Whispering Progress: Fear of Automation and Voluntary Disclosure*

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Abstract

We provide evidence that firms tailor their disclosure policies to achieve the objectives of task automation and workforce stability. Using local cable news transcripts to measure the fear of job displacement due to automation, we find that firms reduce public disclosures about their automation strategies when automation fear intensifies. The diminished disclosure is more pronounced for forward-looking information about future automation plans, in industries with occupations more susceptible to displacement, and when unfavorable employee reactions are more likely. To strengthen identification, we exploit two quasi-natural experiments: layoffs by local high-tech firms and the introduction of ChatGPT. We also find suggestive evidence that firms increase private communication with investors to compensate for the reduction in public information provision. Overall, our findings shed light on the trade-offs between maintaining transparency and mitigating adverse employee responses in the era of rapid technological advancement.

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1. Introduction

The advancement of automation, robotics, and artificial intelligence (AI) has significantly disrupted labor markets (e.g., Acemoglu and Restrepo, 2019; Friedman, Sutherland, and Vetter, 2025). While these technologies foster task automation and enhance productivity, they have also fueled the fear of job displacement, which has triggered employee backlash against automation technologies.[1] To help employees manage their expectations and prepare for adaptation, there is an increasing demand for firms to enhance transparency concerning their automation strategies.[2] Disclosing automation plans, however, could trigger concerns about job losses among employees, potentially reducing their productivity and provoking resistance. Against this backdrop, our study provides evidence on how firms tailor disclosure policies to balance the objectives of task automation and workforce stability.

We investigate how the fear of job displacement due to automation (automation fear, *hereafter*) influences firms' disclosures regarding their adoption of automation technologies. The optimal level of disclosure depends on managers' perceptions of how information recipients will react (e.g., Newman and Sansing, 1993; Bond and Zeng, 2022; Breuer, Hombach, and Müller, 2023). On the one hand, we posit that public automation disclosure (and its dissemination by intermediaries) increases the awareness of automation plans among

[1] The fears of job displacement due to technological advancement is not a new phenomenon. The Luddites, for instance, were a group of English textile workers in the 19th century who destroyed machinery as a form of protest. The recent surge in automation, driven by industrial robots and AI, has prompted resistance from both blue-collar and white-collar workers. For example, dockworkers requested a ban on automation at cargo ports (see fortune.com). Hollywood screenwriters initiated labor strikes against the implementation of AI in script writing (see brookings.edu). In November 2023, the unions representing U.S. journalists launched collective bargaining efforts to secure protections against AI in writing (see poweratwork.us). In January 2025, the National Nurses United (NNU) engaged in negotiations to oppose hospital automation (see nationalnursesunited.org).

[2] For example, Dan Schawbel, managing partner at Workplace Intelligence, stressed that "organizations must be more upfront about how they're using AI in the workplace, if they want a competitive advantage and want to earn, and keep, the trust of their employees" (see cnbc.com). The American Staffing Association called for transparency in firms' automation transitions to manage employee expectations and support upskilling (see americanstaffing.net). New York Governor Kathy Hochul proposed a mandate requiring firms to assess and disclose the impact of AI automation on layoffs (see natlawreview.com).

employees, an assumption that we subsequently validate. While some employees may possess private knowledge about automation, such knowledge is likely incomplete (particularly regarding future automation plans), not accessible to the entire workforce, and lacks credibility.[3] Moreover, public disclosures increase the salience of automation transition to employees. This increased awareness of automation could lead to diminished productivity, employee departures, and collective bargaining against automation, thereby disrupting firms' operations and their automation transition process (e.g., Golin and Rauh, 2025). Consequently, we posit that managers have reduced incentives to disclose their automation strategies when automation fear intensifies. Supporting this prediction, anecdotal evidence suggests that some firms remain silent about their automation transitions.[4]

On the other hand, there are several reasons why automation fear may not decrease disclosures. Disclosure could serve as a mechanism to align employees' expectations regarding the labor impacts of automation. It could also work as an early warning mechanism that enables employees to set expectations and allocate time for adaptation (e.g., through upskilling or working harder to maintain employment, or opting for earlier departure), potentially mitigating resentment in the event of future layoffs (Innocenti and Golin, 2022). If so, managers may even increase disclosure when automation fear intensifies. Moreover, managers may prioritize meeting investors' information demands, thereby limiting the influence of employees' fears about automation on disclosure.

To test these predictions, we construct an index of automation fear across all Designated Market Areas (DMAs), geographic regions defining U.S. media markets, using local cable news transcripts. Local cable outlets traditionally cover locally relevant topics that reflect their

[3] For example, anecdotal evidence suggests that employees are largely unaware of their companies' AI implementation plans (see cnbc.com). A Home Depot employee noted on Glassdoor that the company restricts the dissemination of information within the organization about its AI investment (see Appendix A).
[4] For example, a survey reveals that "only 36% of leaders feel their organization has been clear and open about the use of AI with its employees" and "only 39% [of employees] feel like their employer has been transparent about how they are using AI and how it could affect employees." (see beyonderpdrivingthedigitalbusiness.cio.com)

community, serve democratic functions, and engage their audiences (Pew Research Center, 1999). They thus function as information hubs for local residents, capturing the "mainstream" view and meanwhile influencing their viewpoints (e.g., Romer, Jamieson, and Aday, 2003; Bergbrant and Bradley, 2024). In a similar spirit to the literature that quantifies economic uncertainty based on news (e.g., Baker, Bloom, and Davis, 2016), the cable news-based index allows us to capture variation in *actual* sentiment on automation-induced job risk driven by multiple factors without predetermining a particular driver.[5] We define the automation fear index for each DMA-quarter as the frequency of local news voicing concerns about job displacement due to industrial robots and AI. We focus on robots and AI as they represent the most prominent automation technologies in the past decades (Acemoglu and Restrepo, 2019).[6] A firm's exposure to automation fear in each quarter is calculated as the average automation fear index across all DMAs, weighted by the number of the firm's employees in each DMA.

Three key pieces of evidence confirm that our approach yields a meaningful measure of automation fear. First, using a Large Language Model (LLM) to identify economic themes triggering the automation-fear news, we find that the most prevalent discussions concern general automation impacts (49.3%) by citing scientific reports or surveys of residents, followed by shifting labor market conditions (19.6%), upskilling needs (11.2%), layoff incidences (8.4%), and technology rollouts (4.2%). This also suggests that automation fear mainly stems from broad concerns about job displacement rather than reflecting firm-specific events. Second, the DMA-level automation fear index rises with local unemployment rates and

[5] These factors may include local attention shocks, such as layoffs or labor advocacy programs, or heterogeneous attention to national shocks, such as the introduction of new technologies. In Section 4.4, we examine two such shocks (i.e., layoffs by local high-tech firms and nationwide technological advancements) and reach similar conclusions. Unlike the shock-based approach that rely on a binary treatment variable and assume a material effect on automation fear, our measure is advantageous as it quantifies the degree to which an event changes automation fear (e.g., Baker et al., 2016; Edmans, Fernandez-Perez, Garel, and Indriawan, 2022).

[6] Robotics and AI have become increasingly integrated, especially in industrial settings where AI now empowers modern robots to perform complex, adaptive tasks that far exceed the capabilities of traditional, pre-programmed robotic arms. This convergence not only expands the spectrum of workers impacted by automation, but also blurs the line between robotics and AI, making it natural to examine their combined effects on the modern workplace.

automation exposure, and it exhibits a pronounced spike in response to local layoff events and advancements in automation technologies. Third, the index is positively correlated with the frequency of employee online reviews expressing concerns about job loss.

We study the association between this automation fear index and automation disclosure using a sample of 78,831 firm-quarters over the 2010-2024 period. We employ textual analysis to identify firms' disclosures about their automation strategies on earnings conference calls. These calls often attract significant public attention and receive extensive intermediary coverage, which effectively disseminates information to employees (Ham, Hutzler, Pacelli, and Volant, 2024). We find that 17% of earnings conference calls include automation-related disclosures, and among these, 46% are forward-looking (i.e., discussing future automation plans). Supporting the premise that automation disclosures convey incremental information to employees, we observe a 76% increase in the number of employee reviews expressing job loss concerns following firms' disclosures.

Our two-way fixed effects (i.e., firm and quarter fixed effects) panel regressions reveal a negative association between a firm's automation disclosure and its exposure to automation fear at the beginning of the period. An interquartile increase in the automation fear index is associated with a 5% reduction in automation disclosure. These results are robust to alternative measures of both key variables, including (i) automation fear measured at the firm's headquarters to reflect manager-proximate employees, and (ii) disclosure measures, such as an indicator for the presence of automation disclosure or automation-related press releases. To provide further nuance, we separately investigate industrial robots and AI-powered tools and find that the fear of job loss due to robots (AI) deters the disclosure of robot (AI) automation.

To further attribute the findings to diminished disclosure incentives (rather than automation fear impeding automation rollout), we track firms' automation rollout based on imports of industrial robots and recruitment of AI-competent employees. We find little evidence to suggest that automation fear deters automation rollout. Moreover, while disclosures in general increase with measures of automation rollout, this association is attenuated by automation fear, suggesting that firms' incentives to disclose their automation plans are weakened by heightened automation fear. Additional analyses further rule out alternative explanations that the automation fear index merely captures general economic uncertainties, reflects proprietary costs of disclosure, or is driven by a single firm's automation disclosure.

Next, we explore cross-sectional variations in our findings to corroborate the argument that firms reduce disclosures to mitigate adverse employee responses. First, we examine the informativeness of automation disclosures to employees. We find that, compared to disclosures about existing investments, automation fear more strongly deters forward-looking disclosures about future automation plans, which are less likely to be known by employees without disclosure. Additionally, automation fear more strongly deters disclosures containing specific automation plans, which are more likely to convey credible, incremental information to employees. In contrast, the effect is weaker when peer disclosures are more prevalent (proxied by higher public firm presence in the industry), which increases the likelihood of information spillover across firms (Badertscher, Shroff, and White, 2013; Shroff, Verdi, and Yost, 2017).

Second, silence is preferable when appeasing employees outweighs other considerations (Bond and Zeng, 2022). As predicted, the effect is greater in industries where occupations are more susceptible to automation substitution. Third, we expect a stronger effect when adverse employee reactions are more likely. Anecdotal and survey evidence (Golin and Rauh, 2025) suggest that automation threats motivate both blue- and white-collar workers to engage in collective bargaining and/or switch jobs. Consistent with these observations, we find a stronger effect in industries with a higher prevalence of labor unions and in local labor markets with higher mobility.

To strengthen identification, we leverage two quasi-natural experiments that exogenously increase local automation fear, capturing distinct sources of variation: (i) shocks to local residents' attention to the workplace impacts of technological advancement and (ii) heterogeneous exposure to nationwide shock that accelerates automation. First, we exploit major layoffs by high-tech firms in the same DMA, which heighten local attention to the labor impact of AI-powered tools. We find that automation fear in affected DMAs escalates following tech firm layoffs, and *non-technology* firms in these DMAs reduce their automation disclosures. Our second identification strategy explores the introduction of ChatGPT, which heightened employees' awareness of automation risks. We find that DMAs with more automation-prone jobs experience a greater increase in the automation fear index, and firms in these areas are less likely to discuss automation strategies compared to those in DMAs with fewer automation-prone jobs. Overall, the results based on both panel regressions and quasi-natural experiments strengthen the credibility of the inference that firms reduce disclosures in response to heightened fear of automation (Armstrong, Kepler, Samuels, and Taylor, 2022).

Our findings thus far suggest that firms reduce public disclosure to mitigate employees' fear of job displacement. This strategy can be costly, as it limits investor information regarding firms' automation plans, which is essential for forecasting future cash flows and assessing capital needs to support automation investment. A natural question is whether firms take actions to offset the impact of reduced public disclosures. Theoretically, when targeted disclosure to investors is feasible, firms will take advantage of this opportunity, enabling them to communicate with investors without sharing information with employees (Bond and Zeng, 2022). Supporting this prediction, we find that, when automation fear heightens, firms are more likely to host shareholder/analyst days, an effective avenue that allows managers to privately communicate with investors and analysts.

Our findings contribute to the literature on technology-related disclosures (see Glaeser and Lang 2024 for a comprehensive survey), particularly disclosure about emerging technologies (Cao, Goldstein, He, and Zhao, 2024; Jia, Li, Ma, and Xu, 2025).[7] While existing literature primarily focuses on capital providers (Merkley, 2014; Chu, He, Hui, and Lehavy, 2023) or competitors (Cao, Ma, Tucker, and Wan, 2018; Glaeser, 2018; Glaeser and Landsman, 2021) as disclosure recipients, we provide novel evidence on how employees, a critical stakeholder profoundly affected by technological advancements, shape firms' disclosures about technological progress. Our results highlight the workforce-related costs associated with the public disclosure of automation technologies.

Our study also adds to the literature on how labor-related factors affect firms' information environment. Firms manage financial performance to either avoid empowering labor unions (D'Souza, Jacob, and Ramesh, 2000; Hilary, 2006; Bova, 2013; Chung, Lee, Lee, and Sohn, 2016; Hamm, Jung, Lee, and Yang, 2022) or inflate employee perceptions of firm prospects (Dou, Khan, and Zou, 2016; Gao, Zhang, and Zhang, 2018).[8] Our study extends this literature by examining the impact of labor-related concerns on technological disclosure, which differs from financial disclosure that reveals realized performance and available economic resources for workforce allocation. Our results highlight a distinct labor-related factor (i.e., job displacement risk) in shaping firms' disclosure.

Lastly, this study contributes to the literature on how voluntary disclosures are shaped by different non-investor stakeholder groups, including government entities (Samuels, 2021; Huang, 2022), competitors (Li, 2010; Glaeser, 2018; Sran, 2025), and strategic partners (Bourveau, She, and Žaldokas, 2020; Kepler, 2022; Oh, Yeung, and Zhu, 2024; Bourveau, Kepler, She, and Wang, 2024). Choi, Pacelli, Rennekamp, and Tomar (2023b) show that firms provide more diversity-related information to cater to employees' preferences for workplace

[7] We acknowledge that some emerging technologies have the potential to complement workers and create new jobs. Our paper focuses on automation technologies to underscore the tension between technological advancement and employee concerns.

[8] Another line of research shows that employees incorporate firms' public disclosures to inform their job market decisions (e.g., Choi, Choi, and Malik, 2023a; deHaan, Li, and Zhou, 2023; Huang, Pacelli, Shi, and Zou, 2024).

diversity. Our findings indicate that the influence of labor factors extends beyond human capital-related disclosures and affects technological investment disclosures via a distinct channel related to job displacement concerns. We offer novel evidence that when employees perceive greater displacement risk, firms not only reduce public disclosures but also increase private interactions with investors.

