7,611 | 13,263 |
| Adjusted $R^2$ | 0.527 | 0.846 | 0.674 | 0.869 |
| Sample | Small & Medium | Large & Medium | Small & Medium | Large & Medium |
| Firm FE | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes | Yes |

**Table 8:** Labor Supply Shock and Future Growth Outcomes (Cont'd)

**Panel C:** Financial Performance

| | $ROA_{q+1}$ | $ROA_{q+1}$ |
|---|---|---|
| | (1) | (2) |
| *Layoff X Small* | 0.017** | |
| | (2.37) | |
| *Layoff X Large* | | 0.000 |
| | | (0.07) |
| *LogMVE* | 0.006** | 0.006*** |
| | (2.39) | (2.75) |
| *ROA* | 0.178*** | 0.176*** |
| | (3.79) | (3.74) |
| *EarnVol* | 0.102* | 0.105* |
| | (1.88) | (1.93) |
| *Leverage* | 0.009 | 0.010 |
| | (0.86) | (1.05) |
| *Investment* | 0.000 | –0.000 |
| | (0.57) | (–0.83) |
| *R&D* | 0.061 | 0.055 |
| | (0.60) | (0.55) |
| *Growth* | 0.018*** | 0.016** |
| | (2.74) | (2.51) |
| Observations | 21,921 | 26,946 |
| Adjusted $R^2$ | 0.422 | 0.457 |
| Sample | Small & Medium | Large & Medium |
| Firm FE | Yes | Yes |
| Month FE | Yes | Yes |
| Small(Large)XControl | Yes | Yes |

This table examines how small and large firms' future growth-related outcomes change in response to the layoff-induced labor supply shock. Panel A studies how announcements about product development activities change in response to the layoff-induced labor supply shock. Panel B studies how patent application activities change in response to the layoff-induced labor supply shock. Panel C studies how financial performance changes in response to the layoff-induced labor supply shock. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered at Firm and Month level are presented in parentheses. Levels of significance are presented as follows: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01.

**Table 9:** Labor Reallocation Outside of Technology Industry

**Panel A:** NAICS Distribution

| | | NAICS Frequency | | |
|---|---|---|---|---|
| | | (1) IT Industry | (2) Non-IT Industry Similar to Large IT | (3) Non-IT Industry Dissimilar to Large IT |
| 334 | Computer and Electronic Product Manufacturing | 16,722 | 271 | |
| 518 | Data Processing, Hosting, and Related Services | 6,690 | | |
| 519 | Other Information Services | 5,394 | | |
| 541 | Professional, Scientific, and Technical Services | 2,187 | 1,728 | 1,555 |
| 511 | Publishing Industries (Except Internet) | 923 | | |
| 325 | Chemical Manufacturing | | 11,232 | 8,367 |
| 339 | Miscellaneous Manufacturing | | 2,403 | 1,736 |
| 513 | Publishing Industries | | 1,854 | |
| 333 | Machinery Manufacturing | | 1,704 | 3,187 |
| 621 | Ambulatory Health Care Services | | 1,486 | |
| 336 | Transportation Equipment Manufacturing | | 1,300 | 3,213 |
| 523 | Securities, Commodity Contracts, and Other Financial Investments | | 1,263 | 1,572 |
| 561 | Administrative and Support Services | | 1,030 | 1,697 |
| 517 | Telecommunications | | 886 | |
| 423 | Merchant Wholesalers, Durable Goods | | 876 | 1,616 |
| 522 | Credit Intermediation and Related Activities | | 837 | |
| 332 | Fabricated Metal Product Manufacturing | | 513 | 1,826 |
| 335 | Electrical Equipment, Appliance, and Component Manufacturing | | 509 | 1,378 |
| 524 | Insurance Carriers and Related Activities | | 439 | 2,588 |
| 622 | Hospitals | | 295 | |
| 531 | Real Estate | | 294 | 2,868 |
| 533 | Lessors of Nonfinancial Intangible Assets | | 266 | |
| 316 | Leather and Allied Product Manufacturing | | 203 | |
| 315 | Apparel Manufacturing | | 178 | |
| 458 | Clothing, Clothing Accessories, Shoe, and Jewelry Retailers | | 131 | 1,555 |
| 455 | General Merchandise Retailers | | 114 | |
| 516 | Broadcasting and content providers | | 112 | 1,168 |
| 331 | Primary Metal Manufacturing | | 103 | 1,017 |
| 221 | Utilities | | | 4,336 |
| 211 | Oil and Gas Extraction | | | 2,327 |
| 311 | Food manufacturing | | | 2,318 |
| 722 | Food Services and Drinking Places | | | 2,189 |
| 424 | Merchant Wholesalers, Nondurable Goods | | | 1,626 |
| 213 | Support Activities for Mining | | | 1,549 |
| 441 | Motor Vehicle and Parts Dealers | | | 1,310 |
| 212 | Mining (except Oil and Gas) | | | 1,283 |
| 484 | Truck Transportation | | | 1,181 |
| 324 | Petroleum and Coal Product Manufacturing | | | 1,081 |
| 312 | Beverage and Tobacco Product Manufacturing | | | 1,014 |
| Others | | | 973 | 24,124 |
| Total | | 31,916 | 31,000 | 79,681 |

