Labor Reactions to Credit Deterioration: Evidence from LinkedIn Activity*

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Abstract

We provide the first analysis of workers' on-the-job networking activity following their firm's credit deterioration. Using high-frequency networking on LinkedIn, we show that workers initiate more connections immediately following adverse credit shocks. We propose a simple model in which workers are driven by concerns about both unemployment and reduced future prospects at their firm. Consistent with this model and distinct from prior work, we find that the stronger response of high-value workers is magnified when the firm is *far* from bankruptcy. We further show that elevated networking activity is associated with departures and diminished profitability in following years, consistent with on-the-job networking being a source of fragility for firms.

JEL Codes: G32, G33, J32, J63, J64, M54.

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1. Introduction

Economists have long speculated that deteriorating financial conditions, or the prospect thereof, may prompt workers to contemplate leaving their firm (e.g., Opler and Titman, 1994). A separate literature explores how such concerns from workers could materialize in a variety of ways; workers could begin on-the-job search (Pissarides, 1994), seek referrals (Topa, 2011), or more generally, tap into and expand their social and professional networks (Montgomery, 1991). Yet we lack large-scale empirical evidence documenting the early symptoms of worker reactions to negative firm news, financial or otherwise. Understanding this potential labor fragility is of first-order importance for gauging the impact of firm shocks, particularly as organizational and human capital become larger components of firm value.

In this paper, we study high-frequency networking activity of workers in response to signals of their firms' economic and financial conditions. Conceptually, we introduce ex ante financial health as a first-order parameter, distinguishing between workers motivated by reduced future prospects at financially healthy firms and workers motivated by job security concerns at financially distressed firms. A novel finding is that workers with desirable outside options drive reactions at financially healthy firms, whereas closer to default, job security concerns dominate, and all workers increase their search effort to insure themselves against job loss.

Empirically, studying high-frequency on-the-job networking rather than slow-moving realized moves helps to identify the start of workers' reactions to signals of economic and financial deterioration. Building on the labor and finance literature (e.g., Brown and Matsa, 2016; Baghai et al., 2021; Graham et al., 2022), we primarily focus on credit deterioration: declines in firms' ability to service debt. In addition to credit shocks, we explore workers' reactions to negative economic shocks related to earnings and equity, and use differences across shock types to shed light on the underlying mechanism.

The lack of direct evidence on workers' search and networking behavior in response to firm shocks is largely due to challenges in observability. To address this limitation, we introduce a new source of data: networking activity on LinkedIn, the world's largest professional networking platform.[1] The data we use covers one million individuals at the start of 2008 to six million by the end of 2017, who create a total of 900 million connections while employed at 1,747 public US firms. Connections are directed and time-stamped at the moment of creation. Connections are also uniquely linked to rich de-identified employment histo-

[1] See `https://about.linkedin.com/`. The data are accessed in a de-identified way with LinkedIn's permission.

ries from LinkedIn, which includes seniority rank, occupation type, employer identifier, and employment dates.

Our main measure of worker reactions is the rate at which a firm's workers initiate new connections, calculated weekly. There are two key advantages to our approach. First, this outcome provides new insights into labor behavior by holistically capturing a wide range of networking activity,[2] and importantly, will be shown to predict future departures at a much lower (i.e., multi-year) frequency. Second, the high frequency nature of the data offers greater confidence in interpreting worker actions as responses to specific news shocks. This helps resolve a basic challenge in the literature to identify the impact of financial decline, which often coincides with broader negative economic shocks that might affect firms over a longer horizon. We are able to isolate reactions at the weekly level, still control for a variety of slow-moving factors, and even show the dynamics of how events affect workers. The rich variation in connection activity allows us to compare the intensity of reactions across a broad range of firms and types of workers, which offers a deeper view into motives and implications of labor reactions.

To guide out intuition, we build a simple model of labor reactions to credit deterioration. In response to negative credit shocks, firms can take actions that reduce credit risk but also reduce resources needed by long-term projects. If the firm defaults, workers face unemployment as in Berk et al. (2010). At the same time, workers benefit from long-term projects, and thus dislike actions that reduce resources to these projects. Workers choose an effort intensity of on-the-job search for attractive outside opportunities, whose quality depends on workers' abilities.

We introduce firms' ex ante credit rating as a first order parameter to unlock a mechanism that primarily operates for firms in no risk of bankruptcy. In the model, firms vary based on ex ante financial health and workers vary based on their value to firms. Two distinct channels drive workers to seek outside opportunities in response to credit deterioration. The first is a "job security" channel, which affects all workers equally, and operates through workers' concern about heightened unemployment risk. The second is an "option value" channel, which captures the *long-term* value of remaining at the firm relative to outside options, and disproportionately affects workers with better outside options.

This duality generates sharp cross-sectional implications along the dimensions of firm health and worker type. At firms close to default, the job security channel dominates, while

[2] A connection may be formed following a physical event (e.g., an encounter in a meeting or conference), or after searching directly on the platform (e.g., through mutual connections or interests).

at firms far from default, the option value channel becomes more important. As a result, the model predicts that high-value workers at financially healthy firms react more strongly and are more likely to search for and successfully move on to desirable positions outside of the firm, whereas at financially unhealthy firms there should be fewer differences based on workers' outside options.

We use these predictions to guide our empirical analysis. To capture credit deterioration, we focus on negative credit watches, or "downwatches." Downwatches are a disclosure tool used by credit rating agencies to announce a likely or impending corporate downgrade.[3] We use these announcements as point-in-time news about a change in the firm's financial condition and examine weekly connection activity before and after the news in an event-study format, where we include week-by-industry and firm-by-year fixed effects.

We find that firms across the entire distribution of credit ratings experience heightened networking activity from their workers following credit deterioration. That is, regardless of the firm's ex ante distance to bankruptcy, the propensity for workers to initiate new connections (or "connection rate") sharply increases in the weeks following a downwatch announcement. Reactions are concentrated *after* downwatch events, and cannot be explained by slow-moving economic deterioration.

Furthermore, our analysis points to a novel finding: the dominant motive to seek outside options depends on firms' ex ante financial conditions. At investment grade firms, individuals with better realized outside opportunities drive the connection response. In contrast, at non-investment grade firms, responses seem less related to the quality of outside options. This is consistent with the model's prediction that workers with desirable outside options drive reactions at financially healthy firms, whereas closer to default, all employees increase their search effort to insure themselves against the risk of job loss.

To understand whether other negative news triggers similar responses, we compare reactions to two other economically significant disclosure events that signal negative information but do not directly relate to credit: missed earnings and equity sell recommendations. Interestingly, we find that workers' connection responses to these alternative events are minimal or non-existent. In the model, workers react to credit deterioration, not only due to concern about firm default, but also in anticipation of firm actions that lower credit risk by

[3]We focus on downwatches rather than downgrades for two reasons. First, by design, downwatches often precede downgrades. This makes downwatches more likely to be unexpected information shocks to workers. Second, downwatches are purely informational: they signal, but do not change the rating of a firm or its securities, which could directly impact a firm's cost of capital. This helps to narrow down the set of possible mechanisms through which the events trigger employee reactions.

appropriating resources from long-term projects. We find evidence that the endogenous responses of firms to credit deterioration may explain the differential response to nonfinancial shocks. Specifically, firms take more meaningful organizational actions, such as announcing sales or spin offs, following downwatches than following missed earnings and sell recommendations. This finding supports past studies (e.g., Graham et al., 2022), which show that default introduces unique labor costs for rank and file employees relative to other events.

Our results raise the possibility of a feedback effect between financial and labor factors not only for firms near bankruptcy, but also for financially healthy firms. We find significant networking activity by workers who eventually leave their firm, especially at investment grade firms. This suggests that the latent build-up of connections triggered by credit deterioration may factor into greater turnover and loss of human capital for a firm. Moreover, we find stronger reactions among mid-level and senior workers, which indicates that credit deterioration can damage a firm's organizational capital by thinning upper ranks.

We provide further suggestive evidence that labor reactions to credit deterioration are tied to real implications for firms. Firm outcomes are observed at a much lower frequency than employee connection activity, making it difficult to establish a causal relation using our event-study approach. Nonetheless, we show that firms with more connection-making around negative credit events see higher turnover and lower profitability, relative to firms with less connection-making around negative credit events. Our results expand on the link between labor and finance: firms face labor repercussions to their financial decisions both when they are close to distress and, emphasized less in the existing literature, when they are financially healthy. Since 72% of debt issuance is investment grade, this is important to take into account.[4]

Our paper contributes to understanding the role of social networks in labor markets. With the widespread use of informal hiring processes such as referrals, workers' networks may impact current and future labor market outcomes (Montgomery, 1991; Calvo-Armengol and Jackson, 2004; Cho et al., 2022). Studies have documented significant referral and neighborhood effects in labor market dynamics (Bayer et al., 2008; Granovetter, 1995; Lin and Dumin, 1986; Hacamo and Kleiner, 2022), as well as increased job flows leading up to takeover announcements and poor stock returns (Agrawal and Tambe, 2019; Agrawal et al., 2021). This suggests that workers' investments in expanding and strengthening their networks could directly impact labor market dynamics.

[4]According to the S&P Global Report, May 17 2019, "U.S. Corporate Debt Market: The State Of Play In 2019," investment grade companies account for 72% of issuance volume.

Recently, significant strides have been made in the labor literature by exploiting large data sets generated from workers' digital activity (e.g., Bernstein et al., 2022). In contrast to traditional data sets, they offer a glimpse into granular information and actions taken at the individual level. Chetty et al. (2022a,b) uses social network data to study the impact of social capital on economic mobility and on network formation along socioeconomic status. Gee et al. (2017) evaluates the relative value of weak and strong ties for labor market outcomes. Our paper shows explicit evidence of dynamic worker behavior: network formation is positively correlated with departures, and is also partly driven by incentives to strengthen outside options in a form of hedging. We also show credit deterioration of employers to be a novel driver of network formation.

Our paper also contributes to a growing understanding of the interaction between labor and capital structure. Theory suggests that firms should factor labor into their leverage decisions (Berk et al., 2010; Matsa, 2018), and some evidence indicates that they do (Agrawal and Matsa, 2013). In the context of our model, firms' re-optimization in response to credit deterioration prompts increased search activity of workers. Our results support a broader view of when labor should be a consideration for firms' capital structure decisions, namely even when the firm is financially healthy and has low leverage.

Existing studies have identified several channels through which financial distress can impact workers' welfare and firms' ability to retain high-quality workers.[5] A notable paper in this literature is Baghai et al. (2021), which uses detailed microdata from Swedish limited liability companies to show talented workers depart at higher rates as firms approach bankruptcy. We also analyze responses to credit shocks, though we study on-the-job networking, a precursor to departures. Moreover, we study large firms in US labor markets (with an average of 3,000 employees on LinkedIn), which a priori could have different dynamics than smaller Swedish firms.[6] Consistent with Baghai et al. (2021), we also find significant differences in responses by worker type in our setting. However, in contrast to the departure

[5]For example, the threat of distress can impact workers' bargaining power and wages (Matsa, 2010; Benmelech et al., 2012; Graham et al., 2022; Dore and Zarutskie, 2023). Distress may also lead to competitors poaching key employees (Opler and Titman, 1994) and worsen firms' ability to attract talent (Brown and Matsa, 2016). Falato and Liang (2016) show that covenant violations lead to employment cuts, and Babina (2020) finds that higher-quality workers tend to leave distressed firms to become entrepreneurs. Our paper adds to this literature by documenting the effect of credit deterioration on networking activity, and showing that feedback effects may exist *outside* of financial distress.

[6]To address concerns about Sweden-specific institutional features (e.g., strong worker protections and social safety nets) and an average of 33 workers per firm (increased to a minimum of 50 in a robustness check), Baghai et al. (2021) show in their Internet Appendix that US firms increase leverage in response to increased enforceability of noncompete agreements. This suggests that large US firms similarly factor labor into their leverage decisions.

patterns they document, we find that networking effects diverge when firms are *far* from bankruptcy, and converge to a similar magnitude across worker types when firms are closer to bankruptcy. Our analysis sheds a new light on the dynamics of worker responses: differences in networking early on may lay the foundation for different departure rates later, even if later networking rates are similar.

2. Data

2.1 LinkedIn Network Data

Our main data source is LinkedIn, an online professional networking platform that began in 2003 and currently has over 900 million global users, 185 million of which are in the United States. We obtain complete anonymous user data from LinkedIn with their permission through the Economic Graph Challenge (EGC) program. Individual information is de-identified and aggregated for analysis to avoid identification of specific users.