2. Conceptual Framework

2.1. Automation and Displacement Risk

The increasing adoption of automation, robotics, and AI technologies has enabled firms to automate operations and enhance productivity (Jame, Markov, and Wolfe, 2022; Babina, Fedyk, He, and Hodson, 2024; Minnis, Sutherland, and Vetter, 2024). However, this shift has also sparked significant concerns regarding its potential impact on employment. For instance, McKinsey & Company (2017) estimated that the widespread implementation of automation technologies could affect up to 1.2 billion workers globally. Supporting these concerns, studies have documented adverse effects of automation on labor demand. Acemoglu and Restrepo (2022), for example, find a negative relationship between industry-level advancements in robotics and local employment levels. Similarly, Acemoglu, Autor, Hazell, and Restrepo (2022) demonstrated that AI adoption tends to reduce hiring in roles not directly related to AI.

The displacement effect of automation varies across occupations. As articulated by Autor, Levy, and Murnane (2003), an occupation can be conceptualized as a bundle of tasks, some of which are more susceptible to technological substitution than others. Moreover, the differential effectiveness of automation technologies across tasks suggests that their impact will likely be unevenly distributed across occupations (Levy, 2018). In general, robots predominantly affect blue-collar workers in manual labor roles, while specialized software and AI-powered tools have increasingly influenced white-collar professionals. Consistent with this observation, Graetz and Michaels (2018) find that robots primarily displace low-skilled workers. Similarly, Acemoglu and Restrepo (2022) demonstrate that task automation exacerbates wage inequality in the U.S. labor market. These findings suggest that automation technologies could potentially reduce jobs, particularly those more amenable to automation.

2.2. Automation Fear and Automation Disclosure

The disclosure theories predict that the optimal level of disclosures hinges on the different information recipients' responses to disclosures and the relative importance of meeting different parties' needs (e.g., Newman and Sansing, 1993; Bond and Zeng, 2022; Breuer et al., 2023). In the context of the automation transition, while public disclosures are primarily aimed at investors for communicating the potential productivity gains resulting from automation (Cao et al., 2024; Jia et al., 2025), disclosures can also reach employees through employees' direct monitoring or intermediary coverage (e.g., deHaan et al., 2023; Ham et al., 2024). Indeed, Choi et al. (2023a) and deHaan et al. (2023) demonstrate that employees intensify their job search efforts during the weeks of earnings announcements.

We assume that public automation disclosure increases the awareness of automation plans among employees for several reasons. First, although employees can observe certain aspects of automation investments, this private information is likely incomplete as automation technologies evolve rapidly over time, and employees usually do not have access to information about *future* automation plans. Second, this knowledge is usually not accessible to the entire workforce due to diversified workforces distributed across different segments and the presence of organizational silos. It also lacks the interpretation, context, and credibility provided by public disclosures (deHaan et al., 2023). Further, public disclosures often garner public attention and increase the salience of automation transition to employees.

As automation poses a potential threat to existing jobs, automation disclosure may trigger adverse employee responses, including departure from the firm, or engaging in collective bargaining against automation (or both). Consistent with this argument, Golin and Rauh (2025) conduct a survey of over 4,000 employees and find that displacement risk due to robots and AI motivates employees to join a union to protect their jobs or switch occupations. Additionally, the potential anxiety and dissatisfaction experienced by employees may lead to psychological consequences, such as reduced productivity and diminished work efficiency (e.g., Bellet, De Neve, and Ward, 2024).

These potentially unfavorable employee responses could, in turn, disrupt firms' operations and their automation transition process. This risk is further heightened as the transition to automation is a long-term and ongoing process characterized by significant risks (Babina et al., 2024).[9] Thus, firms have incentives to avoid adverse employee responses against automation before they complete the transition. As heightened automation fear suggests stronger employee opposition to automation, managers would have greater incentives to reduce disclosure about their adoption of automation technologies when automation fear intensifies.

On the other hand, disclosure could serve as a critical mechanism to align employees' expectations regarding the anticipated labor impacts of automation. By proactively communicating organizational changes related to automation, firms can correct employees' overestimation (if any) of the workplace impact of automation, mitigating employee anxiety and resistance. Furthermore, disclosure functions as an early warning system, providing employees with sufficient time to adjust their career strategies, such as pursuing upskilling opportunities (Innocenti and Golin, 2022). This may, in turn, alleviate employee resentment if layoffs occur in the future after the firm completes its automation transition. Moreover, managers may prioritize disclosing automation to meet investors' information demand (Cao et al., 2024; Jia et al., 2025), rendering employee concerns irrelevant. Specifically, since automation has the potential to fundamentally reshape a firm's business model and enhance its

[9] For example, practitioners note that deploying AI for business purposes can take 18 to 36 months, with some implementations taking as long as five years (see hbr.org). The implementation of automation technologies also necessitates regular subsequent investments due to the rapid advancements in automation technologies.

efficiency, automation disclosure has important implications for a firm's long-term cash flows. Moreover, given the substantial capital investment often required for automation (e.g., the deployment of smart industrial robotics), related disclosures help reduce information asymmetry and in turn lower the cost of external financing. Based on the above discussions, we present our main hypothesis in null form:

Hypothesis: The fear of losing jobs to automation does not affect firms' disclosure about automation.

3. Data and Variable Construction

3.1. Automation Fear Index

3.1.1. Variable Construction

We capture variations in the fear of automation-induced job displacement using cable news transcripts of local TV stations. We assume that local cable news reflects an average employee's sentiment regarding automation's job market impact. Local cable outlets cover topics relevant to their entire community in order to maintain community ties and engage their audiences (Pew Research Center, 1999). In fact, the Federal Communications Commission (FCC) emphasizes that "the essential obligation of licensees is that their stations serve their local communities" by "presenting programming that relates to local issues." Unlike other forms of media, such as social media or print media, cable news is geographically anchored due to the FCC regulations that prohibit TV stations from transmitting outside their DMA. Due to its local specificity, local cable news remains the primary source of information for residents. For instance, the Pew Research Center reports that 41% of Americans identify TV as their principal source of local news, a stark contrast to only 13% who rely on print newspapers.[10]

[10] See www.pewresearch.org. Moreover, despite the rise of social media, cable news remains highly relevant because it actively engages with these platforms, both to disseminate news and to track trends that matter to local residents (see cjr.org and marketshare.tvnewscheck.com).

Therefore, local cable news functions as the information hub for residents, capturing the "mainstream" view and meanwhile having the potential to shape their viewpoints (Romer et al., 2003; Bergbrant and Bradley, 2024).

In the context of automation fear, local cable news serves a dual role. First, it acts as a reflection of collective employee sentiment regarding automation risk, for instance, by reporting on surveys measuring local workers' perceptions of automation or covering events related to automation.[11] Second, it can amplify employees' fears through its broadcasts. These two channels suggest that local cable news serves as a viable proxy for local employees' automation anxiety. Notably, while the amplification channel depends on the assumption that employees consume local cable news (either through TV programming or social media dissemination), the reflection channel does not require this condition.

We obtain cable news transcripts of local TV stations from News Data Services, a proprietary website that tracks the closed captioning text of TV stations. News Data Services provides us with access to a website feed that records the closed captioning text data of local and national cable news (e.g., ABC, CBS, FOX, and NBC) in 5-minute segments. Using News Data Services' website portal, we search for all 5-minute news segments with keywords or phrases related to automation (e.g., *artificial intelligence*, *AI*, *machine learning*, *data analytics, automation, automated, automating, robotics*) alongside keywords or phrases related to layoffs (e.g., *employee*, *employees*, *employment*, *jobs*, *labor*, *layoff*, *laid off*, *displace*, *job security*, *job loss*, *lose job*, *job displacement*).[12] To refine the news segments specific to the fear of job displacement, we exclude segments where the job-related keywords or phrases appear in a negation context (e.g., "no layoffs," "not replacing jobs," "fewer job losses"). In total, we identify 360,202 5-minute segments beginning in January 2010 and ending in September 2024,

[11] Dyer, Lang, and Oh (2024) show that cable news provides substantial coverage of labor-related news.
[12] Cable news tends not to cover specific software and AI techniques such as "random forest." Rather, the general terms "robot," "automation," and "artificial intelligence" are often used as umbrella phrases that encompass niche terms related to specific techniques.

sourced from 1,334 unique local cable channels spanning the entire U.S. (i.e., 210 unique DMAs). Appendix A.2 presents examples of local cable news containing automation fear.

Figure 1 presents the word cloud of all local cable news segments identified as containing automation fear. Figure 2 presents the geographic distribution of local cable news coverage on automation fear (i.e., the frequency of 5-minute segments that contain automation fear) during two different years in our sample period (e.g., 2013 and 2022). As illustrated, local cable news coverage of automation fear shows an upward trend over time and significant geographic variation. The rich time-series and cross-sectional variations enable us to investigate how firms tailor their disclosure policies regarding automation in response to automation fear.

To measure firm-level exposure to automation fear, we utilize data on the geographic distribution of firms' operations over time from Infogroup, which tracks the number of full-time equivalent employees at the establishment level (Barrot and Sauvagnat, 2016; Even-Tov, She, Wang, and Yang, 2025). We create a time-varying firm-level exposure to automation fear based on the average of automation fear across different DMAs, weighted by the number of employees in each DMA (*Automation Fear Index*). We scale the weighted average measure by the frequency of automation fear news covered by *national* stations over the same period to normalize the raw counts. Note that given the constant nature of the scaler within each quarter, this adjustment does not influence our statistical inferences due to the inclusion of quarter fixed effects in our regression models.[13]

3.1.2. Validation Tests

We conduct three tests to validate that our measure works as intended. First, we deploy GPT 4.0 to analyze the content of news segments identified with automation fear. We randomly select 5,000 automation fear-related news segments each year (75,000 in total) and prompt

[13] Our results are robust when using the inverse hyperbolic sine transformation of the raw count of relevant local news segments as the independent variable (see Section 5.2.2.). However, as such transformation introduces estimation biases with the presence of zeros in data (Chen and Roth, 2024), we decide not to use this approach.

GPT-4.0 to generate a set of ten economic themes that trigger the discussion of automation fear. We then task GPT-4.0 with categorizing each new segment into one of ten economic themes. As shown in Online Appendix Table A1 Panel A, 49.3% of news segments discuss automation's general labor impacts, citing scientific reports, resident surveys, and/or interviews with labor group leaders. Another 19.6% frame discussions around the dynamic labor market demands, attributing unemployment primarily to automation transitions, while 11.2% emphasize educational reforms or enhanced training programs to prepare workers for automated workplaces. We also find that automation fear discussions coincide with local layoffs (8.4%), technology rollouts (4.2%), and union negotiations (1.7%). Collectively, these patterns confirm that our measure effectively captures concerns about automation displacing jobs. They also suggest that the variation in automation fear is unlikely to be primarily driven by a particular firm's automation plan or disclosure.

Second, we conduct a regression analysis to examine the relationship between our DMA-level automation fear index and local demographic characteristics using a DMA-year panel, shedding light on the determinants of the variation of automation fear. We employ a yearly panel for this test (as opposed to a quarterly panel) because demographic characteristics are generally measured at the yearly level. We consider the following demographic characteristics: (i) population (*Log(Population)*), (ii) unemployment rate (*% Unemployment*), (iii) the fraction of the population aged 65 or older (*% Age 65+*), (iv) the fraction of the population with a bachelor's degree or above (*% Bachelors Degree*), (v) the median household income (*Log(Household Income)*), (vi) the level of TV viewership (*Log(Viewership)*), (vii) the fraction of employees in STEM fields (*% Employed in STEM*), and (viii) political leaning (*Conservative*). Online Appendix Table A1 Panel B presents the results. We document a robust positive correlation between DMA-level automation fear and both local unemployment rates and the proportion of individuals employed in STEM occupations. In Section 4.4, we further show that the automation fear index experiences a sharp increase following a local shock to household attention (i.e., major layoffs in the local market) and a national technological shock (i.e., the introduction of ChatGPT). These results are largely consistent with the above-mentioned content analyses that unemployment risk and exposure to automation technologies are important drivers of automation fear.

Third, we conduct an external validity test by examining whether DMA-level automation fear is associated with employees voicing concerns about displacement. To do so, we calculate the number of online reviews that express concerns over job displacement by employees of all firms headquartered in a DMA (*# Displacement Concern Reviews*).[14] Online Appendix Table A1 Panel C presents a positive correlation between DMA-level automation fear and the frequency of employee reviews voicing concerns about job displacement. Overall, these findings validate that our cable news-based measure proxies for automation fear as intended.

3.2. Voluntary Automation Disclosure

We use textual analysis to identify firms' automation-related voluntary disclosures based on their earnings conference calls. We focus on conference calls, as opposed to other corporate disclosures such as 10-Ks, primarily because conference call disclosures are less regulated and attract significant employee attention (Ham et al., 2024). We collect earnings conference call transcripts for the period 2010Q2 to 2024Q2 from Refinitiv Eikon. For each transcript, we parse out the presentation section (i.e., management's planned remarks) and identify voluntary automation disclosures using a set of keywords or phrases related to automation (as listed in Appendix B). We construct the keywords or phrases related to automation using a combination of pre-existing studies' lists (e.g., Cao et al., 2024; Gofman and Jin, 2024). Appendix A.3 presents examples of automation disclosure in conference calls.

[14] We obtain Glassdoor employee reviews data and use textual analysis to identify reviews that mention one of the following keywords or phrases (or variations): *job security, job uncertainty, job loss, lose job, layoff, replace/displace jobs*. Appendix A.1 provides examples of employee reviews that express job displacement concerns, particularly in the context of the firms' automation initiatives.

Our primary measure of automation disclosure is the length of the sentences containing automation-related keywords scaled by the total length of the presentation section (*% Automation Disclosure*). This measure captures not only the likelihood of automation disclosure but also the intensity with which such disclosure occurs. In some of our analyses, we refine this measure by examining the content of the disclosures; for example, by identifying forward-looking statements related to future investment strategies or by focusing on specific disclosures that convey incremental information to employees.

3.3. Sample Construction and Variable Description

For our main analyses, we create a firm-quarter panel with all firm-quarters that have earnings conference call transcripts. We employ the following data screens. First, we remove observations without data on firms' geographic distribution of operations (via Infogroup) necessary to construct the automation fear index. Second, we exclude firms in the 2-digit NAICS sectors: 51 ("Information") and 54 ("Professional, Scientific, and Technical Services"). Automation disclosures by firms in these sectors are more likely to describe their products (e.g., automation software or AI products), rather than automation initiatives. Lastly, we exclude observations with missing control variables used in our main analyses. This sample selection procedure yields 78,831 firm-quarter observations that span 2,324 unique firms over the period 2010Q2 to 2024Q2 (with all independent variables lagged by one quarter). Online Appendix Table A2 details the sample selection procedure.

Table 1 presents the summary statistics of the variables used in our main analyses. The average *% Automation Disclosure* is 0.004. Untabulated results illustrate that 17% of conference calls have automation disclosure, and 46% of them are about future automation plans. The mean and standard deviation of *Automation Fear Index* are 0.037 and 0.030, respectively, indicating significant cross-sectional variation in the level of automation fear.[15]

4. Empirical Results

4.1. Employee Displacement Concerns Following Automation Disclosure

We first validate the premise that automation-related disclosure triggers employee fear of job displacement by increasing the awareness of automation plans among employees. We employ a stacked differences-in-differences (DID) regression analysis (Baker, Larcker, and Wang, 2022) and examine whether disclosure leads to more employee reviews expressing concerns over job displacement on Glassdoor (*# Displacement Concern Reviews*).