**Table 9:** Labor Reallocation Outside of Technology Industry (Cont'd)

**Panel B:** Labor Reallocation in Non-IT Industries

| | *JobPostingFreq* | | | |
|---|---|---|---|---|
| | *Similar to Large IT* | | *Dissimilar to Large IT* | |
| | (1) | (2) | (3) | (4) |
| *Layoff X Small* | 0.217*** | | –0.080 | |
| | (3.38) | | (–1.52) | |
| *Layoff X Large* | | 0.092 | | –0.054 |
| | | (1.24) | | (–1.21) |
| *LogMVE* | 0.308*** | 0.274*** | 0.231*** | 0.202*** |
| | (7.33) | (6.28) | (8.39) | (7.38) |
| *ROA* | –0.021 | –0.073 | 0.376* | 0.406* |
| | (–0.07) | (–0.22) | (1.77) | (1.91) |
| *EarnVol* | –0.815 | –0.896 | –0.352 | –0.293 |
| | (–1.51) | (–1.64) | (–1.02) | (–0.83) |
| *Leverage* | –0.157 | –0.178 | 0.124 | 0.119 |
| | (–1.02) | (–1.15) | (0.97) | (0.92) |
| *Investment* | 0.011 | 0.006 | 0.010** | 0.005 |
| | (0.99) | (0.56) | (2.16) | (1.23) |
| *R&D* | –0.844 | –0.888 | 2.776* | 2.541* |
| | (–0.78) | (–0.83) | (1.97) | (1.75) |
| *Growth* | 0.009 | 0.007 | 0.017 | 0.011 |
| | (0.38) | (0.28) | (0.95) | (0.66) |
| Observations | 21,481 | 22,332 | 43,277 | 71,329 |
| Adjusted $R^2$ | 0.764 | 0.878 | 0.799 | 0.886 |
| Sample | Small & Medium | Large & Medium | Small & Medium | Large & Medium |
| Firm FE | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes | Yes |

This table studies labor reallocation pattern outside of the technology industry, using Hoberg-Phillips product market similarity score to identify industries that are more or less similar to large technology firms. Panel A presents the 3-digit NAICS industry code distribution for those firms in the technology industry as per our definition (IT firms) (Column 1), those that are not in the technology industry as per our definition (non-IT firms) but have positive Hoberg-Phillips product similarity score with the large IT firms in our sample (Column 2), and those that are not in the technology industry as per our definition (non-IT firms) and have zero Hoberg-Phillips product similarity score with the large IT firms in our sample (Column 3). The industry codes that have fewer than 100 (1000) firms in the non-IT similar (dissimilar) industry are aggregated into 'Others'. Panel B examines how the job posting frequency changes in the non-IT industries in response to the layoff-induced labor supply shock in the technology industry. Columns (1) and (3) present how the small firms in the non-IT industries change their job posting frequency using the medium firms as the benchmark. Columns (2) and (4) present how the large firms in the non-IT industries change their job posting frequency using the medium firms as the benchmark. Columns (1) and (2) study firms that are not in the technology industry as per our definition (non-IT firms) but have positive Hoberg-Phillips product similarity scores with the large IT firms in our sample. Columns (3) and (4) study firms that are not in the technology industry as per our definition (non-IT firms) and have zero Hoberg-Phillips product similarity scores with the large IT firms in our sample. The Hoberg-Phillips score is based in year 2021 (i.e., the latest available year) and is the average calculated across all pairs with the large IT firms in our sample. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered at Firm and Month level are presented in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