We use two types of information from the LinkedIn data: connections data and employment histories. Connections are time-stamped at the time of creation and directed, which allows us to characterize information on initiators and receivers. We measure connections at a weekly level, tallying the total number of connections initiated by employees of a firm in each week from 2008 through 2017. We do not observe messages exchanged on the platform or profile update activity.

Our analysis exploits the fact that workers network when exploring outside options. Indeed, studies have shown that workers' networks may directly impact current and future labor market outcomes (e.g., Montgomery, 1991; Calvo-Armengol and Jackson, 2004). LinkedIn's size allows us to study this professional networking activity on an unprecedented scale. Moreover, the level of detail on LinkedIn permits us to study the formation of professional connections at a level of granularity and frequency not typically possible.

Networking on LinkedIn can be targeted or casual. For example, a worker can connect to employees of a specific firm to which they are interested in "jumping ship," or they can connect to existing acquaintances to brush up their profile. Even casual networking can help improve future opportunities, as it expands the worker's second- and third-degree connections, and increases visibility and credibility within the platform.

Our main outcome of interest is a firm's weekly "connection rate," given by the number of connections initiated at the firm level normalized by the number of firm employees present on LinkedIn. The creation of a profile itself could also be an indication of increased interest in outside opportunities, but because users only need to create an account once, this measure loses much power for later events. In contrast, average connection rates are fairly stable during our time period, and allow us to explore more variation. Our results are very similar regardless of whether we fix the number of employees in the denominator to an annual constant or allow it to reflect the weekly stock of profiles.

To allow for easier comparison with other annual outcomes, we annualize weekly connection rates by multiplying by 52. Table 1 presents summary statistics. On average, the workers of a firm in our sample make 1,239 new connections a week. This comes out to an annualized connection rate of 21.5 new connections per worker-year.

Employment histories contain company names and dates of employment, typically at an annual level, along with standardized information about the position held, such as seniority level and occupation type. This allows us to track connection rates by seniority and by when individuals leave the firm.

An employee is considered "leaving" if they are no longer employed at the company, in any capacity, in the following calendar year. If they are still present at the company in the following year, they are considered "staying." Similarly, we classify workers as "leaving next year" if they are present at the company in calendar year $y + 1$ but not $y + 2$. In this case, "staying" refers to those still present at $y + 2$. Table 1 also presents summary statistics for employment information. The average firm in our sample has 15% of employees leaving in year y.

Standardized seniority levels are determined internally by LinkedIn in a relatively granular way. The process is designed to cut across occupations to achieve a consistent measure of position seniority across the workforce. We group together anyone designated as intern or entry level in the most junior group, S1. Senior, manager, or director levels are combined into S2. VPs, executives, owners or partners all fall into S3. S1 employees represent 27% of our sample; S2 employees, 53%; and S3 employees, 20%.

2.2 Event Data and Sample Construction

We collect ratings data from Moody's Default and Recovery Database (DRD) and S&P's entity ratings dataset. For each issuer, we identify the weeks in which either S&P or Moody's places the issuer on a negative credit watch, which we call a "downwatch." We compare these financial deterioration events with events that relate to economic deterioration such as missed earnings and equity sell recommendations. Appendix A describes how we construct all relevant events.

To combine our event data with LinkedIn data, we use Compustat as a cross-walk.

We manually match LinkedIn data with Compustat. Using Compustat as an intermediate dataset provides additional benefits: a relatively standardized set of firms, a standardized industry definition (we use 3-digit NAICS codes), and access to other variables, including stock returns from the combined CRSP-Compustat dataset.

Our analysis sample consists of US firms in our merged LinkedIn-Compustat dataset between 2008 and 2017 with both an issuer rating from S&P or Moody's and valid returns data in CRSP. Since merger analysis is beyond the scope of this paper, we discard all events that occur within two weeks of a merger announcement, closing, or cancellation.

The typical firm and worker in our sample differ from the typical firm and worker in the US. Focusing on CRSP-Compustat firms with issuer ratings means that our results are for fairly large firms that use both debt and equity financing. The median firm in our sample has $5 billion in assets. Within firm, LinkedIn users account for around 30-40% of employees, and tend to be more educated than the typical US worker (Jeffers, 2019).

To dampen the effects of outliers, we winsorize continuous variables at the 1 and 99% levels. Table 1 provides summary statistics for our sample. The top panel has one observation per firm-week, and the bottom two panels have an observation for each firm-year.

Table 2 counts the total number of downwatches, missed earnings, and equity sell recommendations in the sample at weekly and yearly frequencies. In Figure 1, we plot the share of downwatches that are preceded or followed by other negative events. Downwatches typically precede downgrades, which is why we focus on downwatches as the more unexpected credit news events. To ensure that our results are not driven by prior events, we filter out downwatches preceded by other negative credit events in the prior 12 weeks. We also filter out missed earnings and equity sell recommendations that coincide with credit events in a 12 week radius. The resulting sample of events for our weekly analysis is 653 downwatches, 2,274 missed earnings, and 7,380 equity sell recommendations.

3. Theory

Before moving on to our empirical analysis, we develop a stylized model of labor reactions to credit deterioration. The goal of the model is to guide our empirical analysis and identify relevant channels through which the financial health of firms affects workers' incentives to seek outside opportunities (e.g., through networking activity). We also draw cross-sectional implications for both firms, which may vary based on financial health, and workers, who may vary based on their outside options. Given the purpose of the model, we use a parsimonious setting to deliver its insights as clearly as possible while avoiding complications that might arise in a general equilibrium treatment.

In reaction to credit deterioration, firms can take actions, such as restructuring or reorganization, which reduce credit risk, but also reduce resources needed by long-term projects.[7] If a firm defaults, its workers face unemployment risk as in Berk et al. (2010). In addition, workers obtain a portion of the output from their firm's long-term project, conditional on remaining at the firm and on the firm's survival. Thus, workers care not only about the firm's default probability, but also about how the firm's actions may affect future value. While on the job, workers can exert search effort to improve the odds of obtaining an attractive outside opportunity. In our empirics, we study connection activity on LinkedIn as a measure of this search effort. Since exerting effort is costly, workers' propensity to do so depends on their value of remaining at the firm relative to their outside option, in the spirit of Pissarides (1994).

3.1 Model

There are three periods, $t = 1, 2, 3$. There is a firm and a worker. The firm owns a long-term project, with value that depends on retaining the worker. The firm makes a financial strategy decision that can lower the probability of default. The worker obtains a share of the payoff from the long-term project, but can devote effort to increase the likelihood of finding opportunities outside of the firm.

Financial Health. The firm is characterized by financial health $\tilde{H}$, which governs the likelihood that the firm's long-term project reaches fruition (i.e., distance from default):

$$\tilde{H}(y) = H - \tilde{\phi} + y, \tag{1}$$

where $H \in (0,1)$ is the firm's baseline financial health, $\tilde{\phi} \in [0, \phi]$ with $\phi \in (0,1)$ represents a credit deterioration shock, and $y \in (0,1)$ is the firm's action. The firm's action directly improves the financial health of the firm. For example, the firm can reorganize its business and organizational structure, potentially selling or divesting its assets and projects.[8]

Project. While the firm's action y improves credit conditions, for example by bolstering short-term cash flows, it comes at the cost of reducing resources for projects that yield value

[7] For example, Hennessy and Whited (2007) show firms closer to bankruptcy optimally hold more cash.

[8] For example, after Symantec was placed on negative credit watch in 2014, it agreed to spin off its Information Management business; after Supervalu was placed on negative credit watch in 2012, it announced capital spending cuts. This is similar in spirit to Chava and Roberts (2008).

in the future. The firm owns a long-term project that generates a baseline value w, and, conditional on no default and retaining the worker, an additional value $V(A, y) > 0$ at $t = 3$:

$$V(A, y) = v \cdot A \cdot (1 - y). \tag{2}$$

The additional value of the project scales with the worker's ability $A > 0$ and decreases in the firm's financial strategy y. Hence, the firm selects its action to balance its credit standing (i.e., default risk) with the potential yield from its long-term project.

Worker. The worker is characterized by ability A. A worker's ability governs the worker's productivity within the firm as well as her perceived value to outside firms and hence the quality of her outside option.[9] By remaining at the firm, the worker obtains a fixed wage w equal to the baseline value of the firm's project. This payoff represents a baseline compensation arising purely from employment, which is independent of the worker's ability.[10]

The worker also obtains an exogenous share $\sigma \in (0, 1)$ of the additional value from the long-term project, which scales with the worker's ability. We assume that the worker receives this additional payoff only if she remains at the firm. Thus, this payoff represents the long-term potential of building a career at the firm.

The worker can exert costly effort to search for attractive opportunities outside of the firm. The worker exerts effort $x \in (0, 1)$ that determines the probability of success. Effort has a cost $C(x) = \frac{c}{2}x^2$. An attractive opportunity offers the worker a payoff that matches the fixed wage w and gives an additional $S(A) = sA$. We assume $s > \sigma v$ so that workers always prefer moving if they find an attractive opportunity.

Objectives. The worker chooses effort x, or identically the probability of moving to a better opportunity, to solve the following problem:

$$\max_x U(x, y) = \overbrace{(1 - x) \cdot \tilde{H}(y) \cdot \big[w + \sigma V(A, y)\big]}^{\text{Expected value from remaining}} + \overbrace{x \cdot \big[w + S(A)\big]}^{\text{Expected value from moving}} - C(x). \tag{3}$$

The firm chooses its financial strategy y to maximize its payoff, which is a function of its financial health $\tilde{H}(y)$, the probability it retains the worker $(1 - x)$, and the value of its

[9] One interpretation of worker ability A is general human capital, as in the human capital and labor literature (see, e.g., Becker, 1962).

[10] The fixed wage can be interpreted as a reservation price of labor in competitive labor markets for non-specialized workers. The wage is set to the baseline value of the project purely to simplify exposition.

long-term project $V(A, y)$:

$$\max_y \Pi(x, y) = \tilde{H}(y) \cdot (1 - x) \cdot (1 - \sigma) V(A, y). \tag{4}$$

Timeline. The sequence of events and actions are as follows. At $t = 1$, the shock $\tilde{\phi}$ is realized. At $t = 2$, taking each others' actions as given, the worker chooses effort x and the firm chooses its financial strategy y. At $t = 3$, the worker's opportunity set and the firm's default outcome are realized, and the long-term project matures.

3.2 Equilibrium Analysis

Our goal is to draw implications on worker and firm reactions to credit deterioration. In the context of the model, this relates to adjustments in the firm's equilibrium financial strategy y^* and the worker's outside search intensity x^* to credit deterioration $\tilde{\phi}$. Starting with the first order condition for the firm's problem and rearranging, we obtain[11]

$$y^* = \frac{1 - H + \tilde{\phi}}{2}. \tag{5}$$

The firm's equilibrium strategy y^* involves a fairly straightforward decision that balances its financial health $\tilde{H}(y)$ with the payoff conditional on survival, $V(A, y)$. As expected, the firm more aggressively lowers the risk of default when its baseline financial health H is lower.

The worker's decision involves weighing the long-term value of remaining at the firm (which is influenced by the firm's strategy) against the prospect of attractive outside opportunities. Through costly effort, the worker increases the probability of finding an attractive outside opportunity. To understand the channels that motivate the worker to exert effort, we decompose the worker's equilibrium effort as follows:[12]

$$\begin{aligned} cx^* &= \overbrace{A\big[s - \sigma v(1 - y^*) \cdot \tilde{H}(y^*)\big]}^{\text{Option value channel}} + \overbrace{w\big[1 - \tilde{H}(y^*)\big]}^{\text{Job security channel}} && (6) \\ &= A\Big[s - \sigma v\big(\tfrac{1+H-\tilde{\phi}}{2}\big)^2\Big] + w\Big[1 - \tfrac{1+H-\tilde{\phi}}{2}\Big]. && (\leftarrow y^*) \end{aligned}$$

Equation (6) highlights two different channels through which a firm's financial health affects workers' incentives to search for outside options. The first arises from weighing benefits from staying at the firm against outside benefits. This "option value" channel

[11]The assumptions $H \in (0, 1)$ and $\phi \in (0, 1)$ guarantee an interior solution $y^* \in (0, 1)$.