We take the following steps to create the stacked DID panel. First, we identify the first instance of the firm disclosing automation initiatives in quarterly earnings conference calls (i.e., treated firms; *Discloser* = 1). Second, for each disclosing firm, we identify a set of peer firms based on the text-based network industry classification (Hoberg and Phillips, 2010) (i.e., control firms; *Discloser* = 0).[16] We select up to ten closest peer firms based on the product similarity score. Lastly, we focus our DID analysis on the four quarters before (*Post* = 0) and after (*Post* = 1) the automation disclosure. In sum, we identify 716 "events" of automation disclosure, resulting in a panel of 9,418 observations. We estimate the following Poisson regression model (Cohn, Liu, and Wardlaw, 2022):

$$Y_{e,i,t} = \alpha + \beta_1 Discloser_{e,i} \times Post_{e,t} + X_{i,t} + \gamma_{e,i} + \nu_{e,t} + \varepsilon_{e,i,t} \qquad (1)$$

where *e*, *i*, and *t* index event, firm, and quarter, respectively. The dependent variable (*Y*) is *# Displacement Concern Reviews* for firm *i* in period *t*. The primary explanatory variable of our

[15] Untabulated autoregression analysis reveals that shocks to automation fear persist for three to four quarters, with statistically significant autoregressive coefficients at one-, two-, and three-quarter lags.
[16] We additionally impose the following constraints when selecting the control firms: (i) the firm is sufficiently similar to the disclosing firm (i.e., product similarity score of at least 0.03) and (ii) the firm has not made automation disclosures during the entire sample period (i.e., a "clean" control firm).

interest is the interaction term (*Discloser* × *Post*). *X* refers to a vector of firm-level control variables, which include (i) firm size (*Size*), (ii) return on assets (*ROA*), (iii) R&D intensity (*R&D/Sales*), (iv) institutional ownership (*Institutional Ownership*), (v) analyst following (*Log(1+#Analysts)*), and (vi) the level of industry concentration proxied by the Herfindahl-Hirschman Index (*HHI*). Variable definitions are provided in Appendix C.

Following Baker et al. (2022), we include *event*-firm fixed effects (γ) and *event*-quarter fixed effects (v).[17] Table 2 presents the results of Eq. (1). In both columns 1 and 2, we document a positive and statistically significant (1% level) coefficient on *Discloser* × *Post*. The economic magnitude is also significant: focusing on column 2, the coefficient estimate suggests that the number of employee reviews expressing concerns about job displacement increases by 76% following the firm's automation disclosures. We further conduct a pre-trends analysis by replacing *Post* with indicator variables for each quarter (with quarter *t-4* omitted as the benchmark). Figure 3 shows no evidence of pre-trends: the coefficients on the interaction terms become statistically significant only after the company makes the automation disclosure.

We also examine whether the effect of automation disclosure on employee displacement concerns is amplified under heightened automation fear. To do so, we augment Eq. (1) with *High Automation Fear Index*, an indicator for events in which the disclosing firm's *Automation Fear Index* is in the top quartile, and its interaction with *Discloser* × *Post*.[18] The results are tabulated in column 3 of Table 2. The positive and statistically significant (5% level) coefficient on the triple interaction term suggests that automation disclosures trigger employee job displacement concerns to a greater extent when automation fear intensifies.

4.2. Effect of Automation Fear Index on Automation Disclosure

To examine the impact of employees' automation fear on automation disclosure, we

[17] Our results are robust to controlling for automation investment in the regression model (untabulated). The coefficients for *Discloser* and *Post* are subsumed by the fixed effects structure.

[18] Lower order interaction terms (e.g., between *Discloser* and *High Automation Fear Index*) are absorbed by event-firm fixed effects.

estimate the following regression on a firm-quarter panel spanning from 2010Q2 to 2024Q2:

$$Y_{i,t+1} = \alpha + \beta_1 \textit{Automation Fear Index}_{i,t} + X_{i,t} + \gamma_i + \nu_t + \varepsilon_{i,t} \quad (2)$$

where *i* and *t* index firm and quarter, respectively. The dependent variable (*Y*) is *% Automation Disclosure* measured using the earnings conference call held by firm *i* in quarter *t+1*. The primary explanatory variable of our interest is *Automation Fear Index*. We include the same set of firm-level control variables (*X*) as in Eq. (1).[19]

We further include firm fixed effects (γ) and quarter fixed effects (ν) to control for slowly moving firm characteristics (e.g., nature of operations) and time-varying macroeconomic factors. Our model thus exploits changes in DMA-level automation fear that influence firms' disclosure practices, net of time-invariant firm characteristics and common nationwide time shocks. The identification relies on within-DMA, temporal variation in automation fear. Specifically, the model captures the effect of two sources of variation: (i) idiosyncratic local shocks to a DMA, such as layoff events, publicity surrounding employee surveys, or labor advocacy activities; and (ii) nationwide shocks, such as technological advancements or release of scientific reports, that have heterogeneous impacts across DMAs due to pre-existing local characteristics that moderate their effects. If firms' exposure to automation fear deters voluntary disclosures of automation plans, we expect β_1 to be negative.

We present our main findings in Table 3 Panel A. Consistent with our hypothesis, the coefficient for *Automation Fear Index* is negative and significant (column 1; coef. = -0.0185; t-stat: -3.70). These findings are robust in the full model with firm-level control variables (column 2; coef. = -0.0178; t-stat: -3.63). In terms of economic magnitude, an interquartile increase in the automation fear index reduces firms' disclosures of automation strategies by 13%

[19] All of our findings are robust when we control for DMA-level demographic characteristics (i.e., those examined in Online Appendix Table A1). However, the inclusion of these variables may cause estimation biases as these variables themselves could reflect the underlying factors that we intend to study (e.g., unemployment reflects public concern about unemployment risk; Angrist and Pischke, 2009; Iliev and Vitanova, 2025). Therefore, we decide not to include these variables throughout the paper.

(= (0.046-0.017) × -0.0178 ÷ 0.004) relative to the sample mean, and by 5.2% (= (0.046-0.017) × -0.0178 ÷ 0.010) relative to the within fixed effects variance.[20]

To attribute the diminished disclosure to firms' reduced disclosure incentives (rather than the absence of automation plans), we construct measures to capture automation rollout. We leverage the granular database on firms' imports of industrial robots from the S&P Global Panjiva database and recruitment of AI-competent employees (Babina et al., 2024) to identify firms' automation rollout. We then create an indicator variable that equals one for firms that either have (i) imported industrial robots during the year, or (ii) employed workers with AI-related skills during the year, else zero (*Automation Rollout*). We examine whether *Automation Fear Index* predicts one-year ahead automation investments. As illustrated in Online Appendix Table A3, we find little evidence to suggest that automation fear deters automation rollout.[21]

Next, we examine whether the average effect documented in Table 3 Panel A is more pronounced among firms deploying automation. The findings are reported in Table 3 Panel B. Focusing on column 2, we find that automation rollout is positively associated with automation disclosures (coef. = 0.0014; t-stat: 4.31) and this relationship is attenuated by *Automation Fear Index* (coef. = -0.0254; t-stat: -3.48). Among firms deploying automation, an interquartile increase in the automation fear index reduces automation disclosures by 11% (= (0.046-0.017) × (-0.0060-0.0254) ÷ 0.008). Overall, these findings indicate that firms' incentives to disclose automation strategies are weakened under heightened automation fear.

4.3. Cross-sectional Tests

4.3.1. Informativeness of Automation Disclosure

Our hypothesis is predicated on the assumption that public automation disclosures provide incremental information to employees, thereby prompting their response. While

[20] We evaluate economic significance based on the within-firm fixed effects variance (Breuer and deHaan, 2024).
[21] We employ a yearly panel for this test because *Automation Rollout* is measured at the firm-year level.

employees may already be aware of some ongoing automation initiatives, the informativeness of disclosures can vary substantially. For example, disclosures that concern future automation plans, contain specific implementation details, or cannot be easily inferred from peer firms are more likely to provide incremental information to employees. To test these predictions, we examine how the negative effect of automation fear on disclosure varies across three dimensions: (i) whether disclosures are forward-looking or backward-looking, (ii) whether disclosures are specific or boilerplate, and (iii) whether employees have access to comparable information through disclosures by peer firms in the same industry.

First, we distinguish between forward-looking disclosures (i.e., sentences that include both automation-related terms and forward-looking language) and backward-looking disclosures (i.e., sentences describing existing automation investments). We construct two dependent variables: *% Automation Disclosure (Forward)* and *% Automation Disclosure (Backward)*, defined as the frequency of these types of sentences in earnings conference calls. We find that about 50% of automation disclosures involve forward-looking information. Table 4 Panel A re-estimates Eq. (2) using these measures. Column 1 shows a significant negative association between *Automation Fear Index* and forward-looking disclosure (coef. = -0.0385; t-stat = -3.45), whereas column 2 shows a smaller effect for backward-looking disclosure (coef. = -0.0165; t-stat = -1.98). These findings support the notion that, since employees are less likely to possess information about future automation plans, managers have stronger incentives to withhold such information to avoid negative reactions.

Second, we examine whether the deterrent effect of automation fear is stronger for disclosures that are more specific, as such disclosures are more likely to convey credible and incremental information. We define *% Automation Disclosure (Specific)* as the frequency of automation-related sentences in earnings conference calls that contain at least one named entity, as identified by the Stanford Named Entity Recognizer (e.g., specific organizations, locations, or numerical values). An example of a specific disclosure is R1 RCM's announcement of plans to automate 110 million tasks, as shown in Appendix A3. In contrast, *% Automation Disclosure (Boilerplate)* refers to automation-related sentences that do not contain any recognized named entities, reflecting more generic or vague disclosures. Table 4 Panel B reports a stronger negative association between automation fear and specific disclosures (coef. = -0.0437; t-stat = -3.97) than with boilerplate disclosures (coef. = -0.0310; t-stat = -3.05).

Lastly, we assess whether the effect of automation fear weakens based on the availability of alternative information sources. To proxy for such alternative information sources, we use the level of public firm presence in the same 2-digit NAICS industry (e.g., Badertscher et al., 2013; Shroff et al., 2017). Because disclosures or media coverage of public peer firms may generate information spillovers to focal firms, it is plausible that employees can gain some insight into the automation practices of the focal firm. As predicted, Table 4 Panel C shows that the negative effect of automation fear on automation disclosure is more pronounced in industries with low public firm presence (coef. = -0.0174; t-stat = -3.43) compared to industries with high public firm presence (coef. = -0.0072; t-stat = -1.66). This finding suggests that when employees have fewer alternative sources of information, firms have stronger incentives to withhold automation disclosures.

4.3.2. Variation in Relative Level of Employee Concern

We explore cross-sectional variation in our findings to corroborate the channel of perceived adverse employee responses in deterring automation disclosures. Bond and Zeng (2022) argue that managers may prefer to remain silent when the importance of appeasing employees outweighs other considerations. We thus hypothesize that our results are more pronounced when employees' jobs are more susceptible to automation substitution.

We create an industry-level occupational exposure to automation following the approach in Webb (2020). Specifically, Webb (2020) measures the overlap between the text of job task descriptions and the text of patents to construct a measure capturing each six-digit SOC (Standard Occupation Classification) job's exposure to automation. Webb (2020) classifies jobs that have a larger fraction of overlapping tasks as those more exposed to automation. We aggregate these exposures to the NAICS industry level using the weighted average based on the number of employees for each job type in the industry, sourced from U.S. Census.

We split the sample into two groups based on the median level of automation exposure and re-estimate Eq. (2) for each group. Table 5 presents the results. The coefficient on *Automation Fear Index* in the subsample with high levels of job exposure to automation is negative and statistically significant at the 1% level (t-stat: -3.43), whereas the coefficient on the interaction term in the subsample with low levels of job exposure to automation is statistically insignificant. This finding suggests that the effect of automation fear on automation disclosure is magnified among firms with employees who are highly susceptible to job displacement. Such firms have a greater need to alleviate employee concerns before successfully transitioning their operations to automation.

4.3.3. Variation in Potential Employee Backlash

Next, we examine the cross-sectional variation of our results according to the level of potential employee backlash. We posit that the disclosure deterrent effect is stronger in two scenarios where automation disclosure is more likely to provoke adverse employee reactions.[22]

First, we anticipate automation fear to have a stronger deterrence effect on automation disclosure when firms' employees have greater collective bargaining power. In such environments, employees may collectively negotiate against policies they perceive as threatening to job security, including automation implementation, as noted by recent anecdotes (see footnote 2). Golin and Rauh (2025) also provide survey evidence that the perceived risk

[22] Automation fear may also have psychological impacts that impair employee productivity. For instance, anxiety over automation could reduce focus and engagement, ultimately affecting workplace performance. However, empirically quantifying such psychological effects is challenging.

of losing one's job to robots or artificial intelligence increases employees' willingness to join a union and switch jobs. We use the level of industry unionization, constructed using data from Unionstats, as a proxy for labor strike risk (*Unionization*).

Second, we expect the disclosure deterrence effect of automation fear to be stronger in regions with higher labor mobility, where employees, particularly high-skill workers, facing the risk of displacement have more feasible opportunities to switch jobs. We proxy for labor mobilities in the local market based on the enforcement of non-compete agreements (Garmaise, 2011). We compute the firm-level exposure to non-compete enforcement as the average state-level non-compete enforcement index (Garmaise, 2011; Ertimur, Rawson, Rogers, and Zechman, 2018) across all states, weighted by the number of employees in each state (*Non-Compete Enforcement*).

Table 6 presents the results. In Panel A, we report the results of partitioning our sample based on the level of unionization. The coefficient on *Automation Fear Index* is negative and statistically significant at the 1% level in the high unionization partition (t-stat: -3.78), whereas the coefficient on *Automation Fear Index* in the low unionization partition is statistically insignificant. The findings indicate that firms are more likely to adjust their automation disclosures in response to heightened automation fear when employees have greater collective bargaining power.

In Panel B, we report the results of partitioning our sample based on the level of non-compete enforcement. The coefficient on *Automation Fear Index* in the low enforcement partition is significantly smaller than that in the high enforcement partition. The results are consistent with the argument that firms facing increased labor mobility are more likely to adapt their automation disclosures in response to heightened automation fear. Collectively, these findings suggest that our results are stronger when automation disclosures are more likely to elicit unfavorable employee responses.

4.4. Exogenous Shocks to Automation Fear Index

We employ two quasi-natural experiments that exogenously escalate local automation fear, reflecting two distinct sources of variation: (i) shocks to local sentiment regarding the labor market effects of technological advancement, and (ii) nationwide technological progress that substantially accelerates automation. Using multiple empirical settings, including panel regression and quasi-natural experiments, allows us to enhance identification and bolster the credibility of our inferences (Armstrong et al., 2022).

4.4.1. Technology Firm Layoffs

We use layoffs by firms in the high-tech industry (hereafter simply "tech layoffs") as a "shock" that unexpectedly heightens local automation fear since tech layoffs have increased the attention towards the labor impact of technological advancement.[23] We then examine how firms in non-high-tech industries respond to these shocks, excluding high-tech firms from the analyses to eliminate the effect of confounding industry-level economic shocks that jointly affect layoffs and disclosure decisions.