## Appendix A. Variable Definitions

| Variable | Definition | Data source |
|---|---|---|
| $Layoff_{m}$ | An indicator variable that equals 1 if the year-month is on or after 2022-11, and 0 otherwise. | - |
| $JobPostingFreq_{i,m}$ | Natural logarithm of one plus the number of new jobs a firm *i* posts in a year-month *m*. The variable is filled with 0 if firm *i* does not post a new job in a month that is after its first posting month and before its last posting month in the sample. | Lightcast |
| $PostingLength_{i,m}$ | Natural logarithm of one plus the average number of words contained in the job posting posted by a firm *i* in a year-month *m*. | Lightcast |
| $TimeToHire_{i,m}$ | The average number of days a firm *i* takes to fill in the job positions and take down the job postings posted in the year-month *m*. | Lightcast |
| $Tobin'sQ_{i,m}$ | The ratio of the market value of total assets (defined as the book value of total assets plus the market value of equity minus the book value of equity) to book value of total assets for firm *i* measured at the beginning of quarter *q*. | Compustat |
| $HighLength_{i,m}$ | An indicator variable that equals one if *PostingLength* (*ExperPostingLength*) is above median within each size group, and zero otherwise. | Lightcast |
| $ExperJobPostingFreq_{i,m}$ | Natural logarithm of one plus the number of new jobs for experienced workers that a firm *i* posts in a year-month *m*. The variable is filled with 0 if firm *i* does not post a new job for experienced workers in a month that is after its first posting month and before its last posting month in the sample. Jobs for experienced workers are defined as those that explicitly require at least one year of work experience. | Lightcast |
| $ExperPostingLength_{i,m}$ | Natural logarithm of one plus the average number of words contained in the job posting for experienced workers posted by a firm *i* in a year-month *m*. | Lightcast |
| $ExperTimeToHire_{i,m}$ | The average number of days a firm *i* takes to hire an employee and fill in its job for experienced workers posted in the year-month *m*. | Lightcast |
| $Media\_PR_{i,m}$ | Natural logarithm of one plus the number of unique news stories about firm *i* in year-month *m*, with relevance ≥ 80, and identified as a "press release (corporate announcement originated by an entity and distributed via a news provider)" by at least one of the news provider sources on RavenPack. | RavenPack |
| $Media\_PRTech_{i,m}$ | Number of unique news stories about firm *i* in year-month *m*, with relevance ≥ 80, and identified as a "press release (corporate announcement originated by an entity and distributed via a news provider)" by at least one of the news provider sources on RavenPack and carried by one of the following "tech news sources" on RavenPack: TechCrunch, The Verge, Ars Technica, Wired, CNET, Mashable, Engadget, TechRader, ZDNet, VentureBeat, Gizmodo, Recode, Tom's Hardware, PCMag, Android Authority, MIT Technology Review, and Digital Trends. | RavenPack |
| $HiringNeed_{i,m}$ | A variable that equals two if the number of job postings (*JobPostingFreq*) and the average number of days it takes to fill a position (*TimeToHire*) from the past two months are both above median within each size group (i.e., want to hire but cannot hire in a timely manner), one if only one of the two is above median, and zero otherwise. | Lightcast, RavenPack |
| $HighMedia\_PR_{i,m}$ | An indicator variable that equals one if *Media_PR* is above median within each size group, and zero otherwise. | RavenPack |
| $HighMedia\_PRTech_{i,m}$ | An indicator variable that equals one if *Media_PRTech* is above median within each size group, and zero otherwise. | RavenPack |
| $ProductAnn_{i,m+1}$ | Natural logarithm of one plus the number of product-related announcements about firm *i*'s products in year-month *m+1*. These are announcements pertaining to the introduction, change, improvement, or discontinuation of a company's product or services. According to Capital IQ, this covers introducing/announcing/unveiling a new product/service/software/solution/platform and technology along with new product line, new models, brands, and new versions of its products or services as well as announcements related getting permission/receiving patent rights for releasing new product into the market. | Capital IQ Key Developments |
| $ProductAnn_{i,q+1}$ | Natural logarithm of one plus the number of product-related announcements about firm *i*'s products in quarter *q+1*. | Capital IQ Key Developments |
| $Patent_{i,m+1}$ | Natural logarithm of one plus the number of patent applications filed by firm *i* in month *m+1*. | USPTO |
| $Patent_{i,q+1}$ | Natural logarithm of one plus the number of patent applications filed by firm *i* in quarter *q+1*. | USPTO |