[12]The assumption $s > \sigma v$ guarantees $x^* > 0$. We assume the cost parameter c is large enough that $x^* < 1$.

reflects the upside opportunity enjoyed by workers with high ability, so it scales with the worker's ability A and increases as the wedge between the firm's value and the outside value widens.

The second channel reflects the worker's incentive to secure the baseline wage w. This "job security" channel scales with the wage w, is primarily associated with maintaining employment, and is independent of the worker's ability. Intuitively, greater risk of job loss (i.e. low $\tilde{H}$) translates into greater effort.

Through these two channels, workers are motivated to exert costly effort to improve their chances of finding attractive outside opportunities. To understand how each channel is affected by credit deterioration, consider comparative statics with respect to the shock $\tilde{\phi}$:

$$\frac{\mathrm{d}(cx^*)}{\mathrm{d}\tilde{\phi}} = \sigma v A\left[\overbrace{\left(1-\frac{\mathrm{d}y^*}{\mathrm{d}\tilde{\phi}}\right)\cdot(1-y^*)}^{\substack{\text{Direct reaction to}\\ \text{additional value}}} + \overbrace{\tilde{H}(y^*)\cdot\frac{\mathrm{d}y^*}{\mathrm{d}\tilde{\phi}}}^{\substack{\text{Indirect reaction from}\\ \text{anticipated firm action}}}\right] + \overbrace{w\left(1-\frac{\mathrm{d}y^*}{\mathrm{d}\tilde{\phi}}\right)}^{\substack{\text{Reaction to}\\ \text{lower job security}}} \tag{7}$$

$$= \sigma v A\left[\tfrac{1+H-\tilde{\phi}}{2}\right] + \tfrac{w}{2} > 0. \qquad (\leftarrow y^*)$$

Equation (7) highlights three factors that contribute to increased effort. The first two terms are from the impact of credit deterioration on the option value channel. Because the firm only partially offsets credit deterioration through its action, $\frac{\mathrm{d}\tilde{H}(y^*)}{\mathrm{d}\tilde{\phi}} = -(1-\frac{\mathrm{d}y^*}{\mathrm{d}\tilde{\phi}}) < 0$, an increase in default risk directly lowers the worker's expected payoff from the long-term project. The firm's action also destroys some of the long-term project's value. The second term arises as a consequence: workers anticipate that firms will take actions that are detrimental to the firm's maximum output. The third term, which is from the job security channel, represents the direct effect of a drop in job security resulting from credit deterioration. All three factors lead to increased effort.

Implication 1 (Labor reaction to credit deterioration)**.** *Following credit deterioration (i.e., an increase in $\tilde{\phi}$), workers exert more effort (i.e., a greater x^*) to find attractive opportunities outside the firm.*

An empirically relevant question is whether we should expect one of these terms to be more important than the others. Comparative statics of Equation (7) with respect to baseline financial health H and worker ability A provide empirical implications about the cross-section of firms and workers.

Implication 2 (Cross-sectional implications)**.** *The reaction to credit deterioration is greater* *for workers with more attractive outside opportunities (i.e., large A). Furthermore, this difference in reaction is greater for those at financially healthy firms (i.e., large $\tilde{H}$).*

As a final note, we consider the overall impact of credit deterioration on the firm's action and performance. First, we can draw an immediate implication from the firm's optimal action y^* in Equation (5).

Implication 3 (Firm reaction to credit deterioration)**.** *Firms are more likely to take organizational actions following credit deterioration (i.e., y^* is increasing in $\tilde{\phi}$).*

Second, we consider comparative statics of the firm's payoff in Equation (4) with respect to the shock $\tilde{\phi}$:[13]

$$\frac{\mathrm{d}\Pi(x^*, y^*)}{\mathrm{d}\tilde{\phi}} \propto \overbrace{-\left(1 - \frac{\mathrm{d}y^*}{\mathrm{d}\tilde{\phi}}\right) \cdot (1 - x^*) \cdot (1 - y^*)}^{\text{Net impact of credit deterioration}} + \tilde{H}(y^*)\left[\overbrace{-\frac{\mathrm{d}y^*}{\mathrm{d}\tilde{\phi}} \cdot (1 - x^*)}^{\text{Long-term cost of firm actions}} \overbrace{- \frac{\mathrm{d}x^*}{\mathrm{d}\tilde{\phi}} \cdot (1 - y^*)}^{\text{Cost of labor fragility}}\right]. \quad (8)$$

Following credit deterioration, the firm's actions dampen credit-related costs (e.g., Boot et al., 2005), which partially offsets the increased risk of default. However, the firm's actions also lower the payoff conditional on survival and workers intensify their search, increasing the likelihood of departures. Since all three terms are negative, credit deterioration unambiguously damages the firm's performance.

Implication 4 (Firm performance and credit deterioration)**.** *Following credit deterioration, the firm's expected payoff drops due to long-term costs associated with the firm's actions and increased fragility of its labor capital (greater effort towards search).*

After describing our empirical approach in Section 4, we focus on testing the above implications in Section 5.

4. Empirical Approach

We use an event-study framework to measure the effect of credit deterioration news on each firm's connection rate. Our preferred regressions compare the 12 weeks following an event to the rest of the year, but results are robust to using shorter windows.

[13] The proportionality constant is $(1 - \sigma)vA > 0$.

Our model for the dynamic effect of an event $z_{it} \in \{0, 1\}$ on the connection rate r_{it} of firm i in industry $j(i)$, week t, and year $y(t)$, is

$$r_{it} = \alpha_{i,y(t)} + \gamma_{t,j(i)} + \sum_{s=-12}^{12} \beta_s \cdot z_{i,t-s} + \varepsilon_{it}. \tag{9}$$

We include firm-by-year fixed effects to absorb slow-moving differences between firms that experience credit deterioration and those that do not. We also include week-by-industry fixed effects to absorb fast-moving confounds correlated with when firms experience credit deterioration. The identifying assumption for this approach is that any such confounds are low-dimensional sums of firm-by-year and industry-by-week invariant components.

Following best practices outlined in Freyaldenhoven, Hansen, Pérez, and Shapiro (2021), we adapt a common approach in finance and report event-study graphs that show the evolution of the estimated cumulative effect $\hat{\delta}_S = \sum_{s=-12}^{S} \hat{\beta}_s$ from $S = -12$ weeks before to $S = 12$ weeks after the event. Each event-study graph is followed by a regression table that reports the total cumulative effect $\hat{\delta}_{12}$, the mean connection rate r_{it} for comparison, and the p-value from a Wald test with null hypothesis $\delta_{-12} = \cdots = \delta_{-1} = 0$ of no pre-trend. Our tables also report the number of identifying events and the number of fixed effects.

Estimates should be interpreted as the cumulative abnormal connection rate within firm-year and week-industry, relative to the cumulative effect in the week before the event, which we normalize to $\delta_{-1} = 0$. In practice, we follow Freyaldenhoven et al. (2021) and impose this normalization by estimating a differenced regression that directly recovers each $\hat{\delta}_S$,

$$r_{it} = \alpha_{i,y(t)} + \gamma_{t,j(j)} - \delta_{-13} \cdot z_{i,t+12} + \sum_{\substack{S=-12 \\ S \neq -2}}^{11} \delta_S \cdot \Delta z_{i,t-S} + \delta_{12} \cdot z_{i,t-12} + \varepsilon_{it}. \tag{10}$$

This is equivalent to the model in (9) in the sense that the model and the normalization $\sum_{s=-12}^{-1} \beta_s = 0$ imply $\delta_{-13} = 0$ and that each other $\delta_S = \sum_{s=-12}^{S} \beta_s$. In the rest of the paper, we present extensions of the model using the clearer notation in (9) but estimate these extensions with their differenced counterparts.

We use Driscoll-Kraay standard errors with a five week lag,[14] which account for both cross-sectional dependence across firms and temporal dependence across weeks (Driscoll and Kraay, 1998; Hoechle, 2007). We prefer Driscoll-Kraay standard errors because they allow

[14] This corresponds to $\lfloor 4 \times (T \div 100)^{2/9} \rfloor$ from the first step of the plug-in procedure in Newey and West (1994) with $T = 52 \times (2017 - 2008)$. Results are very similar with other lag lengths.

for serial correlation to degrade for observations that are further apart. Results are very similar when we cluster on both firm and week.

Heterogeneous treatment effects as discussed in Sun and Abraham (2020) are a concern in settings with staggered treatments and persistent treatment effects. In Appendix C we discuss why heterogeneous treatment effects are unlikely to be problematic in our setting and show that our results are very similar when using the "stacked" approach of Gormley and Matsa (2011).

5. Empirical Results

We use the empirical model described in Section 4 combined with the insights from Section 3 to study how labor reacts to credit deterioration shocks. In Section 5.1, we present our main results on the increase of connection activity following negative credit events (Implication 1). In Section 5.2, we explore heterogeneity in the cross-section of workers who connect (Implication 2). In Section 5.3, we compare reactions across types of events, focusing in particular on differences in firm actions (Implication 3). Finally, in Section 5.4, we discuss the potential implications of increased connection activity for firms (Implication 4).

5.1 Labor Reactions to Credit Deterioration

We start by examining whether workers increase their networking activity following the announcement of a downwatch for their firm, in line with Implication 1 of the model. Figure 2 documents that in the periods preceding a downwatch, the cumulative abnormal connection rate is close to zero. Starting in the week of the downwatch, we see an immediate increase in connection-making, which is sustained for a number of weeks after.

Table 3 reports the cumulative effect in the 12 weeks following the event. The third column corresponds to the specification used in Figure 2, with firm-by-year and week-by-industry fixed effects. The results show a consistent pattern, with smaller estimates for specifications that include progressively more granular fixed effects.[15] Following a downwatch, affected firms experience a statistically significant increase in the connection rate of their workers. Our estimate in the third column indicates that there are nine additional connections per individual on an annualized basis. On a weekly basis, this represents a 3.2% increase in the connection rate in the twelve weeks following a downwatch. When discussing implications for firms in Section 5.4, we find that unconditionally, nine additional

[15] Observation counts decrease as we add more fixed effects because we drop singleton groups with only one observation (Correia, 2015, 2017).

connections per year corresponds to a two percentage point higher departure rate.[16]

How does this reaction vary based on the firm's ex ante financial health? To address this question, we extend our model in (9) to allow for different dynamic effects by ex ante rating group $g(i, t-24)$ lagged by 24 weeks: investment grade (BBB- or better) or below investment grade (BB+ or worse). When rating agencies disagree, we use the higher rating as a tiebreaker, but this does not affect results. Among the firms in our sample that experience a downwatch, roughly 55% are investment grade firms and 45% are below investment grade. Our extended model is

$$r_{it} = \alpha_{g(i,t-24),i,y(t)} + \gamma_{g(i,t-24),t,j(i)} + \sum_{s=-12}^{12} \beta_{g(i,t-24),s} \cdot z_{i,t-s} + \varepsilon_{it}. \tag{11}$$

Figure 3 and Table 4 show connection activity after downwatches, broken down by credit rating. We find that both groups of firms experience heightened connections rates after credit deterioration, including investment grade firms. Again, as we include progressively more granular fixed effects in Table 4, the magnitude of the downwatch effect diminishes. In the third column, weekly connection rates are still 3.5% higher for investment grade firms and 2.5% higher for below investment grade firms after adjusting for both annual firm trends and weekly industry trends.

If labor reactions to credit deterioration were primarily driven by bankruptcy costs borne by workers, we should observe reactions predominantly at firms near or in financial distress. The fact that we observe equal reactions for investment grade firms suggests there are additional motives that come into play when the firm is financially healthy. We explore these potential motives below.

5.2 Cross-sectional Implications and Motives for Connecting

A prominent explanation for labor responses to credit news stems from the costs borne by workers at firms near or in bankruptcy. In the model, this is captured by the job security channel: workers' welfare depends on sustaining employment, which is at risk when their firm defaults. Indeed, studies have found that workers at firms in financial distress tend to experience both pecuniary and non-pecuniary negative outcomes, including wage cuts, worsening working conditions, and unemployment (Agrawal and Matsa, 2013; Benmelech et al., 2012; Graham et al., 2022). As a consequence, financial distress pushes workers to

[16]In Table 11 we regress departure rates on connection rates at an annual frequency, adjusting for firm and year-by-industry fixed effects.

pursue outside opportunities (Baghai et al., 2021). Under the job security channel, labor reactions reflect an upward revision in the probability of default.