We first validate that tech layoffs are associated with an increase in local automation fear. We conduct a stacked DID regression analysis to examine the change in automation fear index four quarters before and after the events.[24] For each event cohort, we examine whether automation fear increases for DMAs affected by layoffs, compared to control DMAs that were not affected by layoffs. We select control DMAs as those within 300 miles of the treated DMAs, but outside 100 miles to avoid geographic spillover of layoffs.[25] Specifically, we run the

[23] The rise of AI has been directly linked to workforce reductions in the technology industries, where firms like Meta, Google, and Amazon have cited AI efficiency improvements as part of their rationale for layoffs. (see technologymagazine.com). The recent tech layoffs are also associated with redirected resources towards AI-driven initiatives, which in turn increases attention to job displacement resulting from AI automation. Duolingo, for instance, announced job cuts to create room for AI-related shifts in content generation (see cnn.com).

[24] We identify tech layoffs using the website Layoffs.fyi. We extract the date of the layoff announcement and the location of the employees affected by the layoff from the website. We then aggregate the number of layoffs to the DMA-quarter level and keep DMA-quarters with at least ten layoff events, resulting in 31 unique events.

[25] Regions in close proximity to treated DMAs may experience indirect exposure to the same factors driving sentiment changes due to shared labor markets. For instance, layoffs in one area may create concerns about job security for employees in nearby DMAs. Our findings are not sensitive to this condition.

following stacked DID regression at the event level:

$$Y_{e,c,t} = \alpha + \beta_1 \textit{Tech Layoffs}_{e,c} \times \textit{Post Layoffs}_{e,t} + X_{c,t} + \gamma_{e,c} + \nu_{e,t} + \varepsilon_{e,c,t} \tag{3}$$

where *e*, *c*, and *t* index event, DMA, and quarter, respectively. The dependent variable (*Y*) is *Automation Fear Index* in DMA *c* in quarter *t*. The primary explanatory variable of our interest is the interaction term (*Tech Layoffs* × *Post Layoffs*). *Tech Layoffs* is an indicator variable that equals one for DMAs affected by major tech firm layoffs, else zero. *Post Layoffs* is an indicator variable that equals one for the four quarters following the layoffs for the event cohort *e*, else zero. *X* refers to a vector of DMA-level control variables: *Log(Population)*, *% Unemployment*, *% Age 65+*, *% Bachelors Degree*, *Log(Household Income)*, *Log(Viewership)*, *% Employed in STEM*, and *Conservative*. We include *event*-DMA fixed effects (γ) and *event*-quarter fixed effects (ν).

Column 1 of Table 7 Panel A presents the results of Eq. (3). Affected DMAs exhibit a statistically significant increase (at the 1% level) in automation fear following the layoffs, compared to control DMAs. We further conduct a pre-trends analysis by replacing *Post* with indicator variables for each of the three quarters pre-layoffs and four quarters post-layoffs, setting the benchmark period to *t-4*. Figure 4 Panel A shows little evidence of pre-trends.

We next examine non-high-tech firms' automation disclosures following the tech layoffs (i.e., we remove firms in the 2-digit NAICS sectors 51 and 54). Again, we estimate the following stacked DID regression model (4) at the firm-quarter level, limiting the sample to firms with automation rollout (e.g., *Automation Rollout* = 1 in the year prior to the layoffs).

$$Y_{e,i,t} = \alpha + \beta_1 \textit{Tech Layoffs}_{e,i} \times \textit{Post Layoffs}_{e,t} + X_{i,t} + \gamma_{e,i} + \nu_{e,t} + \varepsilon_{e,i,t} \tag{4}$$

where *e*, *i*, and *t* index event, firm, and quarter, respectively. The dependent variable (*Y*) is *% Automation Disclosure* by firm *i* in quarter *t*. The primary explanatory variable of interest is the interaction term (*Tech Layoffs* × *Post Layoffs*). For this firm-quarter panel, *Tech Layoffs* is an indicator variable that equals one for firms headquartered in DMAs affected by tech layoffs, else zero. Control firms are firms headquartered in neighboring DMAs (e.g., those that are within 300 miles, but not within 100 miles). We include firm-level control variables (X) as in Eq. (1) and include event-firm fixed effects (γ) and event-quarter fixed effects (ν).

Column 2 of Table 7 Panel A presents the results of Eq. (4). We find that affected firms decrease automation disclosures by 31% relative to its within-firm variance (= -0.0038 ÷ 0.012) following high-tech layoffs. Figure 4 Panel B shows no evidence of pre-trends surrounding the event. These findings suggest that firms reduce automation disclosure following heightened local automation fear. Further, to support the exclusion restriction, we conduct a triple-differences analysis in Online Appendix Table A4, examining variation in firms' exposure to automation and including DMA-quarter fixed effects to control for unobservable local factors jointly affecting layoffs and disclosures. We demonstrate that tech layoffs lead to a decline in automation disclosures specifically among firms with high exposure to automation, consistent with the layoffs influencing disclosure via the channel of heightened automation fears.

4.4.2. Introduction of ChatGPT

Our second analysis exploits the introduction of ChatGPT, which represents a national technological shock that heightened the awareness of automation risks due to its advanced natural language processing capabilities. We conduct a generalized DID regression analysis centered around the introduction of ChatGPT. To construct a treatment group, we create a measure that captures the intensity of automation-prone jobs in each DMA before the event. We take the following steps. First, for each DMA, we identify the number of establishments by each industry using Census data.[26] Second, we merge this data with the industry-level occupational exposure to automation (Webb, 2020). Lastly, we compute the average occupational exposure (i.e., the intensity of automation-prone jobs at the DMA level), weighted

[26] The Census' County Business Patterns data provides the composition of business establishments by NAICS industry at the county level. We aggregate the number of establishments to the DMA level.

by the number of establishments. We consider our treatment group as DMAs with an above-median intensity of automation-prone jobs (i.e., *High Automation DMA* = 1), whereas other DMAs serve as the control group (i.e., *High Automation DMA* = 0).

We first examine whether ChatGPT's introduction increases automation fear in DMAs with more automation-prone jobs by estimating the following regression:

$$Y_{c,t} = \alpha + \beta_1 High\ Automation\ DMA_c \times Post\ ChatGPT_t + X_{c,t} + \gamma_c + \nu_t + \varepsilon_{c,t} \quad (5)$$

where *c* and *t* index DMA and quarter, respectively. The dependent variable (*Y*) is *Automation Fear Index* in DMA *c* in period *t*. *Post ChatGPT* is an indicator variable that equals one for the four quarters following ChatGPT's introduction, else zero. *X* refers to the DMA-level control variables as in Eq. (3). We include DMA (γ) and quarter (*v*) fixed effects. Column 1 of Table 7 Panel B presents the results of Eq. (5). DMAs with high levels of automation-prone jobs exhibit a statistically significant increase (at the 5% level) in automation fear following ChatGPT's introduction. The effect is economically significant as these DMAs exhibit an increase in the automation fear index by 45% (= 0.0018 ÷ 0.004). These findings are not driven by pre-trends, as illustrated in Figure 5 Panel A.

We next examine firms' automation disclosures following ChatGPT introduction, where the treated firms are those headquartered in the affected DMAs (i.e., *High Automation DMA* = 1). We conduct the following regression at the firm-quarter level:

$$Y_{i,t} = \alpha + \beta_1 High\ Automation\ DMA_i \times Post\ ChatGPT_t + X_{i,t} + \gamma_i + \nu_t + \varepsilon_{i,} \quad (6)$$

where *i* and *t* refer to firm and quarter, respectively. The dependent variable (*Y*) is *% Automation Disclosure* by firm *i* in quarter *t*. We include firm-level control variables (*X*) as in Eq. (1) and include firm (*γ*) and quarter (*v*) fixed effects. Column 2 of Table 7 Panel B presents the results of Eq. (6). We document that firms located in DMAs with high levels of automation-prone jobs decrease automation disclosures following ChatGPT's introduction, relative to control firms located in DMAs with low levels of automation-prone jobs. The effect is statistically significant at the 1% level and economically significant: affected firms reduce automation disclosures by 37% relative to its within-firm variance (= -0.0030 ÷ 0.014).[27] Further, Figure 5 Panel B shows no evidence of pre-trends surrounding the event. Overall, these results (alongside the results in Section 4.4.1.) bolster our inference that firms reduce disclosures in response to employees' heightened fear of automation.

5. Additional Analyses

5.1. Alternative Disclosure Venue

Our results thus far suggest that firms are less prone to provide automation disclosure when automation fear is heightened. However, investors, as the primary users of public disclosures, may encounter heightened uncertainty regarding firms' automation strategies. Given that automation has the potential to fundamentally transform a firm's business model and enhance operational efficiency, the lack of disclosures could prevent investors from accurately assessing future cash flows. Furthermore, because automation initiatives typically require substantial capital investment and create external financing needs, opacity exacerbates information asymmetry related to these investments and increases the cost of external financing. To mitigate the negative impact, firms may seek alternative disclosure channels, targeting investors while limiting dissemination among employees (Bond and Zeng, 2022).

We explore whether firms shift to alternative disclosure venues by hosting more private meetings with analysts or investors. We examine the frequency of shareholder/analyst days held by the firm during the quarter (*# Private Meetings*), which allows managers to engage in private communication with investors (e.g., Kirk and Markov, 2016).[28] We replace the

[27] In untabulated analysis, we find that this decrease in automation disclosures is primarily driven by forward-looking disclosures regarding future automation plans.

[28] Such meetings are not necessarily prohibited under Regulation Fair Disclosure (Reg FD), since the notion of materiality is not well defined (Soltes, 2018). Moreover, while the transcripts of management presentations during shareholder/analyst days may become publicly available, there are frequent informal interactions between analysts and managers not captured by the transcripts.

dependent variable of Eq. (2) with *# Private Meetings* and estimate a Poisson regression.

Column 1 of Table 8 presents the results. We find a positive and statistically significant coefficient (coef. = 1.5265; t-stat: 1.86) on *Automation Fear Index*, suggesting that firms target their disclosure by holding more private meetings with analysts and investors under heightened automation fear. In column 2, we interact *Automation Fear Index* with *Automation Rollout* and find a positive and statistically significant coefficient (coef. = 6.2217; t-stat: 4.74), suggesting that the increase in private meetings is primarily driven by firms deploying automation (i.e., firms with the strongest incentive to convey this information to investors). These findings suggest that employee concerns not only impact the level of public disclosures regarding automation, but also impact firms' choice of disclosure outlet.

5.2. Alternative Explanations and Robustness

5.2.1. Alternative Explanations

We conduct additional analyses to rule out potential alternative explanations. One explanation is that the automation fear index reflects broader local economic uncertainty, leading to a general decline in disclosure (Chen, Matsumoto, and Rajgopal, 2011). To mitigate this concern, we examine whether three alternative disclosures, which are less likely to be related to automation, exhibit a similar relation. We examine (i) the number of capital expenditure forecasts (*# Capex*), (ii) the number of voluntary 8-K filings identified as Item 8.01 (*# 8-Ks*), and (iii) the absolute value of management forecast error regarding earnings per share (*Abs(MFE)*). We re-estimate Eq. (2) using each alternative dependent variable. As shown in Table 9 Panel A, the *Automation Fear Index* coefficients across all columns are statistically insignificant, mitigating the concern that our results are driven by local economic uncertainty.

The second concern is that *Automation Fear Index* may comove with proprietary costs of disclosure, as our measure could reflect herding behavior in automation investments or heightened industry competition. However, the lack of a significant correlation between automation fear and actual investment (as shown in Section 4.2) is inconsistent with this explanation. To further address this concern, we conduct subsample analyses based on industry competition intensity (proxied by HHI). The results, presented in Online Appendix Table A5, illustrate that the effect does not differ across high- and low-competition industries. This finding suggests that proprietary costs are unlikely to be driving our results.

The third concern is that a focal firm's automation activities may influence local cable news. However, the observation that our measure mainly captures news discussion regarding the labor market implications of automation in general, and that less than 2% of automation-related cable news quotes CEOs suggests that firm-specific news is not the primary concern. To further mitigate this concern, we partition our sample using proxies that capture the potential influence of a focal firm on local TV news. We posit that a firm is more influential when (i) the firm is larger and (ii) the DMA is smaller. Online Appendix Table A6 shows that our main effect is similar across these partitions, suggesting that the impact of a specific firm's disclosure on local cable news is not a significant concern within our context.

5.2.2. Robustness Tests

We assess whether our findings extend beyond conference calls by examining another major disclosure channel: firm-initiated press releases. Press releases attract substantial public attention and are a key avenue for firm communication (Bushee, Core, Guay, and Hamm, 2010). Using RavenPack News Analytics, we create an indicator variable (*I (Automation PR)*) that equals one if the firm has issued an automation-related press release, else zero. Consistent with our inferences, column 1 of Table 9 Panel B shows that *Automation Fear Index* is negatively associated with the likelihood of automation-related press releases. In column 2, we use an analogous binary variable, *I (Automation Disclosure)*, which equals one if automation-related keywords or phrases are mentioned in the conference call, else zero, and find similar inferences.

To provide further nuance, we separately investigate the effect of industrial robots and AI. Columns 3 and 4 show that *Automation Fear Index* is significantly and negatively associated with automation disclosures when we restrict the analysis to robots and AI, respectively. Interestingly, the statistical significance appears stronger for AI-related automation. One potential explanation is that investments in AI often take place at headquarters and are generally less visible to most employees, whereas the installation of industrial robots in factories is more likely to attract the attention of blue-collar workers in those facilities. This visibility makes it more challenging to conceal robot-related automation strategies.

Next, we test the robustness of our results using alternative constructions of automation fear in Table 9 Panel C. Column 1 uses the inverse hyperbolic sine of the raw count of automation fear news segments without scaling. Column 2 restricts the measure to news segments from the firm's headquarters DMA to better reflect local sentiment among employees co-located with managers. Column 3 narrows the focus to news segments where automation- and layoff-related words occur within 200 words of each other. Column 4 reconstructs the measure using news segments where automation- and layoff-related words are conjoined with forward-looking words (e.g., *will*, *might*, *could*, *may*). Our inferences remain intact.

5.3. Automation Disclosure and Layoff Likelihood

Lastly, we examine whether automation disclosures negatively predict the likelihood of major layoffs. Managers may have strategic incentives to withhold automation disclosures until the firm completes the automation transition. In contrast, disclosure is more likely when the automation transition is unlikely to result in major layoffs and thus would not provoke employee resistance. This argument implies that firms refraining from automation disclosures will be more likely to undergo significant layoffs in the near future as automation renders certain jobs redundant (assuming successful transition to automation). Using a sample of firm-years with automation rollout, we find results consistent with this argument. As shown in

Online Appendix Table A7, the coefficient on *% Automation Disclosure* is negative and statistically significant at the 1% level across both columns, suggesting that firms scale back disclosures to avoid triggering disruptions to the automation transition. However, this result should be interpreted with caution as disclosure is an endogenous firm choice.