| Variable | Definition | Data source |
|---|---|---|
| $ROA_{i,q+1}$ | Return on assets, equal to the net income divided by the book value of total assets, for firm *i* in quarter *q+1*. | Compustat |
| Controls | | |
| $LogMVE_{i,q}$ | Natural logarithm of the market value of equity for firm *i* measured at the beginning of quarter *q*. | Compustat |
| $ROA_{i,q}$ | Return on assets, equal to the net income divided by the book value of total assets, for firm *i* in quarter *q*. | Compustat |
| $EarnVol_{i,q}$ | The standard deviation of return on assets for the 4 quarters leading up to quarter *q* for firm *i*. | Compustat |
| $Leverage_{i,q}$ | Leverage, equal to the sum of short-term and long-term debts divided by total assets for firm *i* measured at the beginning of quarter *q*. | Compustat |
| $Investment_{i,q}$ | Investments, equal to the capital expenditures multiplied by 100 and divided by total assets for firm *i* in quarter *q*. | Compustat |
| $R\&D_{i,q}$ | The research and development expenditures divided by total assets for firm *i* in quarter *q*. | Compustat |
| $Growth_{i,q}$ | The percentage change in sales for firm *i* in quarter *q* relative to quarter *q−1*. | Compustat |

## References

Acharya, V. V., Baghai, R. P., and Subramanian, K. V. (2014). Wrongful discharge laws and innovation. *The Review of Financial Studies*, *27*(1), 301-346.

Arellano-Bover, J. (2024). Career consequences of firm heterogeneity for young workers: First job and firm size. *Journal of Labor Economics*, 42(2), 549-589.

Babina, T. (2020). Destructive creation at work: How financial distress spurs entrepreneurship. *The Review of Financial Studies*, *33*(9), 4061-4101.

Babina, T., Ouimet, P., and Zarutskie, R. (2022). IPOs, human capital, and labor reallocation. *Available at SSRN 2692845*.

Ball, R., and Brown, P. (1968). An empirical evaluation of accounting. *Journal of Accounting Research, 6*(2), 159-178.

Bapna, R., Langer, N., Mehra, A., Gopal, R., and Gupta, A. (2013). Human capital investments and employee performance: An analysis of IT services industry. *Management Science*, 59(3), 641-658.

Batish, A., Gordon, A., Kepler, J. D., Larcker, D. F., Tayan, B., and Yu, C. (2021). Human Capital Disclosure: What Do Companies Say About Their 'Most Important Asset'?. *Rock Center for Corporate Governance at Stanford University Working Paper Forthcoming*.

Beaver, W. H. (1968). The information content of annual earnings announcements. *Journal of Accounting Research*, 67-92.

Beyer, A., Cohen, D. A., Lys, T. Z., and Walther, B. R. (2010). The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics*, *50*(2-3), 296-343.

Bidwell, M., Won, S., Barbulescu, R., and Mollick, E. (2015). I used to work at Goldman Sachs! How firms benefit from organizational status in the market for human capital. *Strategic Management Journal*, *36*(8), 1164-1173.

Bishop, D. (2012). Firm size and skill formation processes: an emerging debate. *Journal of Education and Work*, *25*(5), 507-521.

Brown, J., and Matsa, D. A. (2016). Boarding a sinking ship? An investigation of job applications to distressed firms. *The Journal of Finance*, *71*(2), 507-550.

Cao, Y., Cheng, S., Tucker, J. W., and Wan, C. (2023). Technological peer pressure and skill specificity of job postings. *Contemporary Accounting Research*, *40*(3), 2106-2139.

Cetin, F. M. (2023). The Real Effects of Accounting on Innovation: Evidence from ASC 606. *Available at SSRN 4609780*.

Chakravarthy, J., deHaan, E., and Rajgopal, S. (2014). Reputation repair after a serious restatement. *The Accounting Review*, *89*(4), 1329-1363.

Chang, X., Fu, K., Low, A., and Zhang, W. (2015). Non-executive employee stock options and corporate innovation. *Journal of Financial Economics*, *115*(1), 168-188.

Choi, B. G., Choi, J. H., and Malik, S. (2023a). Not just for investors: The role of earnings announcements in guiding job seekers. *Journal of Accounting and Economics*, *76*(1), 101588.