While the job security channel motivates workers at all firms, it takes on relatively more importance in the model when ex ante financial health H is lower. As distance to default decreases, the likelihood of losing one's job increases, and job security becomes a more serious concern for workers. The job security channel is independent of workers' value to outside firms, which in the model scales with the workers' "ability" A.

The model highlights a second channel through which credit deterioration may affect workers' search effort: the option value channel, which plays a significant role for firms with high ex ante financial health H. In addition to job security, workers evaluate the long-term value of remaining at their firm, relative to their outside opportunities. When the firm experiences a credit shock, the long-term value of remaining at the firm diminishes, which in turn makes outside opportunities relatively more attractive. Unlike the job security channel, the option value channel scales with workers' value to outside firms, and hence the attractiveness of workers' outside options.

Implication 2 summarizes the predictions that result from the presence of these two channels. For financially healthy firms (e.g., above investment grade), we should expect reactions to credit deterioration to be largely driven by workers with more attractive outside opportunities. For less financially healthy firms (e.g., below investment grade), there should be less difference by worker "ability" because the job security channel becomes relatively more important.

Connections by Leaving Status. Measuring the ex ante attractiveness of outside opportunities is a challenge. In practice, we observe *realized* outside opportunities. We use matched employment histories to identify workers who are employed elsewhere in the next calendar year ("leaving"), and contrast their connection activity to that of workers who are still employed by the firm in the following year ("staying"). Later, we also compare across types of departures (e.g., leaving to a position of higher or lower seniority). Realized moves are directly related to the attractiveness of outside opportunities, though they can also depend on workers' search effort and other characteristics. We first explain how we empirically compare the connection activity across groups of leaving and staying employees and present our findings. We then unpack possible explanations for our results, including the extent to which realized moves are a reasonable proxy for the attractiveness of outside opportunities.

To compare connection responses, we assign workers to a group g based on whether they are no longer at the firm in the following year. We then extend our model in (9) to allow for different dynamic effects by group, which allows us to isolate the contribution to connection activity made by workers who are leaving relative to those who are staying:

$$r_{git} = \alpha_{g,i,y(t)} + \gamma_{g,t,j(i)} + \sum_{s=-12}^{12} \beta_{gs} \cdot z_{i,t-s} + \varepsilon_{git}. \tag{12}$$

The top panel in Figure 4 and the first column of Table 5 report estimates for the full sample of firms. We find that workers who end up leaving their firm contribute more to the reaction following a downwatch.

To the extent that leaving proxies for the quality of workers' outside opportunities, the results are in line with the prediction that workers with better outside opportunities have a stronger incentive to connect. Leaving serves as only a noisy proxy for the quality of outside opportunities because idiosyncratic factors can also influence the decision to move. For example, a worker's subjective preferences, such as geographical location or cultural fit, could influence her decision to accept an offer. This introduces misclassification error, which, like classical measurement error, biases our estimates towards zero (Aigner, 1973).

Naturally, it may be easier for workers with larger cumulative social networks to find attractive outside opportunities. Additional post-downwatch connections marginally increase the size of a worker's network and enhance the chances of matching with a new employer. In simulations calibrated to our data, we find that for such endogeneity to have any perceptible effect, the correlation between departure rates and post-downwatch connections would need to be an order of magnitude larger than observed.[17]

In the bottom panels in Figure 4 and subsequent columns of Table 5, we compare investment grade firms (BBB- or better) with those that are below investment grade (BB+ or worse). We find that connection rates for leaving workers are highest at highly rated firms. At these firms, we observe a little bit of activity for leaving employees prior to the downwatch, but the abnormal activity is roughly four times as high after a downwatch. For firms with below investment grade ratings, the responses of leaving and staying employees to downwatches are statistically indistinguishable. The cross-sectional difference in reactions by credit rating group suggest different underlying motives for forming connections at each end of the credit rating spectrum. For investment grade firms, reactions appear to be driven

[17]Specifically, we expect a small positive correlation between the leaving-downwatch interaction and the error term in (12). We expect the resulting upward bias in the leaving-downwatch effect to be very small because post-downwatch connections have a small effect on the probability of leaving relative to the pre-existing stock of workers' connections.

by those with better outside opportunities. As financial distress becomes a serious prospect, that distinction fades.

Information about leaving workers' new positions relative to old positions can also inform us about the attractiveness of outside opportunities. Conditional on moving to a new firm, we group employees by whether their new positions are of higher or lower seniority than that of their departed positions. Estimates from this analysis will inevitably be much noisier because we are measuring connections only among individuals leaving to higher or lower seniority, which represent on average 6% of employees (Table 1). Regardless, comparing these groups will be helpful for understanding which employees drive connection-making among those who leave.

We present the results in Figure 5 and Table 6. Looking across all firms, we see a slight separation between the groups, both before and after the downwatch. Splitting between investment grade and below investment grade firms, we see that the stronger response of those leaving to a higher seniority mostly comes from investment grade firms. For below investment grade firms, connections increase equally among both groups of employees, although there are some non-statistically significant but noticeable differences between the groups in the pre-period. The results are again consistent with upside opportunities playing a relatively greater role at firms far from distress and downside risk playing a relatively greater role when closer to distress.

Lastly, we split the connection activity of staying employees based on future departure decisions. We compare the networking response of (1) workers leaving in the year of the credit event, (2) workers leaving one year after the credit event, and (3) workers staying through two years after the credit event. This is important to understand from a firm's perspective, as workers who react now and leave later represent a latent fragility.

Figure 6 and Table 7 show the results. In the full sample, all three groups have increased networking activity, but workers who leave one year later connect more than workers who stay, and workers who leave in the same calendar year connect the most. The bottom panels in Figure 6 and the last two columns of Table 7 show that this differentiation is driven by investment grade firms. At firms with below investment grade ratings, responses are nearly identical for staying and leaving employees. Again, these differences are consistent with job security being a more dominant motive below investment grade and option value being more dominant above investment grade.

Alternative Explanations. A possible concern is that negative credit events coincide with layoffs at the firm, and that the connection activity we observe reflects job search efforts by recently unemployed workers, rather than strategic reactions to worsening financial conditions.[18] However, this explanation does not align with the patterns we see in Figures 4 to 6. Connections increase among individuals who stay, especially at firms closer to distress, which is inconsistent with a laid-off worker explanation. Moreover, among those who leave, connections increase at least as much for individuals who leave to higher seniority positions, and more at firms further from distress. In other words, firms are losing workers who are externally promoted, which is less likely to represent the subset of workers who should be laid off first.

Another possibility is that increased connection activity could stem from new or renewed emphasis on certain tasks following negative credit events. For example, a downwatch may require executives to reach out to investor relations firms, or it may lead to increased activity among sales representatives trying to make up for lost revenue. In this case, connection activity should be highest among employees who *stay* with the firm, as it represents employees doing their job well. This is contrary to what we observe in Figure 4. Moreover, we show in Appendices D and E that connection-making responses are spread across many different seniority and occupation groups, and not concentrated among, for example, executives or sales representatives.

5.3 Firm Reactions and Other Events

Our analysis so far has focused labor reactions to credit deterioration. Through the lens of the model, credit deterioration affects workers through a combination of the direct effect of job security and through the anticipation of actions the firm will take to protect its financial health. As negative credit shocks belong to a broader class of adverse shocks, a natural question is whether other negative signals trigger similar responses from workers and firms.

We consider two other types of events that communicate negative economic news, but do not necessarily involve credit deterioration. The first is a substantial negative deviation from consensus earnings, or "missed earnings." We view missed earnings as fairly salient events that reflect the firm's economic condition, but have potentially different consequences than credit events. Earnings management is mainly motivated by stock price considerations, and while managers can take real actions to avoid missing targets, once earnings are missed the consequences seem mostly felt in the market's short-run price reactions (Graham et al.,

[18]Note that in order for layoffs to drive the connection responses we report, they would need to happen systematically in the same week as downwatches.

2005; De Jong et al., 2014; Skinner and Sloan, 2002).[19]

The second type of event we consider is a deterioration in equity analysts' recommendation for the stock. Like missed earnings, equity sell recommendations represent negative economic news about the firm, and predict lower equity prices in the short run (Womack, 1996). We describe how we construct these events in Appendix A and verify that our results are robust to different event definitions in Appendix B.

As a benchmark, we compare the economic relevance of various types of events by examining stock market reactions in Figure 7 and Table 8. We use a Carhart (1997) four-factor model and report results for 20-day windows around the events.[20] As documented in past studies, markets show a sharp and timely negative reaction to negative earnings surprises, and, unsurprisingly, to equity sell recommendations as well. The market reaction for all the events we consider are within the same order of magnitude, with a cumulative abnormal return (CAR) of about -5% for downwatches, -4% for missed earnings, and -3% for equity sell recommendations.[21]

To understand whether workers' reactions are similarly comparable, we extend our specification in (9) to allow for different dynamic effects by event e with indicator $z_{eit} \in \{0, 1\}$:

$$r_{it} = \alpha_{i,y(t)} + \gamma_{t,j(i)} + \sum_{e} \sum_{s=-12}^{12} \beta_{e,s} \cdot z_{e,i,t-s} + \varepsilon_{it}. \tag{13}$$

We report results in Figure 8 and Table 9. For both missed earnings and equity sell recommendations, we find a fairly tightly estimated zero: on average, workers do not significantly change their networking activity following a negative earnings surprise or a negative change in equity analysts' recommendations.[22] In Appendix B we show this result is robust to alternative definitions of missed earnings and equity sell recommendations.

Credit deterioration may especially affect workers by inducing firms to manage or curb impending increases in the cost of capital (Boot et al., 2005). Managers may pursue organiza-

[19]Repeatedly failing to meet earnings can be cause for career concern for the CEO or CFO, but beyond that employee concerns do not seem to particularly motivate earnings management (Graham et al., 2005).

[20]For each stock-event, we use at most 300 trading days of valid return data starting 360 trading days before the event to estimate the Carhart (1997) four-factor model. We skip stock-events with fewer than 50 valid returns in this period. Starting 10 trading days before the event, we compute the stock's abnormal returns relative to this estimated model, and accumulate up through 10 trading days after the event.

[21]Part of the negative CAR following downwatches is due to subsequent downgrades. If we remove subsequent downgrades, CAR flattens for downwatches, though not for other events. Connection responses remain after removing subsequent downgrades.

[22]Among investment grade firms, there is a slight increase in connection activity following missed earnings, but this appears to be a reversion following a slight decrease in activity leading into the missed earnings.

tional restructuring to shore up cash flows: shutting down riskier, long-term projects, selling assets, and even spinning off certain operations. Such corporate actions could improve debt investors' confidence, but at the same time diminish perceived future opportunities within the firm. In the model, this is captured by firms' optimal action y^* and Implication 3 that firms are more likely to take organizational actions following credit deterioration.

To test this implication, we examine the frequency of announcements related to organizational restructuring around downwatches, missed earnings, and equity sell recommendations. We collect key development announcements from Capital IQ, and identify the following events related to organizational: seeking to sell/divest, discontinued operations/downsizing, business reorganizations, and spin-offs/split-offs.

We estimate the probability of organizational announcements in the 12 weeks following each type of event. Results are summarized in Figure 9 and Table 10. The probability of organizational announcements increases following downwatches, both above and below investment grade. In addition, downwatches are more likely to be followed by such announcements, compared to missed earnings or equity sell recommendations. Workers' anticipation of firms' actions in response to negative credit events can explain workers' differential responses to downwatches, compared to missed earnings and equity sell recommendations. In Appendices F and G we further show that less-anticipated downwatches trigger larger reactions, consistent with the idea that larger shocks to credit information cause stronger responses.

5.4 Firm Performance

Our results thus far already indicate that workers' reactions to negative credit events could be costly for firms. Figures 4 and 6 show that connection activity is associated with departures and Figure 5 shows that this includes employees who find promotions elsewhere. In Appendices D and E, we further show that connection activity is driven by senior and skilled workers, who represent a greater fraction of a firm's organizational and human capital.

The future departure results in Figure 6 carry a particularly important implication for firms, especially for those with investment grade credit ratings. Even if workers do not leave their firms immediately as a response to credit news, the search activity prompted by credit deterioration reflects a persistently higher probability of leaving. Such search activity could also broaden outside options of workers and facilitate future moves when the outlook of the firm fails to improve. Delayed departures represent a fragility for firms that is not apparent in immediate departures after credit deterioration, but instead manifests in a lagged fashion.