6. Conclusion

We create a novel measure to capture employee fear of automation-induced displacement across different geographic regions based on local cable news transcripts over the 2010-2024 period. We find that firms reduce disclosure about automation strategies in earnings conference calls when automation fear increases. To strengthen identification, we exploit two quasi-natural experiments that serve as shocks to automation fear: (i) layoffs by high-tech firms in the same local market, and (ii) the introduction of ChatGPT. Cross-sectionally, the disclosure deterrence effect is more pronounced concerning forward-looking information about future investments and specific automation implementation plans. The results are also stronger in industries with jobs more susceptible to automation and where public disclosures are more likely to provoke employee backlash. Finally, we find that, to offset the cost of diminished public disclosures, firms engage in informal private meetings (e.g., shareholder/analyst days) with investors.

Overall, these results support the theoretical proposition that when firms are confronted with potential adverse reactions of information recipients to their disclosures, it is optimal to maintain silence or shift disclosure avenues to focus on specific information recipients.

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Figure 1: Automation Fear in Cable News

This figure illustrates the word cloud based on local cable news transcripts that express automation-related fear. We classify cable news 5-minute segments as reflecting automation fear if they contain the following textual pattern:

> (*"artificial intelligence"* **OR** *"AI"* **OR** *"machine learning"* **OR** *"data analytics"* **OR** *"robotics"* **OR** *"automation"* **OR** *"automated"* **OR** *"automating")* **AND** *("workforce"* **OR** *"work force"* **OR** *"jobs"* **OR** *"employment"* **OR** *"labor"* **OR** *"employee"* **OR** *"employees"* **OR** *"layoff"* **OR** *"lay off"* **OR** *"layoffs"* **OR** *"laid off"* **OR** *"displace"* **OR** *"job security"* **OR** *"job loss"* **OR** *"lose job"* **OR** *"job displacement")*

Figure 2: Geographic Distribution of Automation Fear Coverage

This figure illustrates the geographic distribution of cable news coverage about automation fear during two different years over our sample period (2013 and 2022).

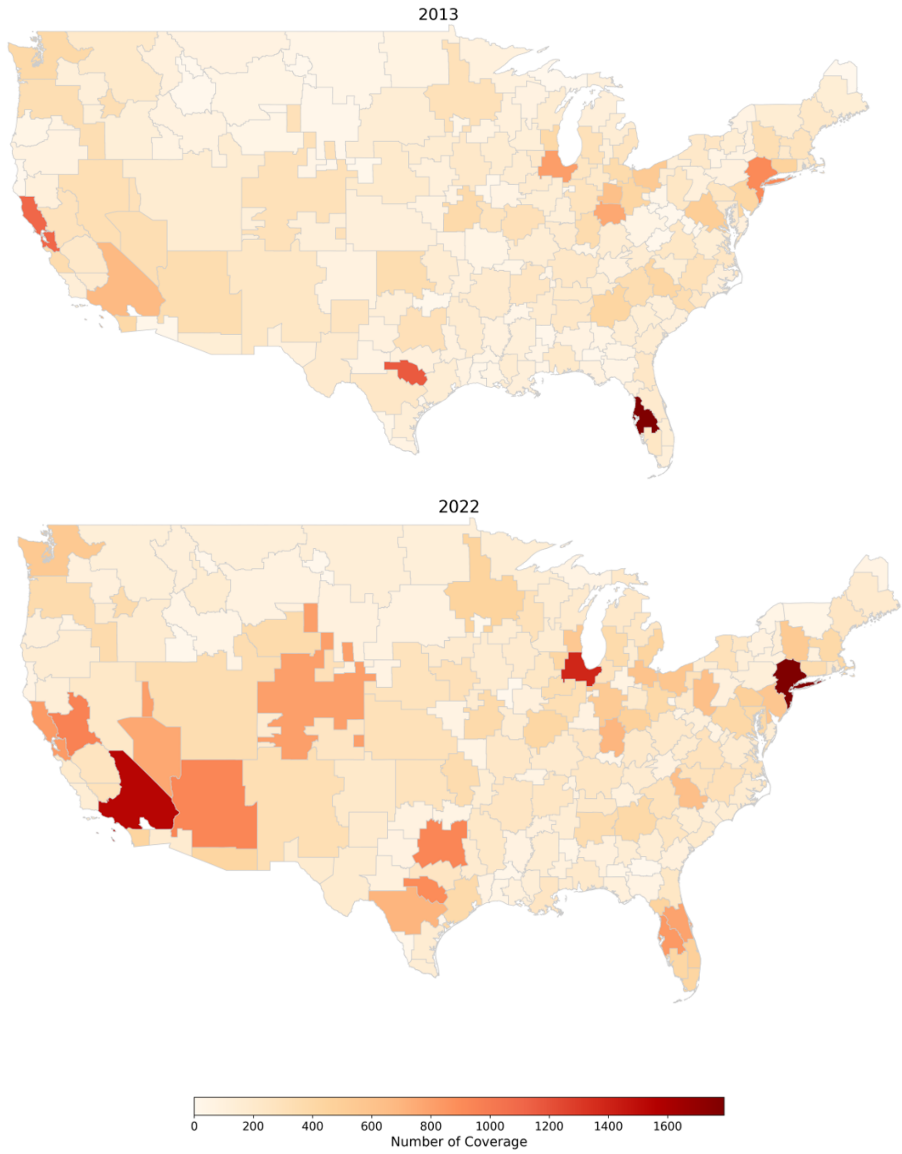


Figure 3: Dynamics of Displacement Concerns Around Automation Disclosure

This figure presents pre-trend analyses for Table 2. We replace *Post* with indicator variables for each of the three quarters pre-automation disclosure and four quarters post-automation disclosure (The quarter, *t-4*, is omitted and used as our baseline). The regression includes event-firm and event-quarter fixed effects and clusters at the event-firm level. We plot the coefficient value for the interaction terms and their 95% confidence interval over time.

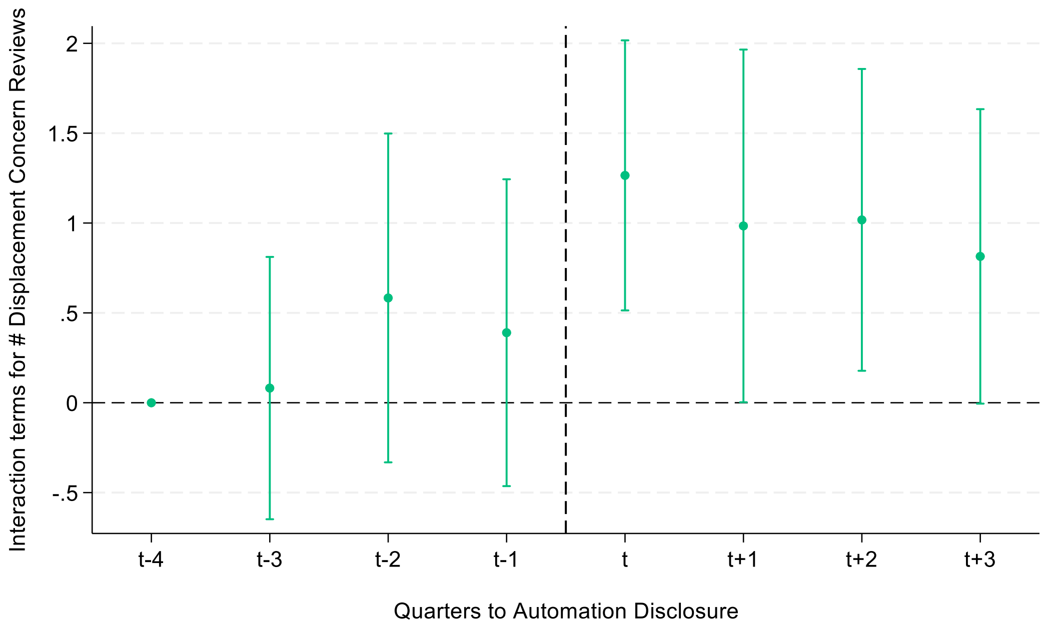
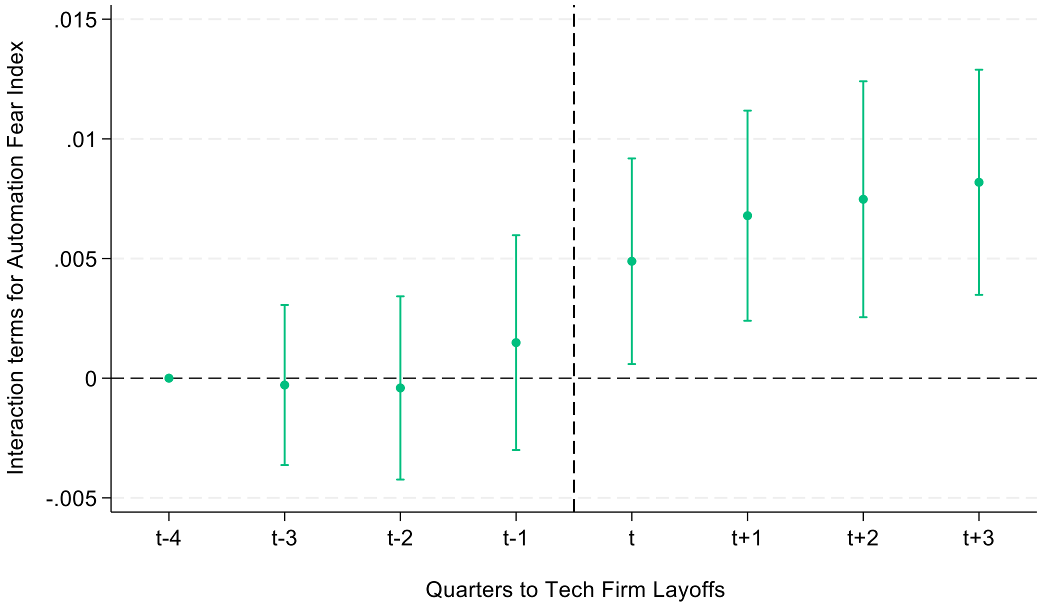


Figure 4: Dynamic Effects of Technology Firm Layoffs

This figure presents pre-trend analyses for Table 7 Panel A. We replace *Post Layoffs* with indicator variables for each of the three quarters pre-layoffs and four quarters post-layoffs (The quarter, *t-4*, is omitted and used as our baseline). Each regression includes the respective fixed effects and clusters at the event-DMA level (Panel A) or event-firm level (Panel B). We plot the coefficient value for the interaction terms and their 95% confidence interval over time for each of our main tests.

Panel A: Automation Fear Index



Panel B: % Automation Disclosure

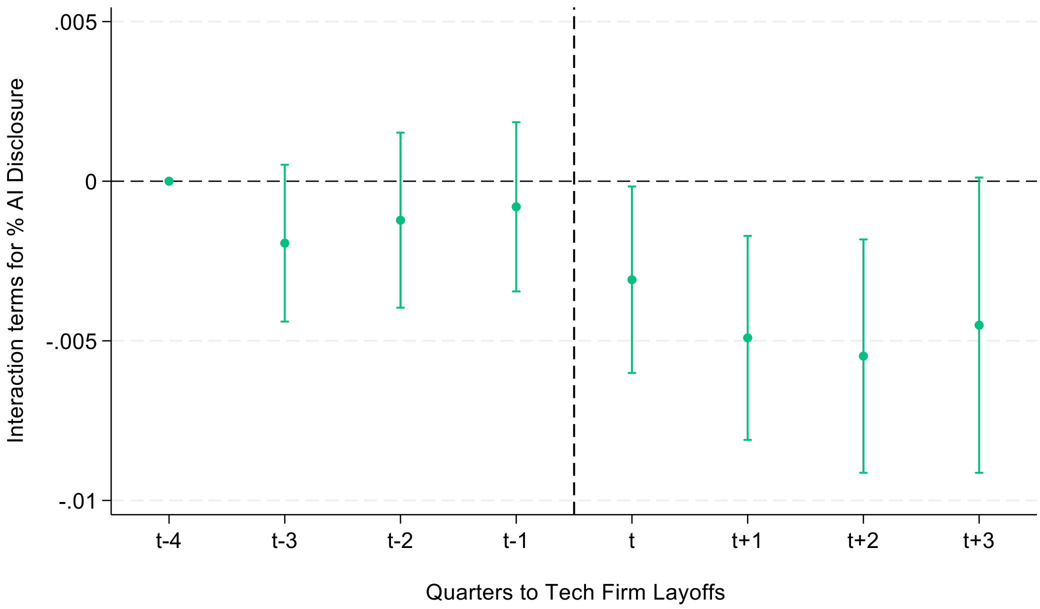
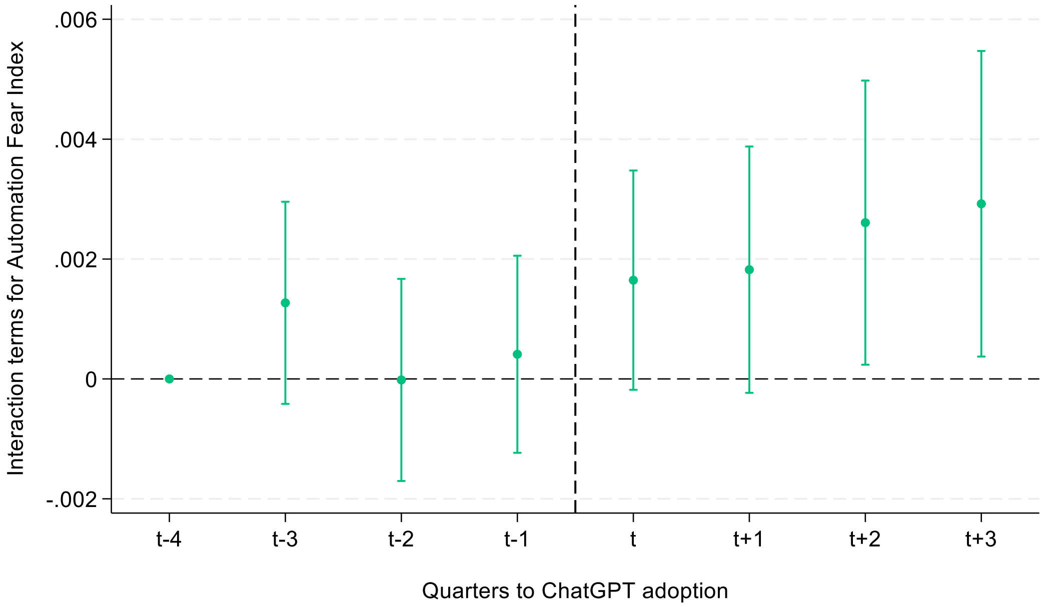


Figure 5: Dynamic Effects of ChatGPT Introduction

This figure presents pre-trend analyses for Table 7 Panel B. We replace *Post ChatGPT* with indicator variables for each of the three quarters pre-ChatGPT introduction and four quarters post-ChatGPT introduction (The quarter, *t-4*, is omitted and used as our baseline). Each regression includes the respective fixed effects and clusters at the DMA level (Panel A) or firm level (Panel B). We plot the coefficient value for the interaction terms and their 95% confidence interval over time for each of our main tests.