Choi, J. H., Pacelli, J., Rennekamp, K. M., and Tomar, S. (2023b). Do jobseekers value diversity information? Evidence from a field experiment and human capital disclosures. *Journal of Accounting Research*, *61*(3), 695-735.

deHaan, E., Li, N., and Zhou, F. S. (2023). Financial reporting and employee job search. *Journal of Accounting Research*, *61*(2), 571-617.

Derrien, F., Kecskés, A., and Nguyen, P. A. (2023). Labor force demographics and corporate innovation. *The Review of Financial Studies*, *36*(7), 2797-2838.

Dunn, L. F. (1986). Work disutility and compensating differentials: Estimation of factors in the link between wages and firm size. *The Review of Economics and Statistics*, 67-73.

Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics*, *101*(3), 621-640.

Graham, J. R., Kim, H., Li, S., and Qiu, J. (2015). The labor impact of corporate bankruptcy. *Unpublished Working Paper*.

Healy, P. M., and Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of accounting and economics*, *31*(1-3), 405-440.

Hoberg, G., and Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, *23*(10), 3773-3811.

Hoberg, G., and Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, *124*(5), 1423-1465.

Lambert, R., Leuz, C., and Verrecchia, R. E. (2007). Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research*, *45*(2), 385-420.

Lanteri, A. (2018). The market for used capital: Endogenous irreversibility and reallocation over the business cycle. *American Economic Review*, *108*(9), 2383-2419.

McNichols, M. F., and Stubben, S. R. (2008). Does earnings management affect firms' investment decisions?. *The Accounting Review*, *83*(6), 1571-1603.

Moscarini, G., and Postel-Vinay, F. (2009). *Large employers are more cyclically sensitive* (No. w14740). National Bureau of Economic Research.

Moscarini, G., and Postel-Vinay, F. (2012). The contribution of large and small employers to job creation in times of high and low unemployment. *American Economic Review*, *102*(6), 2509-2539.

Noh, S., So, E. C., and Zhu, C. (2023). Financial reporting and consumer behavior. *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*.

Oi, W. Y., and Idson, T. L. (1999). Firm size and wages. *Handbook of Labor Economics*, 3, 2165-2214.

Pacelli, J., Shi, T., and Zou, Y. (2022). Communicating corporate culture in labor markets: Evidence from job postings. *Available at SSRN 4235342.*

Roychowdhury, S., Shroff, N., and Verdi, R. S. (2019). The effects of financial reporting and disclosure on corporate investment: A review. *Journal of Accounting and Economics*, *68*(2-3), 101246.

Sran, G. (2021). Disclosing labor demand. *Available at SSRN 3964310.*

Verdi, R. S. (2006). Financial reporting quality and investment efficiency. *Available at SSRN 930922*.

vom Berge, P., and Schmillen, A. (2023). Effects of mass layoffs on local employment—evidence from geo-referenced data. *Journal of Economic Geography*, *23*(3), 509-539.

# Internet Appendix

**Table IA1:** Alternative Definitions of Small, Medium, and Large Firms

**Panel A:** Small (≤ 200), Medium (200 < and < 3,000), and Large (≥ 3,000) Firms

| | *JobPostingFreq* | | *PostingLength* | | *TimeToHire* | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Layoff X Small X HighLength* | | | | | | | –4.735** |
| | | | | | | | (–2.17) |
| *Layoff X Small* | 0.248*** | | 0.076** | | –2.167** | | 0.925 |
| | (2.89) | | (2.45) | | (–1.91) | | (0.47) |
| *Layoff X Large* | | –0.116 | | –0.021 | | –0.329 | |
| | | (–1.44) | | (–1.10) | | (–0.45) | |
| *LogMVE* | 0.192*** | 0.183*** | 0.016* | 0.018** | –0.877* | –0.833* | –0.839* |
| | (4.80) | (4.74) | (1.79) | (2.16) | (–1.89) | (–1.80) | (–1.82) |
| *ROA* | –0.145 | –0.130 | –0.017 | –0.025 | 0.340 | –0.082 | 0.119 |
| | (–0.45) | (–0.40) | (–0.17) | (–0.26) | (0.09) | (–0.02) | (0.03) |
| *EarnVol* | –0.464 | –0.424 | –0.132 | –0.142 | 6.692 | 6.052 | 6.588 |
| | (–1.08) | (–0.99) | (–0.96) | (–1.04) | (1.16) | (1.05) | (1.14) |
| *Leverage* | –0.222 | –0.223 | 0.060 | 0.061 | –3.830** | –3.140* | –3.794** |
| | (–1.29) | (–1.29) | (1.26) | (1.33) | (–2.13) | (–1.79) | (–2.12) |
| *Investment* | 0.027** | 0.023** | –0.001 | –0.003 | 0.129 | 0.116 | 0.126 |
| | (2.38) | (2.16) | (–0.24) | (–0.92) | (1.16) | (1.00) | (1.14) |
| *R&D* | –1.518 | –1.892 | 0.363 | 0.377 | 14.607 | 3.980 | 12.743 |
| | (–1.09) | (–1.34) | (0.66) | (0.68) | (0.63) | (0.18) | (0.55) |
| *Growth* | 0.100 | 0.104* | –0.010 | –0.016 | –0.278 | –0.450 | –0.275 |
| | (1.59) | (1.70) | (–0.52) | (–0.80) | (–0.35) | (–0.55) | (–0.34) |
| Observations | 19,235 | 27,217 | 15,214 | 24,684 | 14,397 | 23,501 | 14,397 |
| Adjusted $R^2$ | 0.770 | 0.854 | 0.602 | 0.586 | 0.251 | 0.308 | 0.251 |
| Sample | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Main Effects | N/A | N/A | N/A | N/A | N/A | N/A | Yes |
| Interacted Effects | N/A | N/A | N/A | N/A | N/A | N/A | Yes |