In addition, we show that credit deterioration is directly associated with more departures on the extensive margin. We define a firm's departure rate as the number of employees leaving divided by the number of employees at the firm.[23] In Table 11 we report results from regressions of departure rates on connection rates to show that connection-making is unconditionally associated with higher departure rates, both contemporaneously and to a lesser degree with a lag of one year.[24] Since employment histories are annual, the results in Table 11 are also at an annual level.

We create annual event-studies to understand the dynamics of departure rates in years leading up to and following credit events. Since credit events are less sparse at the annual frequency and we expect treatment effects to last longer, we adopt the "stacked" approach of Gormley and Matsa (2011) to alleviate concerns about heterogeneous treatment effects.[25] For each year, we construct a cohort c of treated firms that experience a downwatch and control firms that do not. We exclude treated firms that experience downwatches in prior years and control firms that experience a downwatch during any year in our sample. Within each cohort c, for each firm i and year y we compute the residualized annual connection rate by taking out firm and year-by-industry fixed effects:

$$r_{ciy} = \alpha^r_{ci} + \gamma^r_{c,y,j(i)} + \varepsilon^r_{ciy}. \tag{14}$$

We then define two different downwatch events e based on whether the downwatched firm in that year had an abnormal connection rate $\hat{\varepsilon}^r_{ciy}$ above or below the median. Our model for the dynamic effect of a downwatch $z_{eciy} \in \{0, 1\}$ on an annual firm variable v_{ciy} is

$$v_{ciy} = \alpha^v_{ci} + \gamma^v_{c,y,j(i)} + \sum_e \sum_{s=-4}^{4} \beta_{e,s} \cdot z_{e,c,i,y-s} + \varepsilon^v_{ciy}. \tag{15}$$

Figure 10 and Table 12 show that firms with higher connection rates in the year of a downwatch experience much higher departure rates in that year and in following years. Moving to the annual level means we cannot control for high-frequency confounds, so it is difficult to establish causality. However, along with the departure timing results in Figure 6 and Table 7, the results tie future departures to employees' reaction to credit deterioration.

[23]For consistency with the rest of our results, we limit our analysis to employees who are LinkedIn members in the relevant year. We observe information for employees who join later, but these employees would not have been connecting on LinkedIn.

[24]With annual data our time dimension is short, so we do not use Driscoll-Kraay standard errors and instead simply cluster by firm.

[25]In Appendix C we discuss and provide evidence for why heterogeneous treatment effects are not a concern for our weekly event-studies.

It is hard to estimate the cost of potential lost productivity from those employees who stay but are looking for alternatives, but we have some indication of costs for employees who leave. Recent research into hiring costs (specifically, into direct search costs and indirect costs of training and low initial productivity), has been mostly focused on European countries due to the availability of micro data from the 2000s. This body of research shows that the costs of hiring amount to 8-17 weeks of wage payments and that they vary based on firm characteristics and macroeconomic conditions (Blatter et al., 2012; Muehlemann and Leiser, 2018). Research into hiring costs in the U.S. rely mostly on older data, yet direct and indirect hiring costs are similarly estimated at about 8 weeks of wage payments (Dolfin, 2006).

Finally, we investigate whether labor responses to credit events appear to have any relationship with other firm outcomes, such as profitability. It is difficult to establish the causal direction of this relationship because data on firm decision-making is much slower-moving than employee connection-making. For example, unobserved firm deterioration could both strengthen labor responses and weaken profitability. Instead, we provide suggestive evidence by using the annual event-study framework in (15) to compare high- and low-connection-making firms. We measure profitability as the annual operating income before depreciation scaled by the previous year's assets.

Figure 11 and Table 13 show that firms with above-median abnormal connection activity in the same year as a downwatch have worse profitability in the following year, relative to other firms that experience a downwatch but whose employees make fewer connections. There is no divergence in years prior to the downwatch, but high connection-making firms continue to lag behind their counterparts up to four years after the credit event. The effect appears to be strongest for below investment grade firms, though we cannot reject the null of similar declines once we split our sample into investment grade and below investment grade. While we cannot attribute a causal direction to these results, they show that connection activity picks up a real difference between firms, and align with Implication 4 that firms' expected payoff drops in the long run.

6. Conclusion

We examine employees' on-the-job networking in response to news of their firm's economic and financial conditions. Workers systematically form connections following signals of credit deterioration, even when the firm is far from default. Our results shed new light on what motivates search behavior, and its consequences for the entire cross-section of firms.

The networking activity triggered by negative credit events results in a latent build-up of connections that represents a source of fragility for firms. Connection activity especially increases among workers who leave financially healthy firms and find higher-seniority positions, consistent with networking leading to voluntary departures of high-value workers. Stronger reactions to credit events are followed by larger drops in firm profitability in following years. Our results complement prior work by showing on-the-job networking could lead to a negative feedback loop between financial conditions of the firm and its intangible capital.

Our findings reveal new facets of how and when workers respond to worsening conditions at their firm. Negative credit events cause workers to increase their networking activity even without a material threat of bankruptcy. Networking behavior varies most across workers at firms with strong credit ratings, and becomes more similar for firms closer to bankruptcy. We believe the seeds of differences across workers in times of crisis (e.g., bankruptcy) are sown in relatively "healthy" times. Other economic news, like missed earnings and equity sell recommendations, do not trigger an equivalent networking response, which also appear to elicit differential firm actions. Taken together, our results are consistent with a unique labor cost borne by firms when they finance with debt, as they expose themselves to adverse labor reactions.

The broader link between labor and finance leads to several interesting questions. What types of firms are more vulnerable to labor fragility, and what firm policies might improve firm resiliency? Do worker reactions exhibit features of contagion, and bring rise to strategic complementarities in labor decisions? Can we use the evolution of worker networks to draw implications on firm productivity? We hope to explore these questions in future research.

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Table 1: Summary Statistics

	Mean	SD	25th	50th	75th	Count
Weekly LinkedIn Variables						
Initiated Connections (Weekly)	1,239	2,535	73	307	1,087	652,455
Connection Rate (Annualized)	21.50	12.48	12.33	19.99	28.35	652,455
S1 (Entry)	14.85	11.31	7.09	12.75	19.76	645,204
S2 (Mid-level)	20.61	12.70	11.40	19.08	27.33	647,937
S3 (Most Senior)	33.67	22.50	17.33	30.85	45.43	645,757
Staying	20.00	11.85	11.40	18.48	26.31	651,921
Leaving	30.28	21.43	14.97	27.16	41.12	639,899
Staying Next Year	17.90	10.98	9.95	16.37	23.74	585,316
Leaving Next Year	24.40	18.32	11.56	21.67	33.17	573,620
Leaving to Lower Seniority	35.26	35.20	12.00	27.73	48.16	605,983
Leaving to Higher Seniority	36.24	33.52	13.00	29.42	50.21	613,434
Yearly LinkedIn Variables						
Employees on LinkedIn	2,989	6,067	253	855	2,625	12,911
S1 Share (Entry)	0.269	0.099	0.198	0.260	0.331	12,911
S2 Share (Mid-level)	0.531	0.100	0.476	0.540	0.597	12,911
S3 Share (Most Senior)	0.198	0.116	0.115	0.173	0.256	12,911
Leaving Share	0.146	0.069	0.103	0.134	0.176	12,911
Leaving Next Year Share	0.117	0.057	0.082	0.108	0.140	11,596
Leaving to Lower Seniority Share	0.026	0.018	0.015	0.023	0.034	12,911
Leaving to Higher Seniority Share	0.032	0.019	0.021	0.030	0.041	12,911
Yearly Compustat Variables						
Total Employees	27,838	53,402	2,241	7,600	26,734	12,793
Assets (Dollars, Billions)	39.05	136.39	1.98	5.30	18.41	12,905
Profitability	0.123	0.089	0.069	0.114	0.168	12,243

This table summarizes our sample. Observations are at the firm-week or firm-year level between 2008 and 2017. Weekly connection rates are the number of connections initiated at a firm, divided by the number of employees on LinkedIn, and multiplied by 52 for comparison with annual variables. There are three seniority categories: S1 includes to entry-level, unpaid or training employees; S2 includes senior and manager-level employees; and S3 includes directors, VPs, and executives. Employees are "leaving" if they are no longer employed at the company next year; otherwise, they are "staying." Profitability is annual operating income before depreciation scaled by last year's assets.

Table 2: Event Counts

	Weekly		Yearly	
	Unfiltered	Filtered	Unfiltered	Filtered
Downwatches	898	653	743	621
Missed Earnings	3,107	2,274	2,130	1,711
Equity Sell Recommendations	9,384	7,380	5,529	4,630

This table presents counts for the events in our sample. Unfiltered events are those shown in Figure 1. In our regressions, we filter out downwatches that are preceded by other negative credit events in the prior 12 weeks, and we filter out missed earnings and equity sell recommendations that coincide with credit events in a 12 week radius. Please refer to Section 2.2 and Appendix A for event definitions.

Table 3: Connections Initiated After Downwatches

	Connection Rate		
Downwatch	12.18***	10.23***	9.08***
	(1.90)	(1.70)	(1.72)
Mean Connection Rate	21.50	21.50	21.51
Firm Fixed Effects	1,747		
Firm-Year Fixed Effects		12,904	12,838
Week Fixed Effects	519	519	
Week-Industry Fixed Effects			37,942
Pre-trend p-value	0.047	0.098	0.303
R^2	0.663	0.795	0.809
Adjusted R^2	0.662	0.791	0.793
Observations	652,455	652,448	649,065
Firms	1,747	1,747	1,740
Weeks	519	519	519
Downwatches	653	653	649

This table provides estimates of new connections initiated in the 12 weeks following downwatches. The unit of analysis is firm-week. Industries are 3-digit NAICS codes. The estimate in the last column is $\hat{\delta}_{12} = \sum_{s=-12}^{12} \hat{\beta}_s$ from model (9). Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table 4: Connections Initiated After Downwatches, by Credit Rating

	Connection Rate		
Downwatch	17.10***	12.46***	9.78***
	(2.38)	(1.63)	(1.67)
Downwatch × Below Investment Grade	-7.09**	-4.36	-2.66
	(3.29)	(2.94)	(3.22)
Mean Connection Rate for Investment Grade	21.41	21.41	21.45
Mean Connection Rate for Below Investment Grade	21.50	21.50	21.56
Group-Firm Fixed Effects	1,884		
Group-Firm-Year Fixed Effects		12,867	12,575
Group-Week Fixed Effects	1,038	1,038	
Group-Week-Industry Fixed Effects			60,152
Pre-trend p-value for Investment Grade	0.078	0.153	0.263
Pre-trend p-value for Below Investment Grade	0.157	0.247	0.647
R^2	0.670	0.796	0.817
Adjusted R^2	0.668	0.791	0.793
Observations	642,102	642,081	626,734
Firms	1,720	1,720	1,700
Weeks	519	519	519
Downwatches for Investment Grade	312	312	302
Downwatches for Below Investment Grade	335	335	331

This table provides estimates of new connections initiated in the 12 weeks following downwatches. We split firms into two ex ante rating groups lagged by 24 weeks: group $g = 1$ is investment grade (BBB- or better) and group $g = 2$ is below investment grade (BB+ or worse). The unit of analysis is firm-week. Industries are 3-digit NAICS codes. Estimates in the last column are $\hat{\delta}_{1,12}$ and $\hat{\delta}_{2,12} - \hat{\delta}_{1,12}$ where $\hat{\delta}_{g,12} = \sum_{s=-12}^{12} \hat{\beta}_{g,s}$ from model (11). Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table 5: Connections Initiated After Downwatches, by Departure Status

	Connection Rate		
Downwatch	6.30***	5.36***	6.00*
	(1.98)	(1.73)	(3.41)
Downwatch × Leaving	11.32***	18.28***	3.10
	(3.27)	(4.11)	(4.58)
Mean Connection Rate for Staying	20.20	20.04	20.33
Mean Connection Rate for Leaving	30.04	30.73	29.34
Sample of Firms	All	IG	Below IG
Group-Firm-Year Fixed Effects	25,444	13,310	11,600
Group-Week-Industry Fixed Effects	75,848	52,440	67,342
Pre-trend p-value for Staying	0.560	0.787	0.421
Pre-trend p-value for Leaving	0.224	0.026	0.832
R^2	0.722	0.760	0.711
Adjusted R^2	0.699	0.734	0.665
Observations	1,285,056	671,906	568,474
Firms	1,740	880	980
Weeks	519	519	519
Downwatches	648	302	329