Panel A: Automation Fear Index



Panel B: % Automation Disclosure

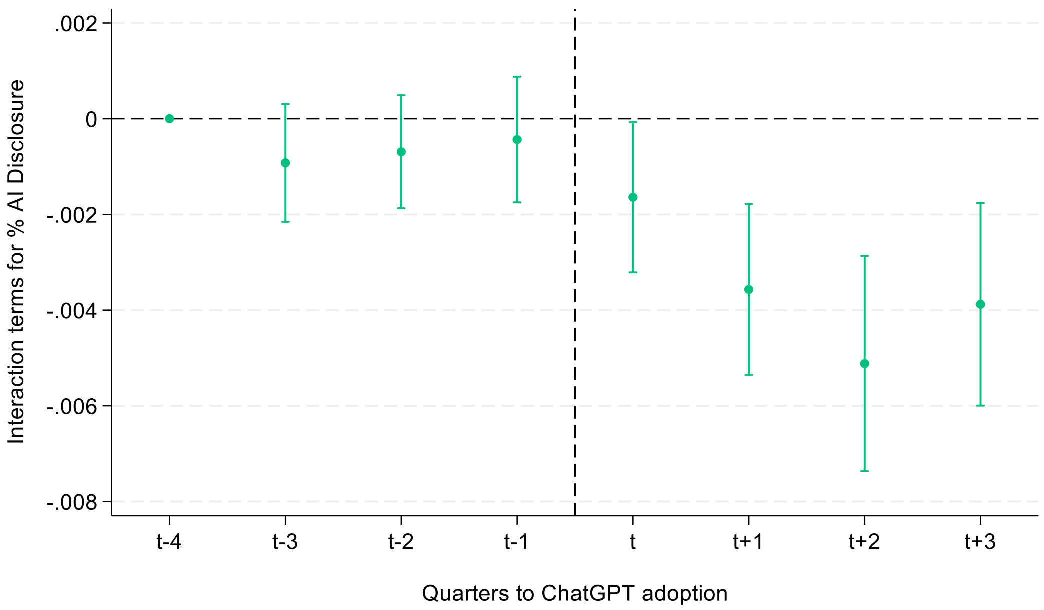


Table 1: Summary Statistics

This table presents the summary statistics of the variables used in our main analyses.

Variable	Mean	Std	P25	P50	P75
# Reviews with Displacement Concern	0.202	0.611	0.000	0.000	0.000
Automation Fear Index	0.037	0.030	0.017	0.028	0.046
% Automation Disclosure	0.004	0.012	0.000	0.000	0.000
Size	7.625	1.964	6.292	7.632	8.919
ROA	0.001	0.044	-0.001	0.008	0.020
R&D/Sales	0.143	0.679	0.000	0.000	0.039
Institutional Ownership	0.544	0.386	0.000	0.691	0.887
Log(1+#Analysts)	1.902	0.904	1.386	1.946	2.565
HHI	0.376	0.309	0.134	0.280	0.533
# Private Meetings	0.073	0.260	0.000	0.000	0.000

Table 2: Employee Displacement Concerns Following Automation Disclosure

This table examines the relation between voluntary automation disclosure and employee concerns over job displacement using a stacked DID specification (Poisson regression). The events are centered around the first instance of the firm disclosing automation initiatives in quarterly earnings conference calls during our sample period. The dependent variable is *# Displacement Concern Reviews*, defined as the number of Glassdoor reviews that express the firm's current employees' concerns over job displacement. The variable of interest for columns 1 and 2 is *Discloser* × *Post*. *Discloser* is an indicator variable that equals one for firms with automation disclosure, else zero. *Post* is an indicator variable that equals one for the four quarters following the automation disclosure, else zero. In column 3, we examine whether automation fear amplifies employee concerns by augmenting an indicator variable for events in which the disclosing firm's *Automation Fear Index* is in the top quartile, else zero (*High Automation Fear Index*). Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include event-firm and event-quarter fixed effects. Standard errors are clustered at the event-firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)
Dep. Var. =	# Displacement Concern Reviews		
Discloser × Post	0.5626	0.7620	0.6035
	[3.36]***	[4.75]***	[3.80]***
Discloser × Post × High Automation Fear Index			2.0554
			[2.16]**
Size		1.7606	1.6172
		[3.73]***	[3.42]***
ROA		5.7288	5.9075
		[1.27]	[1.33]
R&D/Sales		-8.4116	-9.1477
		[-2.37]**	[-2.47]**
Institutional Ownership		-3.5070	-3.4275
		[-4.26]***	[-4.12]***
Log(1+#Analysts)		0.0723	-0.1493
		[0.16]	[-0.32]
HHI		-0.8257	-1.5084
		[-0.47]	[-1.21]
Observations	9,418	9,418	9,418
Pseudo R-squared	0.6972	0.6988	0.6992
Event-Firm & Event-Quarter FE	Yes	Yes	Yes

Table 3: Automation Fear Index and Automation Disclosure

This table examines the relation between employees' automation fear and voluntary automation disclosure. The dependent variable is *% Automation Disclosure*, defined as the length of the sentences that contain automation-related keywords or phrases, scaled by the length of the earnings conference call transcript. In Panel A, the variable of interest is *Automation Fear Index*, defined as the level of automation fear the firm's employees are exposed to during the quarter. In Panel B, we examine whether the effect of automation fear on voluntary automation disclosure is more pronounced for firms deploying automation by interacting *Automation Fear Index* with *Automation Rollout*, an indicator variable that equals one if (i) the firm has imported industrial robots (sourced from S&P Global Panjiva) or (ii) the firms' employee resumes contain AI-related keywords or phrases during the year (Babina et al., 2024), else zero. The sample size in Panel B is smaller due to the availability of the investment rollout information. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include firm and quarter fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Average Effect

	(1)	(2)
Dep. Var. =	% Automation Disclosure	
Automation Fear Index	-0.0185	-0.0178
	[-3.70]***	[-3.63]***
Size		0.0008
		[2.06]**
ROA		-0.0024
		[-1.16]
R&D/Sales		0.0001
		[1.97]**
Institutional Ownership		-0.0003
		[-0.52]
Log(1+#Analysts)		0.0002
		[0.52]
HHI		0.0024
		[1.82]*
Observations	78,831	78,831
Adjusted R-squared	0.4568	0.4575
Firm & Quarter FE	Yes	Yes
Mean Dep. Var.	0.004	0.004
Within-FE Std. Dev.	0.010	0.010

Panel B: Variation in the Intensity of Automation Rollout

	(1)	(2)
Dep. Var. =	% Automation Disclosure	
Automation Fear Index	-0.0069	-0.0060
	[-1.84]*	[-1.62]
Automation Rollout	0.0014	0.0014
	[4.27]***	[4.31]***
Automation Fear Index × Automation Rollout	-0.0250	-0.0254
	[-3.43]***	[-3.48]***
Controls	No	Yes
Observations	56,218	56,218
Adjusted R-squared	0.4204	0.4212
Firm & Quarter FE	Yes	Yes
Mean Dep. Var.	0.003	0.003
Within-FE Std. Dev.	0.008	0.008

Table 4: Variation in Automation Disclosure Informativeness

This table examines whether our main finding varies based on the informativeness of automation disclosure. Panel A decomposes voluntary automation disclosure into (i) forward-looking disclosure (*% Automation Disclosure (Forward)*) and (ii) backward-looking disclosure (*% Automation Disclosure (Backward)*), and estimate Eq. (2) using them as the dependent variable, respectively. Panel B decomposes voluntary automation disclosure into (i) specific disclosure (*% Automation Disclosure (Specific)*) and (ii) boilerplate disclosure (*% Automation Disclosure (Boilerplate)*), and estimate Eq. (2) using them as the dependent variable, respectively. Panel C examines whether the relation between employees' automation fear and voluntary automation disclosure varies based on the availability of alternative information sources. We partition the sample based on the median level of public firm presence in the 2-digit NAICS industry, and estimate Eq. (2) in each subsample. *Automation Fear Index* is defined as the level of automation fear the firm's employees are exposed to during the quarter. For Panels A and B, the disclosure variables and *Automation Fear Index* are standardized to have a mean of zero and a standard deviation of one to ease comparison. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include firm and quarter fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Forward- vs. Backward-Looking Disclosure

	(1)	(2)
Dep. Var. =	% Automation Disclosure (Forward)	% Automation Disclosure (Backward)
Automation Fear Index (β_1)	-0.0385	-0.0165
	[-3.45]***	[-1.98]**
P-Value of Difference in β_1	0.0699	
Controls	Yes	Yes
Observations	78,831	78,831
Adjusted R-squared	0.3597	0.2217
Firm & Quarter FE	Yes	Yes
Mean Dep. Var.	0.000	0.000
Within-FE Std. Dev.	0.789	0.869

Panel B: Specific vs. Boilerplate Disclosure

	(1)	(2)
Dep. Var. =	% Automation Disclosure (Specific)	% Automation Disclosure (Boilerplate)
Automation Fear Index (β_1)	-0.0437	-0.0310
	[-3.97]***	[-3.05]***
P-Value of Difference in β_1	0.0791	
Controls	Yes	Yes
Observations	78,831	78,831
Adjusted R-squared	0.3326	0.3989
Firm & Quarter FE	Yes	Yes
Mean Dep. Var.	0.000	0.000
Within-FE Std. Dev.	0.805	0.764

Panel C: Availability of Alternative Information Sources

% Public Firm Presence =	Low	High
	(1)	(2)
Dep. Var. =	% Automation Disclosure	
Automation Fear Index (β_1)	-0.0174	-0.0072
	[-3.43]***	[-1.66]*
P-Value of Difference in β_1	0.0799	
Controls	Yes	Yes
Observations	43,401	35,352
Adjusted R-squared	0.4803	0.4558
Firm & Quarter FE	Yes	Yes
Mean Dep. Var.	0.003	0.005
Within-FE Std. Dev.	0.008	0.008

Table 5: Variation in Relative Level of Employee Concern

This table examines whether our main finding varies depending on the intensity of job exposure to automation. We partition the sample based on the median job exposure to automation and estimate Eq. (2) in each subsample. Job exposure to automation is constructed at the six-digit SOC (Standard Occupation Classification) level based on the overlap between the text of job task descriptions and the text of patents following Webb (2020), and aggregated at the NAICS industry level based on the number of employees for each occupation in the industry. The dependent variable is *% Automation Disclosure*, defined as the length of the sentences that contain automation-related keywords or phrases, scaled by the length of the earnings conference call transcript. The variable of interest is *Automation Fear Index*, defined as the level of automation fear the firm's employees are exposed to during the quarter. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include firm and quarter fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Job Exposure to Automation =	Low	High
	(1)	(2)
Dep. Var. =	% Automation Disclosure	
Automation Fear Index (β_1)	-0.0062	-0.0234
	[-1.06]	[-3.43]***
P-Value of Difference in β_1	0.0562	
Controls	Yes	Yes
Observations	36,657	42,073
Adjusted R-squared	0.2756	0.5256
Firm & Quarter FE	Yes	Yes
Mean Dep. Var.	0.002	0.006
Within-FE Std. Dev.	0.007	0.011

Table 6: Variation in Potential Employee Backlash

This table examines whether our main finding varies depending on the intensity of potential employee backlash. Panel A partitions the sample based on the median level of unionization in an industry sector and estimates Eq. (2) in each subsample. Panel B partitions the sample based on the median level of non-compete enforcement and estimates Eq. (2) in each subsample. The dependent variable is *% Automation Disclosure*, defined as the length of the sentences that contain automation-related keywords or phrases, scaled by the length of the earnings conference call transcript. The variable of interest is *Automation Fear Index*, defined as the level of automation fear the firm's employees are exposed to during the quarter. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include firm and quarter fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Labor Strike Risk

Unionization =	Low	High
	(1)	(2)
Dep. Var. =	% Automation Disclosure	
Automation Fear Index (β_1)	-0.0070	-0.0264
	[-1.10]	[-3.78]***
P-Value of Difference in β_1	0.0394	
Controls	Yes	Yes
Observations	42,965	35,736
Adjusted R-squared	0.5937	0.4481
Firm & Quarter FE	Yes	Yes
Mean Dep. Var.	0.003	0.005
Within-FE Std. Dev.	0.008	0.010

Panel B: Labor Mobility

Non-Compete Enforcement =	Low	High
	(1)	(2)
Dep. Var. =	% Automation Disclosure	
Automation Fear Index (β_1)	-0.0243	0.0015
	[-3.79]***	[0.34]
P-Value of Difference in β_1	0.0008	
Controls	Yes	Yes
Observations	45,638	33,159
Adjusted R-squared	0.4876	0.4299
Firm & Quarter FE	Yes	Yes
Mean Dep. Var.	0.005	0.003
Within-FE Std. Dev.	0.011	0.007

Table 7: Exogenous Shocks to Automation Fear Index

This table examines two exogenous shocks to automation fear index. Panel A examines technology firm layoffs as a shock to employees' automation fear using a stacked DID specification. Column 1 (2) presents the effect of technology firm layoffs on *Automation Fear Index* (*% Automation Disclosure*). The variable of interest is *Tech Layoffs × Post Layoffs*. *Tech Layoffs* is an indicator variable that equals one for DMAs affected by technology firm layoffs, else zero. *Post Layoffs* is an indicator variable that equals one for the four quarters following the technology firm layoffs, else zero. Panel B examines the introduction of ChatGPT as a shock to employees' automation fear using a generalized DID specification. Column 1 (2) presents the effect of ChatGPT introduction on *Automation Fear Index* (*% Automation Disclosure*). The variable of interest is *High Automation DMA × Post ChatGPT*. *High Automation DMA* is an indicator variable that equals one for DMAs with more automation-prone jobs, else zero. *Post ChatGPT* is an indicator variable that equals one for the four quarters following the introduction of ChatGPT, else zero. Firm-quarter and DMA-quarter analyses include control variables from Eq. (2) and Eq. (3), respectively. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. For Panel A, standard errors are clustered for column 1 (column 2) at the event-DMA (event-firm) level and are reported in parentheses. For Panel B, standard errors are clustered for column 1 (column 2) at the DMA (firm) level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Technology Firm Layoffs as a Shock

	(1)	(2)
Sample =	DMA-Quarter	Firm-Quarter
Dep. Var. =	Automation Fear Index	% Automation Disclosure
Tech Layoffs × Post Layoffs	0.0070	-0.0038
	[5.46]***	[-3.95]***
Controls	Yes	Yes
Observations	4,448	5,500
Adjusted R-squared	0.8635	0.7722
Event-DMA & Event-Quarter FE	Yes	-
Event-Firm & Event-Quarter FE	-	Yes
Mean Dep. Var.	0.008	0.013
Within-FE Std. Dev.	0.003	0.012

Panel B: ChatGPT Introduction as a Shock

	(1)	(2)
Sample =	DMA-Quarter	Firm-Quarter
Dep. Var. =	Automation Fear Index	% Automation Disclosure
High Automation DMA × Post ChatGPT	0.0018	-0.0030
	[2.32]**	[-4.19]***
Controls	Yes	Yes
Observations	1,080	17,975
Adjusted R-squared	0.8502	0.6324
DMA & Quarter FE	Yes	-
Firm & Quarter FE	-	Yes
Mean Dep. Var.	0.011	0.008
Within-FE Std. Dev.	0.004	0.014