**Table IA1:** Alternative Definitions of Small, Medium, and Large Firms

**Panel B:** Small (≤ 300), Medium (300 < and < 5,000), and Large (≥ 5,000) Firms

| | *JobPostingFreq* | | *PostingLength* | | *TimeToHire* | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Layoff X Small X HighLength* | | | | | | | −3.952* |
| | | | | | | | (−1.72) |
| *Layoff X Small* | 0.280*** | | 0.071** | | −1.644 | | 1.119 |
| | (3.53) | | (2.47) | | (−1.52) | | (0.58) |
| *Layoff X Large* | | −0.131 | | −0.012 | | −0.209 | |
| | | (−1.58) | | (−0.57) | | (−0.26) | |
| *LogMVE* | 0.204*** | 0.190*** | 0.007 | 0.011 | −0.746 | −0.806* | −0.729 |
| | (5.08) | (4.82) | (0.79) | (1.27) | (−1.64) | (−1.78) | (−1.61) |
| *ROA* | −0.479 | −0.479 | −0.136 | −0.143 | 2.849 | 2.441 | 2.712 |
| | (−1.33) | (−1.34) | (−1.55) | (−1.64) | (0.79) | (0.67) | (0.75) |
| *EarnVol* | −0.676 | −0.672 | −0.239 | −0.245 | 7.914 | 7.437 | 7.967 |
| | (−1.36) | (−1.35) | (−1.47) | (−1.50) | (1.39) | (1.31) | (1.40) |
| *Leverage* | −0.296* | −0.309* | 0.068 | 0.075 | −3.917** | −3.730** | −3.975** |
| | (−1.71) | (−1.79) | (1.46) | (1.65) | (−2.26) | (−2.18) | (−2.29) |
| *Investment* | 0.025** | 0.025** | 0.001 | −0.001 | 0.140 | 0.145 | 0.140 |
| | (2.23) | (2.23) | (0.31) | (−0.28) | (1.37) | (1.31) | (1.36) |
| *R&D* | −2.829 | −3.119 | 0.039 | 0.026 | −6.956 | −15.669 | −8.473 |
| | (−1.43) | (−1.58) | (0.07) | (0.05) | (−0.31) | (−0.70) | (−0.37) |
| *Growth* | 0.113* | 0.123** | −0.021 | −0.024 | −0.164 | −0.275 | −0.163 |
| | (1.78) | (2.01) | (−1.11) | (−1.27) | (−0.23) | (−0.36) | (−0.22) |
| Observations | 22,134 | 25,904 | 17,933 | 23,884 | 16,991 | 22,733 | 16,991 |
| Adjusted $R^2$ | 0.779 | 0.848 | 0.584 | 0.586 | 0.261 | 0.314 | 0.261 |
| Sample | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Main Effects | N/A | N/A | N/A | N/A | N/A | N/A | Yes |
| Interacted Effects | N/A | N/A | N/A | N/A | N/A | N/A | Yes |