This table provides estimates of new connections initiated in the 12 weeks following downwatches for our full sample of firms, firms with BBB- credit ratings or better (lagged 24 weeks), and firms that are BB+ or worse. We split employees into group $g = 1$, "staying" employees who are still employed at the company in the next year, and $g = 2$, "leaving" employees who are no longer employed at the company in the next year. The unit of analysis is group-firm-week. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{1,12}$ and $\hat{\delta}_{2,12} - \hat{\delta}_{1,12}$ with $\hat{\delta}_{g,12} = \sum_{s=-12}^{12} \hat{\beta}_{g,s}$ from (12). Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table 6: Connections Initiated After Downwatches, by Departure Type

	Connection Rate		
Downwatch	16.02**	10.10	22.00**
	(6.67)	(7.80)	(10.52)
Downwatch × Leaving to Higher Seniority	13.20*	16.85*	6.40
	(7.92)	(10.00)	(13.37)
Mean Connection Rate for Leaving to Lower Seniority	35.31	35.91	34.76
Mean Connection Rate for Leaving to Higher Seniority	36.44	37.41	35.34
Sample of Firms	All	IG	Below IG
Group-Firm-Year Fixed Effects	24,119	12,843	10,782
Group-Week-Industry Fixed Effects	74,903	51,976	65,478
Pre-trend p-value for Leaving to Lower Seniority	0.148	0.303	0.042
Pre-trend p-value for Leaving to Higher Seniority	0.008	0.012	0.567
R^2	0.560	0.586	0.572
Adjusted R^2	0.522	0.540	0.500
Observations	1,212,251	646,452	523,818
Firms	1,722	870	968
Weeks	519	519	519
Downwatches	597	288	294

This table provides estimates of new connections initiated in the 12 weeks following downwatches for our full sample of firms, firms with BBB- credit ratings or better (lagged 24 weeks), and firms that are BB+ or worse. We split "leaving" employees who are no longer employed at the company in the next calendar year into two groups: group $g = 1$ leaves to a position of lower seniority and group $g = 2$ leaves to a position of higher seniority. We discard employees who leave to no position or to a position of the same seniority. The unit of analysis is group-firm-week. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{1,12}$ and $\hat{\delta}_{2,12} - \hat{\delta}_{1,12}$ where $\hat{\delta}_{g,12} = \sum_{s=-12}^{12} \hat{\beta}_{g,s}$ from model (12). Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table 7: Connections Initiated After Downwatches, by Departure Timing

	Connection Rate		
Downwatch	5.55***	2.58	7.68**
	(2.04)	(1.82)	(3.49)
Downwatch × Not Staying	7.39**	12.08***	0.41
	(2.94)	(3.39)	(4.76)
Downwatch × Leaving This Year	4.85	9.20*	1.12
	(4.22)	(4.77)	(6.07)
Mean Connection Rate for Staying	18.11	18.07	18.11
Mean Connection Rate for Leaving Next Year	24.36	24.36	24.41
Mean Connection Rate for Leaving This Year	30.08	30.76	29.39
Sample of Firms	All	IG	Below IG
Group-Firm-Year Fixed Effects	35,424	18,540	16,130
Group-Week-Industry Fixed Effects	106,587	73,360	94,419
Pre-trend p-value for Staying	0.131	0.511	0.232
Pre-trend p-value for Leaving Next Year	0.304	0.011	0.434
Pre-trend p-value for Leaving This Year	0.224	0.026	0.836
R^2	0.693	0.732	0.683
Adjusted R^2	0.667	0.703	0.632
Observations	1,789,536	935,690	790,435
Firms	1,738	880	977
Weeks	519	519	519
Downwatches	616	289	314

This table provides estimates of new connections initiated in the 12 weeks following downwatches for our full sample of firms, firms with BBB- credit ratings or better (lagged 24 weeks), and firms that are BB+ or worse. We split employees into three groups: group $g = 1$ denoted "staying" are employees who remain employed at the company after two calendar years, group $g = 2$ denoted "leaving next year" are employees who remain employed at the company after one calendar year but leave the next year, and group $g = 3$ denoted "leaving this year" are no longer employed at the company in the next calendar year. The unit of analysis is group-firm-week. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{1,12}$, $\hat{\delta}_{2,12} - \hat{\delta}_{1,12}$, and $\hat{\delta}_{3,12} - \hat{\delta}_{2,12}$ where $\hat{\delta}_{g,12} = \sum_{s=-12}^{12} \hat{\beta}_{g,s}$ from model (12). Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table 8: Market Response to Downwatches and Other Events

	Cumulative Abnormal Return		
Downwatch	-5.42***	-1.40	-9.09***
	(0.95)	(1.03)	(1.54)
Missed Earnings	-3.93***	-3.81***	-3.97***
	(0.52)	(0.51)	(0.76)
Equity Sell Recommendation	-2.68***	-2.03***	-3.72***
	(0.16)	(0.15)	(0.34)
Sample of Firms	All	IG	Below IG
Downwatches	478	226	248
Missed Earnings	1,237	421	796
Equity Sell Recommendations	5,160	3,278	1,821

This table provides estimates of cumulative abnormal return in the 10 trading days following downwatches, missed earnings, and equity sell recommendations for three samples of firms. Columns 1 to 3 are for our full sample, firms with BBB- credit ratings or better, and firms that are BB+ or worse. Credit ratings are lagged by 24 weeks. For each stock-event, we use at most 300 trading days of valid return data starting 360 trading days before the event to estimate the Carhart (1997) four-factor model. We skip stock-events with fewer than 50 valid returns in this period. Starting 10 trading days before the event, we compute the stock's abnormal returns relative to this estimated model, and accumulate up through 10 trading days after the event. Standard errors in parentheses are computed from the cross-section of cumulative abnormal returns. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table 9: Connections Initiated After Downwatches and Other Events

	Connection Rate		
Downwatch	9.12***	9.89***	7.10**
	(1.72)	(1.66)	(3.07)
Missed Earnings	1.14	2.62*	0.25
	(0.85)	(1.44)	(1.22)
Equity Sell Recommendation	0.11	0.49	-0.12
	(0.36)	(0.39)	(0.83)
Mean Connection Rate	21.51	21.45	21.56
Sample of Firms	All	IG	Below IG
Firm-Year Fixed Effects	12,838	6,697	5,878
Week-Industry Fixed Effects	37,942	26,220	33,932
Pre-trend p-value for Downwatches	0.309	0.251	0.664
Pre-trend p-value for Missed Earnings	0.668	0.154	0.600
Pre-trend p-value for Equity Sell Recommendations	0.638	0.827	0.697
R^2	0.809	0.830	0.804
Adjusted R^2	0.793	0.812	0.774
Observations	649,065	338,269	288,465
Firms	1,740	880	980
Weeks	519	519	519
Downwatches	649	302	331
Missed Earnings	2,268	635	1,566
Equity Sell Recommendations	7,347	4,439	2,596

This table provides estimates of new connections initiated in the 12 weeks following downwatch events $e = 1$, missed earnings events $e = 2$, and equity sell recommendation events $e = 3$ for three samples of firms. Columns 1 to 3 are for our full sample, firms with BBB- credit ratings or better, and firms that are BB+ or worse. Credit ratings are lagged by 24 weeks. The unit of analysis is firm-week. Estimates are $\hat{\delta}_{e,12} = \sum_{s=-12}^{12} \hat{\beta}_{e,s}$ from model (13). Industries are 3-digit NAICS codes. Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table 10: Organizational Announcements After Downwatches and Other Events

	Organizational Announcement		
Downwatch	0.133***	0.115*	0.148***
	(0.036)	(0.063)	(0.047)
Missed Earnings	-0.000	0.010	-0.010
	(0.011)	(0.025)	(0.014)
Equity Sell Recommendation	0.018**	0.028**	0.010
	(0.007)	(0.011)	(0.010)
Mean Outcome	0.018	0.024	0.011
Sample of Firms	All	IG	Below IG
Firm-Year Fixed Effects	12,838	6,697	5,878
Week-Industry Fixed Effects	37,942	26,220	33,932
Pre-trend p-value for Downwatches	0.029	0.189	0.012
Pre-trend p-value for Missed Earnings	0.263	0.175	0.151
Pre-trend p-value for Equity Sell Recommendations	0.317	0.595	0.193
R^2	0.156	0.183	0.195
Adjusted R^2	0.085	0.097	0.068
Observations	649,065	338,269	288,465
Firms	1,740	880	980
Weeks	519	519	519
Downwatches	649	302	331
Missed Earnings	2,268	635	1,566
Equity Sell Recommendations	7,347	4,439	2,596

This table provides estimates of the probability of organizational restructuring announcements in the 12 weeks following downwatch events $e = 1$, missed earnings events $e = 2$, and equity sell recommendation events $e = 3$ for three samples of firms. Columns 1 to 3 are for our full sample, firms with BBB- credit ratings or better, and firms that are BB+ or worse. Credit ratings are lagged by 24 weeks. Organizational restructuring announcements from Capital IQ include seeking to sell/divest, discontinued operations/downsizing, business reorganizations, and spin-offs/split-offs. The unit of analysis is firm-week. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{e,12} = \sum_{s=-12}^{12} \hat{\beta}_{e,s}$ from model (13) with a reorganization indicator on the left hand side. Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table 11: Departure Rates and Connection Rates

	Percent Leaving					
Connection Rate	0.185***	0.223***	0.199***	0.233***	0.172***	0.220***
	(0.017)	(0.024)	(0.026)	(0.036)	(0.023)	(0.033)
Last Year's Connection Rate		0.053***		0.049***		0.056***
		(0.014)		(0.018)		(0.021)
Mean Percent Leaving	13.531	13.463	12.956	12.901	14.132	14.090
Sample of Firms	All	All	IG	IG	Below IG	Below IG
Firm Fixed Effects	1,642	1,537	835	792	896	815
Year-Industry Fixed Effects	731	657	506	452	658	588
R^2	0.586	0.637	0.655	0.697	0.576	0.635
Adjusted R^2	0.492	0.546	0.568	0.614	0.422	0.489
Observations	12,747	10,987	6,634	5,821	5,842	4,924
Firms	1,642	1,537	835	792	896	815
Years	10	9	10	9	10	9

This table provides estimates of the relationship between departure rates and connection rates. Percent leaving is the percent of employees on LinkedIn who are no longer employed at the company in the next calendar year. The annual connection rate is the number of connections initiated at a firm during the year, divided by the number of employees on LinkedIn at the beginning of the year. The unit of analysis is firm-year. Industries are 3-digit NAICS codes. Standard errors in parentheses are clustered by firm. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table 12: Departure Rate After Downwatches, by High vs. Low Connection Rate

	Percent Leaving		
Downwatch	0.890	-1.470	-0.969
	(1.975)	(2.522)	(2.999)
Downwatch × High Abnormal Connection Rate	8.293***	6.844**	12.804***
	(2.709)	(3.155)	(4.462)
Mean Percent Leaving	14.245	13.670	14.879
Sample of Firms	All	IG	Below IG
Cohort-Firm Fixed Effects	12,309	6,167	6,179
Cohort-Year-Industry Fixed Effects	7,039	4,565	5,864
Pre-trend p-value for Low Abnormal Connection Rate	0.048	0.346	0.082
Pre-trend p-value for High Abnormal Connection Rate	0.000	0.006	0.013
R^2	0.605	0.664	0.633
Adjusted R^2	0.500	0.565	0.463
Observations	92,041	47,607	38,084
Firms	1,642	817	822
Years	10	10	10
Downwatches with Low Abnormal Connection Rates	302	137	145
Downwatches with High Abnormal Connection Rates	303	138	149