Table 8: Private Meetings

This table examines the relation between employees' automation fear and private meetings using a Poisson regression. The dependent variable is *# Private Meetings*, defined as the number of shareholder/analyst days during the quarter. The variable of interest for column 1 is *Automation Fear Index*, defined as the level of automation fear the firm's employees are exposed to during the quarter. The variable of interest for column 2 is *Automation Fear Index × Automation Rollout*. *Automation Rollout* is an indicator variable that equals one if (i) the firm has imported industrial robots (sourced from S&P Global Panjiva) or (ii) the firms' employee resumes contain AI-related keywords or phrases during the year (Babina et al., 2024), else zero. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include firm and quarter fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)
Dep. Var. =	# Private Meetings	
Automation Fear Index	1.5265	-1.6992
	[1.86]*	[-1.29]
Automation Rollout		-0.0774
		[-0.93]
Automation Fear Index × Automation Rollout		6.2217
		[4.74]***
Size	0.0779	0.0667
	[1.43]	[1.07]
ROA	-1.2174	-1.4156
	[-2.52]**	[-2.29]**
R&D/Sales	-0.0075	0.0098
	[-0.52]	[0.46]
Institutional Ownership	0.1944	0.1027
	[1.81]*	[0.84]
Log(1+#Analysts)	-0.0329	-0.0762
	[-0.59]	[-1.32]
HHI	0.0918	0.0292
	[0.40]	[0.12]
Observations	78,831	56,250
Pseudo R-squared	0.3116	0.2899
Firm & Quarter FE	Yes	Yes

Table 9: Falsification and Robustness

This table presents falsification and robustness tests. Panel A presents falsification tests by replacing the dependent variable with three alternative measures of disclosure: *# Capex*, *# 8-Ks*, or *Abs(MFE)*. For columns 1 and 2, we estimate Poisson regressions; for column 3, we estimate an OLS regression. Panel B presents results using alternative measures of voluntary automation disclosure and decomposing the fear of job displacement and automation disclosures into those related to industrial robots and AI-powered tools. Panel C presents results using alternative measures of *Automation Fear Index*. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include firm and quarter fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Falsification

Dep. Var. =	(1) # Capex	(2) # 8-Ks	(3) Abs(MFE)
Automation Fear Index	-0.1421 [-0.24]	0.1609 [0.38]	0.0036 [0.44]
Controls	Yes	Yes	Yes
Observations	78,831	78,831	9,363
Adjusted R-squared	-	-	0.6424
Pseudo R-squared	0.4576	0.2696	-
Firm & Quarter FE	Yes	Yes	Yes
Mean Dep. Var.	-	-	0.004
Within-FE Std. Dev.	-	-	0.007

Panel B: Alternative Measures of Automation Disclosure

Dep. Var. =	(1) I (Automation PR)	(2) I (Automation Disclosure)	(2) % Robot Disclosure	(3) % AI Disclosure
Automation Fear Index	-0.1405 [-2.44]**	-0.1829 [-1.79]*		
Automation Fear Index (Robot)			-0.0195 [-1.99]**	
Automation Fear Index (AI)				-0.0189 [-4.33]***
Controls	Yes	Yes	Yes	Yes
Observations	78,831	78,831	78,831	78,831
Adjusted R-squared	0.2588	0.3337	0.3901	0.4375
Firm & Quarter FE	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.055	0.174	0.002	0.002
Within-FE Std. Dev.	0.193	0.305	0.008	0.007

Panel C: Alternative Measures of Automation Fear Index

	(1)	(2)	(3)	(4)
Dep. Var. =	% Automation Disclosure			
ihs(# of Automation Fear News)	-0.0003 [-1.97]**			
Automation Fear Index (HQ)		-0.0099 [-3.30]***		
Automation Fear Index (within 200 words)			-0.0149 [-3.89]***	
Automation Fear Index (Fwd)				-0.0019 [-4.56]***
Controls	Yes	Yes	Yes	Yes
Observations	78,831	78,831	72,635	71,314
Adjusted R-squared	0.4571	0.4574	0.4147	0.4159
Firm & Quarter FE	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.004	0.004	0.003	0.003
Within-FE Std. Dev.	0.010	0.010	0.008	0.008

Appendix A: Examples of Glassdoor Reviews, Cable News, and Automation Disclosure

A.1. Examples of Glassdoor reviews

Home Depot, 2021-08-06:
"Limited opportunity to move up. Going to HR only alerts management of decent, and will try to gaslight you and defend management. There's a toxic culture that makes the average tenure is 4 months. **They are implementing AI that will replace most everyone with AI and is in all their internal messages that's the plan, but they haven't told the people being replaced by AI that they will be replaced and they are currently training the AI that will replace us. Any messaging about this AI training and replacement; that somehow makes it to us, is quickly removed or retracted**."

International Workplace Group, 2022-01-03:
"Middle Managers think they are gods greatest gift to the sales floor, constant change of systems and procedures, heartless layoffs during the beginning of the COVID-19 pandemic. The CEO is a monster who only cares about **making the company fully automated to eventually fire employees. Job security does not exist here**."

International Business Machines, 2023-05-05:
"Everything. **The CEO announced that he thinks 8000 HR jobs can be replaced by AI**. Talk about out of touch with his company's personnel. Then CEO announced that working remotely will impact your career at IBM. He acts as if IBM is still selling mainframe computers. Don't walk, run from this company."

Amazon, 2025-06-12:
"I just read about how **Amazon is starting to deploy robots for delivery** instead of having their usual delivery drivers. Everything is moving so fast. Everything human is being replaced by something technological. This pace is giving me a lot of anxiety tbh... **how soon before retail employees are replaced with robots?**"

A.2. Excerpts of the 5-minute cable news segments

KHQ, (Spokane) 2011-01-14:
"The U.S. job market is losing more jobs than ever before. **Once-needed jobs are being replaced by computers, robots** […] **Take these jobs, for example—computers and automated systems can get the job done better, more efficiently, and faster than the people that once did them.** For example, travel agents, bank tellers, file clerks, printing press operators, switchboard operators, seamstresses, watch and camera repairmen. The Labor Department predicts that during the next decade there will be fewer workers in almost one-quarter of the 750 occupations it tracks."

KIAH, (Houston) 2016-09-24:
"Robots are taking over the world. Well, the working world, that is. In a new report, scientists predict that **by 2021, machines will take away 6% of all jobs in the U.S., which is nearly 9 million people.** They took our jobs. Why is robotic automation becoming such a popular solution for businesses and consumers? It will be one of the bedrock pivotal technologies. The first to go will be in the service industry—you may have noticed automated touch screens replacing bank tellers and fast food workers, and self-driving taxis. But according to the report, even more jobs will get replaced by intelligent agents, which are basically smarter versions of Siri. […] The report notes that five years from now may be the technological tipping point, where **more jobs are replaced by robots than created—and many of the workers who lose their jobs won't have the skills required to train for a new career path.**"

WJXT, (Jacksonville) 2023-12-04:
"**Lots of jobs could be replaced with artificial intelligence** within the next decade. Some have already been replaced. That's according to the UK's Department of Education. Researchers analyzed 365 categories of jobs and found that jobs requiring a higher level of education—surprisingly—are more likely to be replaced by AI. It's smarter than us. The jobs most at risk include management consultants, your business analyst, financial managers and directors, accountants, and even some office psychologists."

A.3. Examples of automation disclosure in earnings conference calls

Natural Grocers, 2013-08-07:
"Moving to our updated fiscal 2013 outlook, we expect to stay within our projections by […] incurring capital expenditures of between $32 million to $34 million, which includes $1 million for two new non-store related capital projects, which should ***automate*** the hand bagging area at our distribution center and build out corporate offices in the warehouse behind the current offices."

Argos Therapeutics Inc., 2015-05-14:
"The facility will be used to support ***automated*** production of our Arcelis-based personalized immunotherapy product candidates, including AGS-003. We expect the facility to be the first ***automated*** manufacturing facility of its kind, and expect that it will be operational next year. Finally, we expect to have our new ***automated*** commercial manufacturing facility operational next year, as we continue to progress towards our goal of becoming a fully integrated commercial immuno-oncology company."

Patrick Industries, 2021-04-29:
"We further deployed capital within our infrastructure to proactively drive our business model off of as well as ***automating*** and expanding capacity, which will continue to allow us the opportunity to consistently deliver our differentiated products and services to our customers. We are investing in software, ***automation*** and specialized equipment needs, which will enable our team members to have better balance and serve our customers at the highest level. We estimate approximately $45 million to $50 million of CapEx for the full year 2021, which reflects increased investment in ***automation*** projects to offset the expected continued tight labor market, which will enable us to continue to support growth of all of our end markets."

Lannett Co Inc., 2021-11-02:
"These efforts will also help us to create capacity without the need to put up many new buildings and we've allocated a record amount of capital towards these ***automation*** and continuous improvement projects, with over 15 larger ***automation*** projects set to go live in 2022 and the first part of 2023"

R1 RCM INC, 2022-02-17:
"We also uncovered new opportunities for automation and currently have an additional 110 million tasks we can ***automate***. We expect to exit 2022 with over 100 million tasks ***automated***, contributing approximately $45 million to our expected adjusted EBITDA for the year. As a result of the planned acquisition of Cloudmed, we expect to have the broadest coverage on revenue cycle processes ***automation***. We expect our data footprint to increase tenfold, enabling further advancements in ***machine learning*** which will in turn create a more powerful value proposition for customers. Building on our combined capabilities, we plan to launch a multiyear ***AI***-driven strategy to unlock the full potential this expanded data set presents to us."

Appendix B: Automation-related Keywords and Phrases

This appendix lists the automation-related keywords and phrases to identify voluntary automation disclosure in the presentation section of the earnings conference call transcript. For all keywords and phrases, we include the variation of the word (e.g., "Artificial Intelligence" variations such as "Artificially Intelligent" or "Robot" variations such as "Robotics") and plural forms.

AI	Edge Computing	Self-Learning
Algorithm	Facial Recognition	Sentiment Classification
Artificial Intelligence	Image Recognition	Smart Data
Automation	Intelligent System	Smart Technology
Autonomous	Language Model	Speech Recognition
Bayesian Network	LLM	Torch
Big Data	Machine Learning	Transfer Learning
Biometrics	Natural Language Processing	Unstructured Data
Chatbot	Neural Network	Virtual Agent
Cloud Computing	NLP	Virtual Assistant
Cognitive Computing	Predictive Analytics	Virtual Machine
Computer Vision	Quantum Computing	Virtual Reality
Data Mining	Random Forest	Voice Assistant
Data Science	Reinforcement Learning	Voice Bot
Deep Learning	Reinforced Learning	Word2Vec
Digital Transformation	Robot	

Appendix C: Variable Definitions

Variable	Description
Dependent variables	
# Displacement Concern Reviews	The number of Glassdoor reviews that express the firm's current employees' concerns over job displacement, defined as reviews mentioning one of the following keywords or phrases (or variations): *job security*, *job uncertainty*, *job loss*, *lose job*, *layoff*, *replace/displace jobs*
% Automation Disclosure	The length of sentences that contain automation-related keywords or phrases (see Appendix B for the list) in the presentation section of the earnings conference call transcript, scaled by the length of the presentation section of the earnings conference call transcript.
% Automation Disclosure (Forward)	The frequency of automation-related sentences in earnings conference calls with forward-looking automation information. We define forward-looking automation information as sentences with one of the following keywords or phrases: *will*, *could*, *should*, *expect**, *anticipat**, *plan**, *hop**, *believ**, *can*, *may*, *might*, *intend**, *forecast**, *objective*, *outlook*, *going/aim to*, *opportunit**, *look/move forward*, *potentially*, *target**, *promis**, *prospect*
% Automation Disclosure (Backward)	The frequency of automation-related sentences in earnings conference calls with only backward-looking automation information. We define backward-looking automation information as sentences that do not contain one of the following keywords or phrases: *will*, *could*, *should*, *expect**, *anticipat**, *plan**, *hop**, *believ**, *can*, *may*, *might*, *intend**, *forecast**, *objective*, *outlook*, *going/aim to*, *opportunit**, *look/move forward*, *potentially*, *target**, *promis**, *prospect*
% Automation Disclosure (Specific)	The frequency of automation-related sentences in earnings conference calls with specific information, defined as sentences that contain at least one entity recognized from the Stanford Named Entity Recognizer.
% Automation Disclosure (Boilerplate)	The frequency of automation-related sentences in earnings conference calls with boilerplate information, defined as sentences that do not contain any entity recognized from the Stanford Named Entity Recognizer.
I (#Automation PR)	An indicator variable that equals one if the firm issued an automation-related press release during the period, else zero. Firm-initiated press releases are sourced from Ravenpack News Analytics and automation-related press releases are identified as those with headlines including automation-related keywords or phrases.
I (Automation Disclosure)	An indicator variable that equals one if the firm mentions automation-related keywords or phrases (see Appendix B for the list) in the presentation section of the earnings conference call transcript.
% Robot Disclosure	An alternative measure of *% Automation Disclosure* constructed using only sentences that contain robot-related keywords or phrases ("*Automation*" or "*Robot*").
% AI Disclosure	An alternative measure of *% Automation Disclosure* constructed using only sentences that contain AI-related keywords or phrases (all those listed in Appendix B with the exception of "*Automation*" or "*Robot*").
# Private Meetings	The number of private meetings (i.e., shareholder/analyst days) during the period. Private meeting data is sourced from Key Developments.
# Capex	The number of capital expenditure forecasts during the period. Capital expenditure forecasts are sourced from I/B/E/S guidance file.
# 8-Ks	The number of Item 8.01 8-K filings during the period. Item 8.01 8-K filings are sourced from WRDS SEC Analytics Suite.
Abs(MFE)	The absolute value of the management forecast error, measured as the actual earnings per share (EPS) minus the most recent management forecast of EPS before the earnings announcement, scaled by the stock price at the end of the fiscal quarter. Management forecasts of EPS are sourced from I/B/E/S guidance file.
Major Layoff	An indicator variable that equals one if the firm has reduced the number of employees by a significant percentage over the following three years, else zero. For each of the three years, we decile rank the employee

	percentage change for all firms and define significant reductions as those in the bottom decile.