**Table IA1:** Alternative Definitions of Small, Medium, and Large Firms

**Panel C:** Small (≤ 300), Medium (300 < and < 3,000), and Large (≥ 3,000) Firms

| | *JobPostingFreq* | | *PostingLength* | | *TimeToHire* | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Layoff X Small X HighLength* | | | | | | | –3.634* |
| | | | | | | | (–1.69) |
| *Layoff X Small* | 0.279*** | | 0.064** | | –1.558 | | 0.894 |
| | (3.65) | | (2.26) | | (–1.46) | | (0.47) |
| *Layoff X Large* | | –0.091 | | –0.019 | | –0.364 | |
| | | (–1.13) | | (–0.98) | | (–0.50) | |
| *LogMVE* | 0.197*** | 0.185*** | 0.013 | 0.016* | –0.789 | –0.709 | –0.749 |
| | (4.68) | (4.48) | (1.40) | (1.77) | (–1.60) | (–1.46) | (–1.53) |
| *ROA* | –0.387 | –0.363 | –0.062 | –0.072 | 1.443 | 0.944 | 1.111 |
| | (–1.08) | (–1.01) | (–0.65) | (–0.76) | (0.38) | (0.25) | (0.29) |
| *EarnVol* | –0.748 | –0.709 | –0.145 | –0.154 | 4.197 | 3.668 | 3.989 |
| | (–1.59) | (–1.51) | (–0.99) | (–1.05) | (0.69) | (0.60) | (0.65) |
| *Leverage* | –0.259 | –0.263 | 0.058 | 0.062 | –4.366** | –3.589* | –4.387** |
| | (–1.45) | (–1.46) | (1.20) | (1.31) | (–2.31) | (–1.97) | (–2.32) |
| *Investment* | 0.027** | 0.024** | –0.001 | –0.003 | 0.176 | 0.167 | 0.174 |
| | (2.24) | (2.09) | (–0.41) | (–1.09) | (1.62) | (1.44) | (1.60) |
| *R&D* | –1.997 | –2.451 | 0.214 | 0.207 | 9.710 | –2.829 | 6.959 |
| | (–1.13) | (–1.38) | (0.37) | (0.36) | (0.41) | (–0.13) | (0.30) |
| *Growth* | 0.134* | 0.141** | –0.019 | –0.024 | 0.027 | –0.175 | 0.037 |
| | (1.92) | (2.08) | (–0.90) | (–1.15) | (0.03) | (–0.21) | (0.05) |
| Observations | 19,235 | 25,735 | 15,214 | 23,718 | 14,397 | 22,590 | 14,397 |
| Adjusted $R^2$ | 0.771 | 0.849 | 0.602 | 0.585 | 0.250 | 0.314 | 0.251 |
| Sample | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Main Effects | N/A | N/A | N/A | N/A | N/A | N/A | Yes |
| Interacted Effects | N/A | N/A | N/A | N/A | N/A | N/A | Yes |

**Table IA1:** Alternative Definitions of Small, Medium, and Large Firms

**Panel D:** Small (≤ 150), Medium (150 < and < 5,000), and Large (≥ 5,000) Firms

| | *JobPostingFreq* | | *PostingLength* | | *TimeToHire* | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Layoff X Small X HighLength* | | | | | | | −4.178* |
| | | | | | | | (−1.99) |
| *Layoff X Small* | 0.236** | | 0.075** | | −2.910** | | −0.243 |
| | (2.51) | | (2.19) | | (−2.26) | | (−0.13) |
| *Layoff X Large* | | −0.162* | | −0.017 | | −0.121 | |
| | | (−1.98) | | (−0.87) | | (−0.15) | |
| *LogMVE* | 0.206*** | 0.189*** | 0.008 | 0.015* | −0.744 | −0.947** | −0.729 |
| | (5.18) | (5.09) | (0.82) | (1.70) | (−1.64) | (−2.18) | (−1.61) |
| *ROA* | −0.488 | −0.180 | −0.138 | −0.129 | 2.846 | 7.329 | 2.757 |
| | (−1.36) | (−0.62) | (−1.57) | (−1.63) | (0.78) | (1.30) | (0.76) |
| *EarnVol* | −0.668 | −0.369 | −0.238 | −0.264* | 7.911 | 15.228** | 7.936 |
| | (−1.34) | (−0.88) | (−1.47) | (−1.80) | (1.38) | (2.00) | (1.39) |
| *Leverage* | −0.317* | −0.281* | 0.065 | 0.066 | −3.915** | −3.318* | −3.934** |
| | (−1.84) | (−1.75) | (1.39) | (1.48) | (−2.26) | (−1.95) | (−2.28) |
| *Investment* | 0.025** | 0.025** | 0.001 | −0.000 | 0.140 | 0.093 | 0.139 |
| | (2.30) | (2.45) | (0.35) | (−0.02) | (1.37) | (0.87) | (1.35) |
| *R&D* | −2.995 | −2.435 | 0.013 | 0.082 | −6.947 | 2.413 | −7.925 |
| | (−1.50) | (−1.67) | (0.02) | (0.16) | (−0.31) | (0.11) | (−0.35) |
| *Growth* | 0.121* | 0.090* | −0.019 | −0.024 | −0.165 | −0.665 | −0.162 |
| | (1.90) | (1.86) | (−1.03) | (−1.60) | (−0.23) | (−0.98) | (−0.22) |
| Observations | 22,134 | 28,157 | 17,933 | 25,294 | 16,991 | 24,071 | 16,991 |
| Adjusted $R^2$ | 0.778 | 0.857 | 0.584 | 0.593 | 0.261 | 0.302 | 0.261 |
| Sample | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Main Effects | N/A | N/A | N/A | N/A | N/A | N/A | Yes |
| Interacted Effects | N/A | N/A | N/A | N/A | N/A | N/A | Yes |