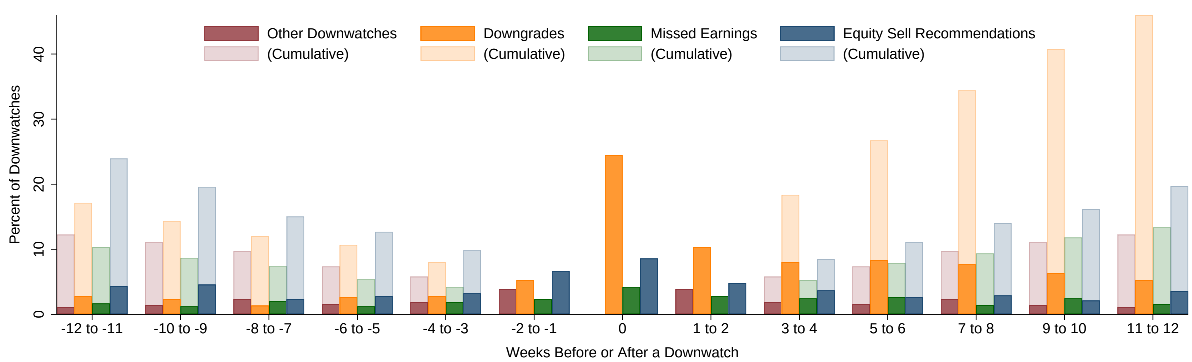
This table provides estimates of the departure rate in the 4 years following downwatches for three samples of firms. Column 1 is our full sample. Column 2 is for firms with BBB- credit ratings or better at the start of the year. Column 3 is for firms with BB+ credit ratings or worse at the start of the year. Percent leaving is the percent of employees on LinkedIn who are no longer employed at the company in the next calendar year. We define two different downwatch events: event $e = 1$ are those for which the downwatched firm in that year had an abnormal connection rate below the median, and event $e = 2$ are those above the median. The unit of analysis is firm-year. Abnormal is what is left over after removing firm and year-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{1,4}$ and $\hat{\delta}_{2,4} - \hat{\delta}_{1,4}$ where $\hat{\delta}_{e,4} = \sum_{s=-4}^{4} \hat{\beta}_{e,s}$ from estimating model (15) with the "stacked" approach of Gormley and Matsa (2011). Standard errors in parentheses are clustered by firm. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table 13: Profitability After Downwatches, by High vs. Low Connection Rate

	Profitability		
Downwatch	-0.074***	-0.027	-0.075**
	(0.019)	(0.020)	(0.034)
Downwatch × High Abnormal Connection Rate	-0.049*	-0.050*	-0.103**
	(0.026)	(0.027)	(0.047)
Mean Profitability	0.128	0.130	0.119
Sample of Firms	All	IG	Below IG
Cohort-Firm Fixed Effects	11,610	5,610	6,056
Cohort-Year-Industry Fixed Effects	6,949	4,565	5,854
Pre-trend p-value for Low Abnormal Connection Rate	0.117	0.536	0.889
Pre-trend p-value for High Abnormal Connection Rate	0.000	0.003	0.536
R^2	0.790	0.880	0.757
Adjusted R^2	0.732	0.842	0.642
Observations	86,179	43,205	37,168
Firms	1,564	756	807
Years	10	10	10
Downwatches with Low Abnormal Connection Rates	296	133	144
Downwatches with High Abnormal Connection Rates	299	135	147

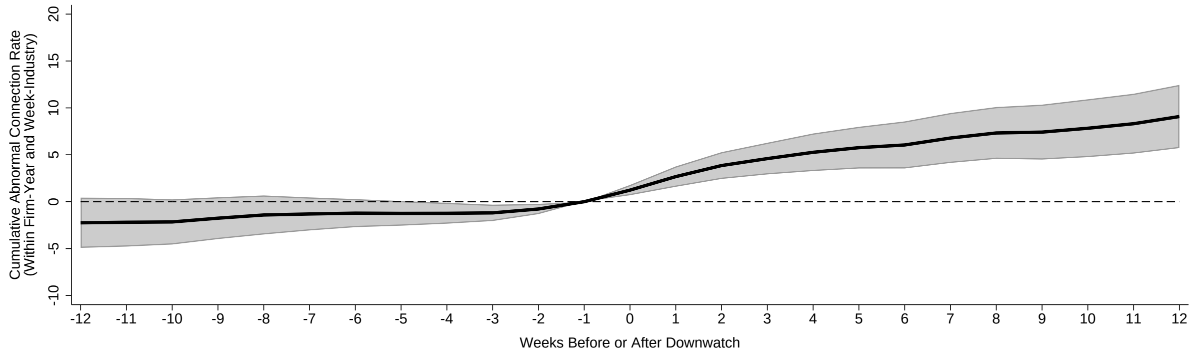
This table provides estimates of profitability in the 4 years following downwatches for three samples of firms. Column 1 is our full sample. Column 2 is for firms with BBB- credit ratings or better at the start of the year. Column 3 is for firms with BB+ credit ratings or worse at the start of the year. Profitability is annual operating income before depreciation scaled by last year's assets. We define two different downwatch events: event $e = 1$ are those for which the downwatched firm in that year had an abnormal connection rate below the median, and event $e = 2$ are those above the median. The unit of analysis is firm-year. Abnormal is what is left over after removing firm and year-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{1,4}$ and $\hat{\delta}_{2,4} - \hat{\delta}_{1,4}$ where $\hat{\delta}_{e,4} = \sum_{s=-4}^{4} \hat{\beta}_{e,s}$ from estimating model (15) with the "stacked" approach of Gormley and Matsa (2011). Standard errors in parentheses are clustered by firm. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Figure 1: Percent of Downwatches Preceded or Followed by Other Events



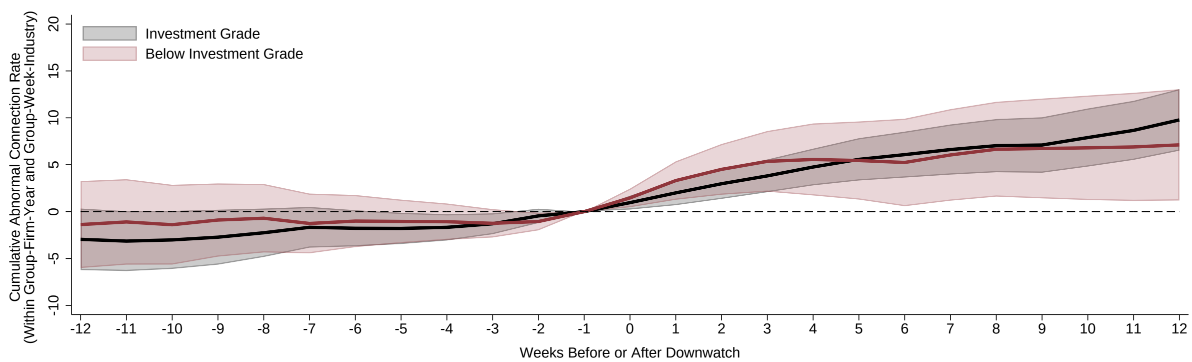
In the weeks before and after the downwatches in our sample, this figure shows the share that are preceded or followed by other downwatches, downgrades, missed earnings, and equity sell recommendations. The lighter bars accumulate these percentages outwards. The events in this figure correspond to the unfiltered counts in Table 2.

Figure 2: Connections Initiated by Week from Downwatch



This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch. The unit of analysis is firm-week. Abnormal is what is left over after removing firm-year and week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_S = \sum_{s=-12}^{S} \hat{\beta}_s$ from model (9). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

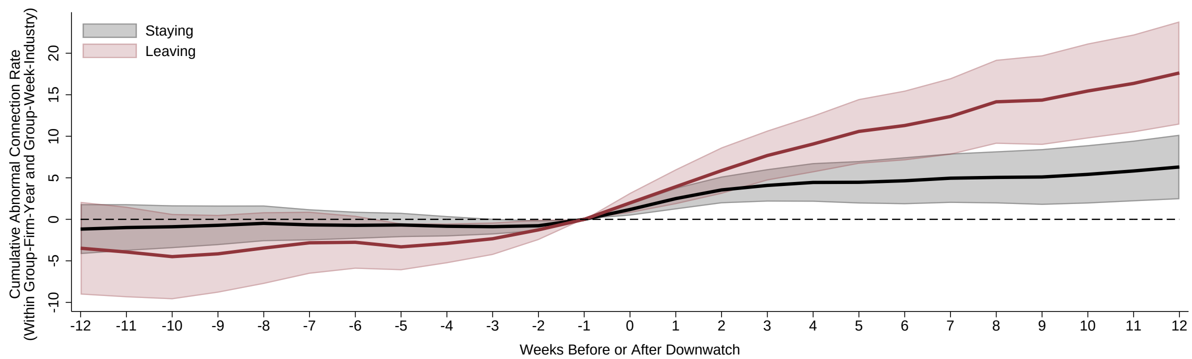
Figure 3: Connections Initiated by Week from Downwatch, by Credit Rating



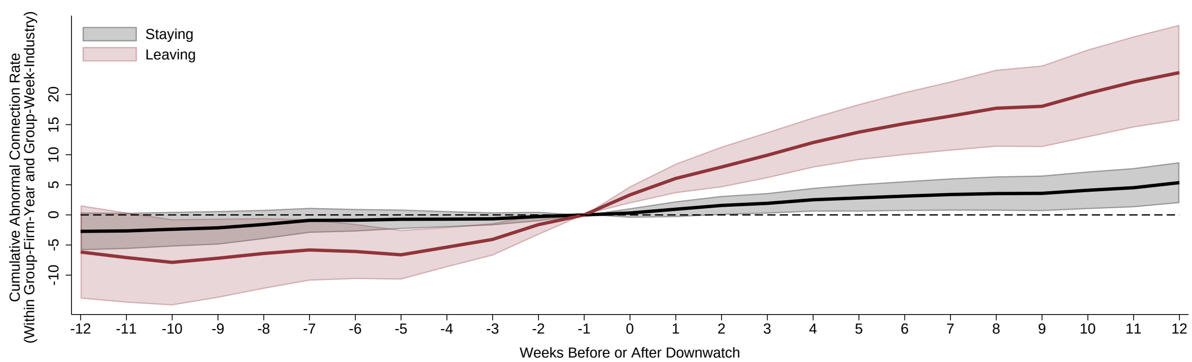
This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch. We split firms into two ex ante rating groups lagged by 24 weeks: group $g = 1$ is investment grade (BBB- or better) and group $g = 2$ is below investment grade (BB+ or worse). The unit of analysis is firm-week. Abnormal is what is left over after removing group-firm-year and group-week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{g,S} = \sum_{s=-12}^{S} \hat{\beta}_{g,s}$ from model (11). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Figure 4: Connections Initiated by Week from Downwatch, by Departure Status