Main independent variables

Automation Fear Index	The level of automation fear the firm's employees are exposed to during the period. The level of automation fear is proxied by the total number of 5-minute cable news segments from local news outlets (measured quarterly at the DMA level) that mention automation-related words in tandem with displacement-related words (i.e., Figure 1), scaled by the total number of respective segments from national news outlets during the same period. We create a weighted average measure based on the firm's geographic distribution of employees (sourced from Infogroup).
DMA Automation Fear Index	The total number of 5-minute cable news segments from local news outlets (measured yearly at the DMA level) that mention automation-related words in tandem with displacement-related words (i.e., Figure 1), scaled by the total number of respective segments from national news outlets during the same period.
Automation Fear Index (Robot)	An alternative measure of *Automation Fear Index* constructed using only 5-minute cable news segments from local news outlets that mention robot-related words in tandem with displacement-related words.
Automation Fear Index (AI)	An alternative measure of *Automation Fear Index* constructed using only 5-minute cable news segments from local news outlets that mention AI-related words in tandem with displacement-related words.
ihs(# of Automation Fear News)	The inverse hyperbolic sine of the total number of 5-minute cable news segments from local news outlets (measured quarterly at the DMA level) that mention automation-related words in tandem with displacement-related words (i.e., Figure 1). We create a weighted average measure based on the firm's geographic distribution of employees (sourced from Infogroup).
Automation Fear Index (HQ)	An alternative measure of *Automation Fear Index* constructed using only 5-minute cable news segments from the firm's headquarters DMA.
Automation Fear Index (within 200 words)	An alternative measure of *Automation Fear Index* constructed using only 5-minute cable news segments in which automation-related words occur within 200 words of layoff-related words.
Automation Fear Index (Fwd)	An alternative measure of *Automation Fear Index* constructed using only 5-minute cable news segments in which automation-related words and layoff-related words are conjoined with the following forward-looking words: *will*, *might*, *could*, *may*.
Discloser	An indicator variable that equals one for firms with automation disclosure, else zero.
Post	An indicator variable that equals one for the four quarters following the firms' automation disclosure, else zero.
Tech Layoffs	An indicator variable that equals one for DMAs affected by technology firm layoffs, else zero. Technology firm layoffs are sourced from layoffs.fyi.
Post Layoffs	An indicator variable that equals one for the four quarters following technology firm layoffs, else zero.
High Automation DMA	An indicator variable that equals one for DMAs with an above-median intensity of automation-prone jobs, else zero. The intensity of automation-prone jobs is measured as the weighted average of the NAICS-level occupational exposure (Webb, 2020), where the weights are equal to the number of establishments in the NAICS industry within the DMA (sourced from Census' County Business Patterns data).
Post ChatGPT	An indicator variable that equals one for the four quarters following the introduction of ChatGPT, else zero.

Cross-sectional variables

High Automation Fear Index	An indicator variable that equals one for events in which the disclosing firms' *Automation Fear Index* is in the top quartile, else zero. *Automation*

	Fear Index is measured as the average value during the pre-period for each event.
Automation Rollout	An indicator variable that equals one if (i) the firm has imported industrial robots (sourced from S&P Global Panjiva) or (ii) the firms' employee resumes contain AI-related keywords or phrases during the year (Babina et al., 2024), else zero.
% Public Firm Presence	The level of public firm presence in the 2-digit NAICS industry, defined as the fraction of sales by public firms in the 2-digit NAICS industry (Badertscher et al., 2013; Shroff et al., 2017).
Job Exposure to Automation	The level of job exposure to automation. Job exposure to automation is constructed at the six-digit SOC (Standard Occupation Classification) level based on the overlap between the text of job task descriptions and the text of patents following Webb (2020). The occupation-level exposures are aggregated to the NAICS industry level based on the number of employees for each occupation in the industry.
Non-Compete Enforcement	The level of non-compete enforcement, proxied by the state-level non-compete enforcement (Garmaise 2011; Ertimur et al., 2018). We create a weighted average index based on the firm's geographic distribution of employees (sourced from Infogroup).
Unionization	The level of unionization in the 2-digit NAICS industry, defined as the percentage of the industry covered by unions. Unionization data is sourced from Unionstats.
Control variables	
Log(Population)	The natural logarithm of the DMA population, sourced from the 5-year estimates of the American Community Survey (ACS).
% Unemployment	The unemployment rate of the DMA, sourced from the 5-year estimates of the American Community Survey (ACS).
% Age 65+	The percentage of the DMA population aged 65 and over, sourced from the 5-year estimates of the American Community Survey (ACS).
% Bachelors Degree	The percentage of the DMA population with a Bachelor's degree or higher, sourced from the 5-year estimates of the American Community Survey (ACS).
Log(Household Income)	The natural logarithm of the median household income of the DMA, sourced from the 5-year estimates of the American Community Survey (ACS).
Log(Viewership)	The natural logarithm of the number of households watching television in the DMA, sourced from Nielsen's Local Television Market Universe Estimates rankings.
% Employed in STEM	The percentage of the DMA population employed in a STEM (Science, Technology, Engineering, and Mathematics) field. STEM field is defined based on the six-digit SOC (Standard Occupation Classification) level. Data is sourced from the Bureau of Labor Statistics.
Conservative	An indicator variable equal to one for DMAs that exceed 50% Republican vote share, and zero otherwise. Data is sourced from MIT Election Data + Science Laboratory.
Size	The natural logarithm of total assets.
ROA	Return on assets, defined as net income scaled by total assets.
R&D/Sales	R&D expense scaled by total sales during the period.
Institutional Ownership	The percentage of firm ownership from institutional investors, sourced from the Thomson 13f database.
Log(1+#Analysts)	The natural logarithm of one plus the number of analysts following the firm, sourced from the I/B/E/S summary file.
HHI	The Herfindahl-Hirschman Index, defined as the sum of squared market shares (based on sales) of the 4-digit SIC industry.

Online Appendix Table A1: Validation of Automation Fear Index

This table presents validation analysis of *Automation Fear Index*. In Panel A, we randomly select 5,000 automation-fear-related news segments each year and prompt GPT-4.0 to generate a set of ten economic themes that trigger the automation fear-related cable news. We then task GPT-4.0 with categorizing each news segment into one of ten economic themes. In Panel B, we examine the determinants of *Automation Fear Index* focusing on demographic characteristics. The dependent variable is *DMA Automation Fear Index*, the frequency of local news discussing concerns about job displacement due to the advancement of industrial robots and AI, aggregated at the DMA-year level. In Panel C, we examine whether *DMA Automation Fear Index* predicts the frequency of employee reviews voicing concerns about job displacement within the DMA using a Poisson regression. The dependent variable is *# Displacement Concern Reviews*, defined as the number of Glassdoor reviews that express the firm's current employees' concerns over job displacement in the following quarter, aggregated at the DMA-quarter level. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns in Panel A (B) include DMA and year (quarter) fixed effects. Standard errors are clustered at the DMA level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Economic Theme of Automation Fear-Related News

Economic Theme	Freq.
Automation impact (e.g., scientific reports, survey)	49.3%
Job demand (e.g., unemployment, labor market demand)	19.6%
Up-skilling needs (education, training)	11.2%
Automation layoff events	6.5%
Tech roll-out	4.2%
Policy change	3.3%
Layoff events	1.9%
Union negotiation	1.7%
Government regulation	1.4%
Economic forecast	0.9%

Panel B: Determinants of Automation Fear Index

	(1)
Dep. Var. =	DMA Automation Fear Index
Log(Population)	-0.0076
	[-0.67]
% Unemployment	0.0011
	[2.54]**
% Age 65+	0.0003
	[0.37]
% Bachelors Degree	-0.0012
	[-1.68]*
Log(Household Income)	0.0167
	[1.31]
Log(Viewership)	-0.0029
	[-0.35]
% Employed in STEM	0.0788
	[1.81]*
Conservative	-0.0012
	[-1.12]
Observations	2,115
Adjusted R-squared	0.7648
DMA & Year FE	Yes
Mean Dep. Var.	0.007
Within-FE Std. Dev.	0.007

Online Appendix Table A1, continued

Panel C: Automation Fear Index and Employee Displacement Concerns

	(1)	(2)
Dep. Var. =	# Displacement Concern Reviews	
DMA Automation Fear Index	5.5479	3.0632
	[3.25]***	[2.09]**
Controls	No	Yes
Observations	6,678	6,678
Pseudo R-squared	0.8543	0.8577
DMA & Quarter FE	Yes	Yes

Online Appendix Table A2: Sample Selection Procedure

This table illustrates the sample selection procedure. Our selection procedure begins by identifying all firm-quarters with an earnings conference call during the period 2010Q2 to 2024Q2. We retain observations with data to construct a firm-level *Automation Fear Index* using the geographic dispersion of the company's employees during the sample period. We remove all observations in 2-digit NAICS sectors: 51 ("Information") and 54 ("Professional, Scientific, and Technical Services") to focus on automation-using sectors. Lastly, we retain observations with control variables.

	Firm-Quarters	Unique Firms
All firm-quarters with an earnings conference call (2010Q2–2024Q2)	190,658	7,250
Less: Firms without data to construct *Automation Fear Index*	(93,622)	(4,639)
Less: Firms in 2-digit NAICS industries: 51 & 54	(12,341)	(80)
Less: Observations with missing control variables	(5,864)	(207)
Main sample	78,831	2,324

Online Appendix Table A3: Do Automation Fear Index Deter Automation?

This table examines whether automation fear deters firms' automation rollout using a firm-year panel. The dependent variable is *Automation Rollout*, an indicator variable that equals one if (i) the firm has imported industrial robots (sourced from S&P Global Panjiva) or (ii) the firms' employee resumes contain AI-related keywords or phrases during the year (Babina et al., 2024), else zero. The variable of interest is *Automation Fear Index*, the level of automation fear the firm's employees are exposed to during the quarter. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include DMA and year fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)
Dep. Var. =	Automation Rollout	
Automation Fear Index	-0.1093	-0.0618
	[-0.44]	[-0.25]
Controls	No	Yes
Observations	13,343	13,343
Adjusted R-squared	0.6923	0.6934
Firm & Year FE	Yes	Yes
Mean Dep. Var.	0.466	0.466
Within-FE Std. Dev.	0.258	0.258

Online Appendix Table A4: Triple-differences Analysis of Tech Firm Layoffs

This table examines the effect of tech firm layoffs on non-tech firms' automation disclosures using a triple-differences analysis. The sample is the same as that in Table 7 Panel A. We estimate the following triple-differences regression model:

$$Y_{e,i,t} = \alpha + \beta_1 \textit{Tech Layoffs}_{e,c} \times \textit{Post Layoffs}_{e,t} \times \textit{High Job Exposure to Automation}_{e,i} + X_{i,t} + \gamma_{e,i} + \nu_{e,i,t} + \varepsilon_{e,i,t}$$

The variable of interest is *Tech Layoffs* × *Post Layoffs* × *High Job Exposure to Automation*. *Tech Layoffs* is an indicator variable that equals one for DMAs affected by technology firm layoffs, else zero. *Post Layoffs* is an indicator variable that equals one for the four quarters following the technology firm layoffs, else zero. *High Job Exposure to Automation* is an indicator variable that equals one for above-median observations of job exposure to automation, else zero. Job exposure to automation is constructed at the six-digit SOC level based on the overlap between the text of job task descriptions and the text of patents following Webb (2020), aggregated at the NAICS industry level based on the number of employees for each occupation in the industry. Control variables from Eq. (2) and event-firm, and event-DMA-quarter fixed effects are included. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)
Dep. Var. =	% Automation Disclosure
Tech Layoffs × Post Layoffs × High Job Exposure to Automation	-0.0024
	[-2.09]**
Controls	Yes
Observations	5,225
Adjusted R-squared	0.7741
Event-Firm & Event-DMA-Quarter FE	Yes
Mean Dep. Var.	0.013
Within-FE Std. Dev.	0.012

Online Appendix Table A5: Variation in Proprietary Costs

This table examines whether our main finding varies with proprietary costs. We partition the sample based on the median level of Herfindahl-Hirschman Index (HHI) and estimate Eq. (2) in each subsample. The dependent variable is *% Automation Disclosure*, defined as the length of the sentences that contain automation-related keywords or phrases, scaled by the length of the earnings conference call transcript. The variable of interest is *Automation Fear Index*, defined as the level of automation fear the firm's employees are exposed to during the quarter. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include firm and quarter fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

HHI =	Low	High
	(1)	(2)
Dep. Var. =	% Automation Disclosure	
Automation Fear Index (β_1)	-0.0168	-0.0169
	[-2.70]***	[-2.34]**
P-Value of Difference in β_1	0.9945	
Controls	Yes	Yes
Observations	39,428	39,379
Adjusted R-squared	0.4958	0.4537
Firm & Quarter FE	Yes	Yes
Mean Dep. Var.	0.004	0.004
Within-FE Std. Dev.	0.009	0.010

Online Appendix Table A6: Variation in Firm Size and DMA Size

This table examines whether our main finding varies with firm size (proxied by the natural logarithm of total assets; Panel A) and DMA size (proxied by population; Panel B). Panel A partitions the sample based on the median level of total assets and estimate Eq. (2) in each subsample. Panel B partitions the sample based on the median population of the firm's headquarter DMA and estimates Eq. (2) in each subsample. The dependent variable is *% Automation Disclosure*, defined as the length of the sentences that contain automation-related keywords or phrases, scaled by the length of the earnings conference call transcript. The variable of interest is *Automation Fear Index*, defined as the level of automation fear the firm's employees are exposed to during the quarter. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include firm and quarter fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

Panel A: Firm Size

	Firm Size =	Small	Large
		(1)	(2)
	Dep. Var. =	% Automation Disclosure	
Automation Fear Index (β_1)		-0.0180	-0.0145
		[-2.84]***	[-2.03]**
P-Value of Difference in β_1		0.7156	
Controls		Yes	Yes
Observations		39,400	39,400
Adjusted R-squared		0.4874	0.4597
Firm & Quarter FE		Yes	Yes
Mean Dep. Var.		0.004	0.004
Within-FE Std. Dev.		0.010	0.009

Panel B: DMA Size

	DMA Size =	Small	Large
		(1)	(2)
	Dep. Var. =	% Automation Disclosure	
Automation Fear Index (β_1)		-0.0282	-0.0175
		[-3.20]***	[-3.65]***
P-Value of Difference in β_1		0.1568	
Controls		Yes	Yes
Observations		47,763	31,054
Adjusted R-squared		0.5342	0.4189
Firm & Quarter FE		Yes	Yes
Mean Dep. Var.		0.004	0.004
Within-FE Std. Dev.		0.010	0.008

Online Appendix Table A7: Automation Disclosure and Layoff Likelihood

This table examines the relation between voluntary automation disclosure and layoff likelihood, conditional on firm-years with automation rollout (*Automation Rollout* = 1). The dependent variable is *Major Layoff*, defined as an indicator variable that equals one if the firm has reduced the number of employees by a significant percentage over the following three years, else zero. For each of the three years, we decile rank the employee percentage change for all firms and define significant reductions as those in the bottom decile. The variable of interest is *% Automation Disclosure*, defined as the length of the sentences that contain automation-related keywords or phrases, scaled by the length of the earnings conference call transcript, aggregated at the year level. Continuous variables are winsorized at the 1% and 99% levels. All variables are defined in more detail in Appendix C. All columns include firm and year fixed effects. Standard errors are clustered at the firm level and are reported in parentheses. *, **, and *** indicate significance levels of 10%, 5%, and 1%, respectively.

	(1)	(2)
Dep. Var. =	Major Layoff	
% Automation Disclosure	-0.3205	-0.3012
	[-2.93]***	[-2.80]***
Controls	No	Yes
Observations	15,925	15,925
Adjusted R-squared	0.2819	0.2919
Firm & Year FE	Yes	Yes
Mean Dep. Var.	0.138	0.139
Within-FE Std. Dev.	0.272	0.272