This table repeats the analyses using alternative thresholds to define small, medium, and large firms. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered at Firm and Month level are presented in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

**Table IA2:** Excluding COVID Time Period

| | *JobPostingFreq* | | *PostingLength* | | *TimeToHire* | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *Layoff X Small X HighLength* | | | | | | | −4.111** |
| | | | | | | | (−2.05) |
| *Layoff X Small* | 0.241*** | | 0.085*** | | −2.188* | | 0.530 |
| | (2.77) | | (2.67) | | (−1.93) | | (0.29) |
| *Layoff X Large* | | −0.162* | | −0.013 | | −0.420 | |
| | | (−1.97) | | (−0.64) | | (−0.54) | |
| *LogMVE* | 0.203*** | 0.196*** | 0.009 | 0.014 | −0.746* | −0.788* | −0.724 |
| | (5.11) | (5.13) | (1.06) | (1.57) | (−1.69) | (−1.80) | (−1.65) |
| *ROA* | −0.368 | −0.363 | −0.120 | −0.128 | 0.188 | 0.074 | 0.057 |
| | (−1.11) | (−1.09) | (−1.30) | (−1.40) | (0.05) | (0.02) | (0.02) |
| *EarnVol* | −0.467 | −0.452 | −0.209 | −0.217 | 10.803* | 10.431* | 10.853* |
| | (−0.99) | (−0.96) | (−1.31) | (−1.36) | (1.90) | (1.84) | (1.92) |
| *Leverage* | −0.237 | −0.249 | 0.063 | 0.067 | −3.606** | −3.462** | −3.596** |
| | (−1.38) | (−1.47) | (1.31) | (1.45) | (−2.10) | (−2.04) | (−2.11) |
| *Investment* | 0.024** | 0.023** | 0.001 | −0.001 | 0.118 | 0.140 | 0.117 |
| | (2.18) | (2.14) | (0.24) | (−0.38) | (1.15) | (1.29) | (1.13) |
| *R&D* | −2.230 | −2.388 | 0.065 | 0.071 | 0.945 | −5.484 | −0.264 |
| | (−1.40) | (−1.49) | (0.12) | (0.13) | (0.04) | (−0.25) | (−0.01) |
| *Growth* | 0.058 | 0.069 | −0.018 | −0.022 | −0.325 | −0.278 | −0.330 |
| | (1.06) | (1.29) | (−1.07) | (−1.24) | (−0.41) | (−0.35) | (−0.42) |
| Observations | 21,282 | 26,077 | 17,326 | 23,687 | 16,378 | 22,504 | 16,378 |
| Adjusted $R^2$ | 0.777 | 0.855 | 0.585 | 0.584 | 0.265 | 0.313 | 0.265 |
| Sample | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium | Large & Medium | Small & Medium |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Small(Large)XControl | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Main Effects | N/A | N/A | N/A | N/A | N/A | N/A | Yes |
| Interacted Effects | N/A | N/A | N/A | N/A | N/A | N/A | Yes |

This table repeats the analyses after dropping the three months that are most severely affected by COVID (Mar 2020, Apr 2020, and May 2020) from the sample. All variables are defined in Appendix A. *t*-statistics based on standard errors clustered at Firm and Month level are presented in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.