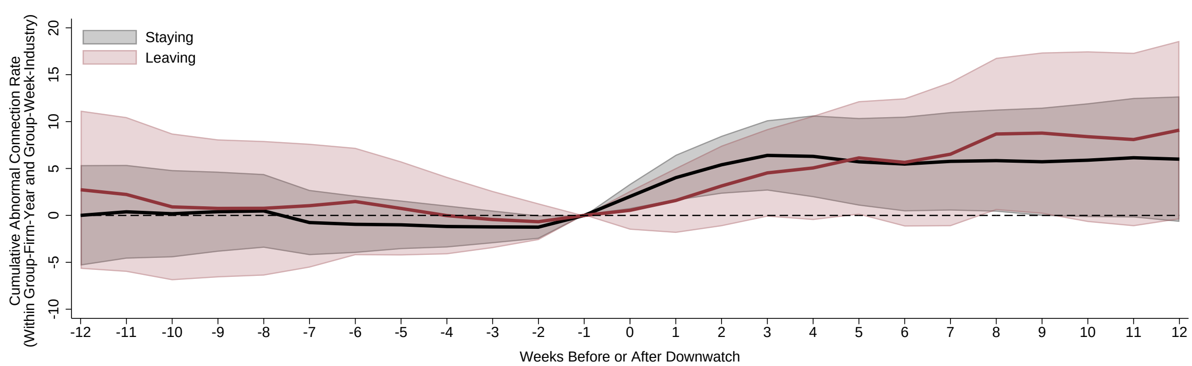
(a) All Firms



(b) Investment Grade



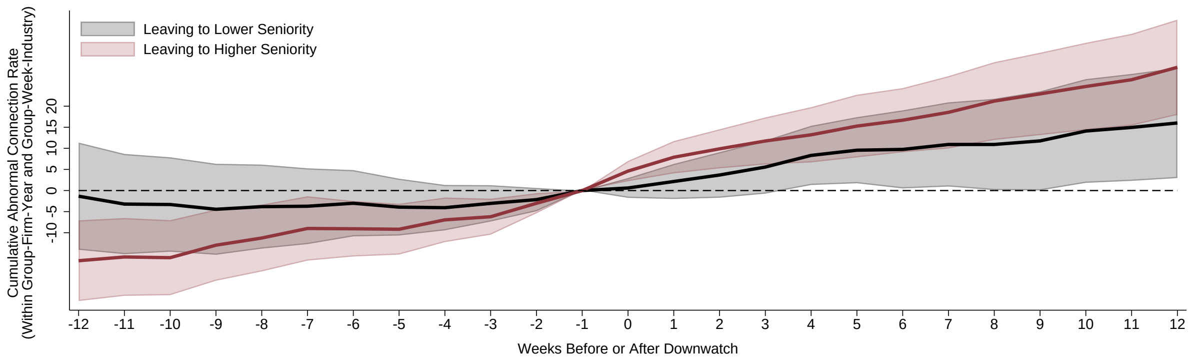
(c) Below Investment Grade



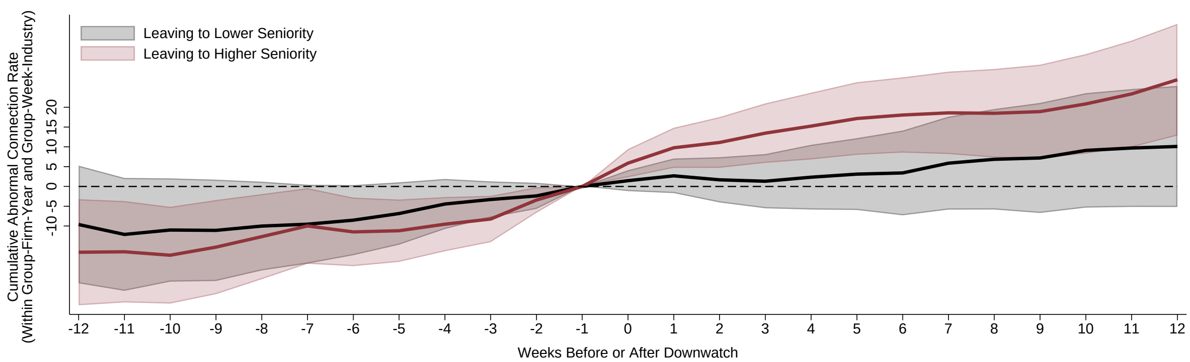
This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. We split employees into two groups: group $g = 1$ are "staying" employees who are still employed at the company in the next calendar year and group $g = 2$ are "leaving" employees who are no longer employed at the company in the next calendar year. The unit of analysis is group-firm-week. Abnormal is what is left over after removing group-firm-year and group-week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{g,S} = \sum_{s=-12}^{S} \hat{\beta}_{g,s}$ from model (12). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Figure 5: Connections Initiated by Week from Downwatch, by Departure Type

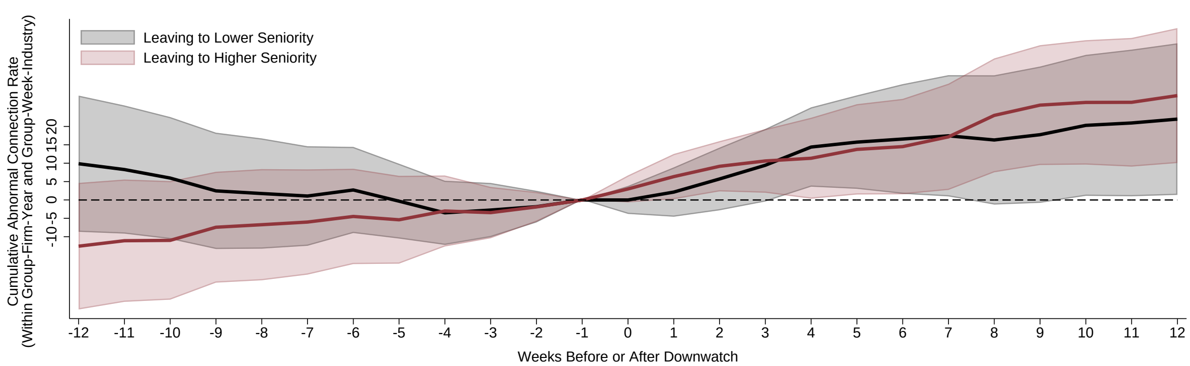
(a) All Firms



(b) Investment Grade



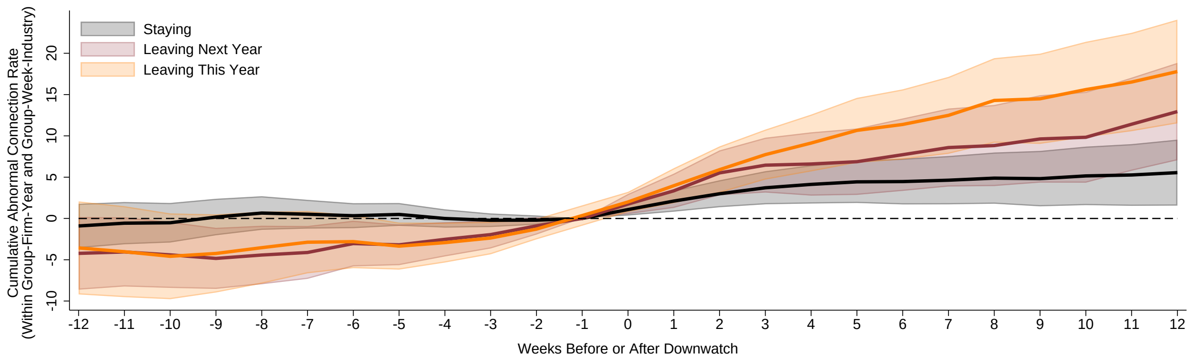
(c) Below Investment Grade



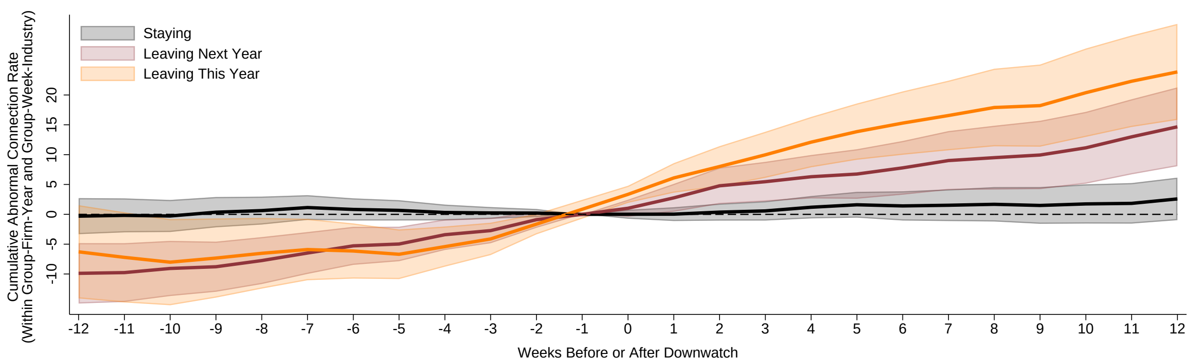
This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. We split "leaving" employees who are no longer employed at the company in the next calendar year into two groups: group $g = 1$ leaves to a position of lower seniority and group $g = 2$ leaves to a position of higher seniority. We discard employees who leave to no position or to a position of the same seniority. The unit of analysis is group-firm-week. Abnormal is what is left over after removing group-firm-year and group-week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{g,S} = \sum_{s=-12}^{S} \hat{\beta}_{g,s}$ from model (12). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Figure 6: Connections Initiated by Week from Downwatch, by Departure Timing

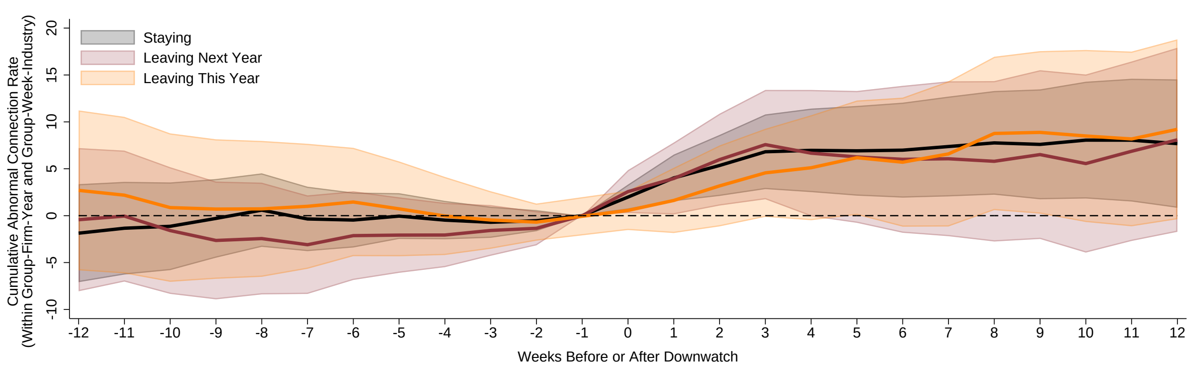
(a) All Firms



(b) Investment Grade



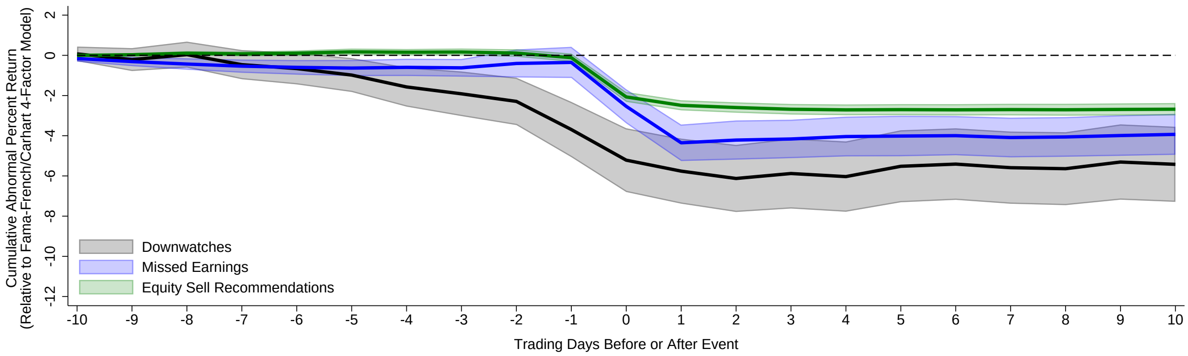
(c) Below Investment Grade



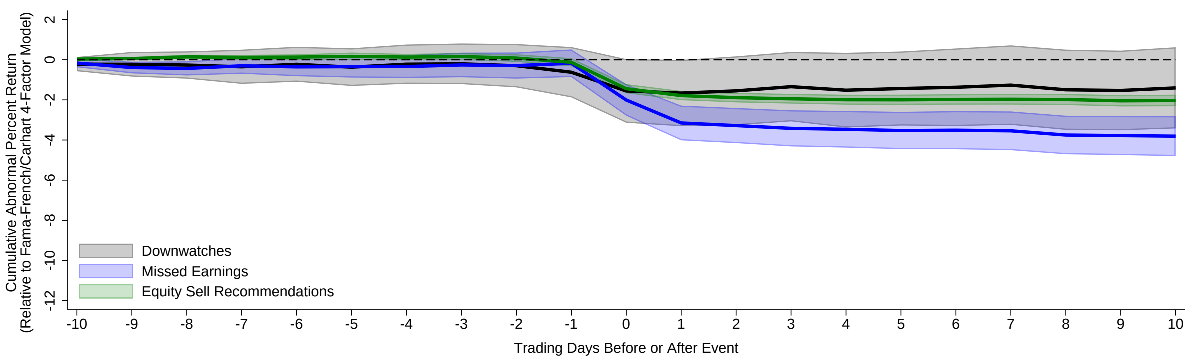
This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. We split employees into three groups: group $g = 1$ denoted "staying" are employees who remain employed at the company after two calendar years, group $g = 2$ denoted "leaving next year" are employees who remain employed at the company after one calendar year but leave the next year, and group $g = 3$ denoted "leaving this year" are no longer employed at the company in the next calendar year. The unit of analysis is group-firm-week. Abnormal is what is left over after removing group-firm-year and group-week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{g,S} = \sum_{s=-12}^{S} \hat{\beta}_{g,s}$ from model (12). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Figure 7: Market Response by Trading Day to Downwatches and Other Events

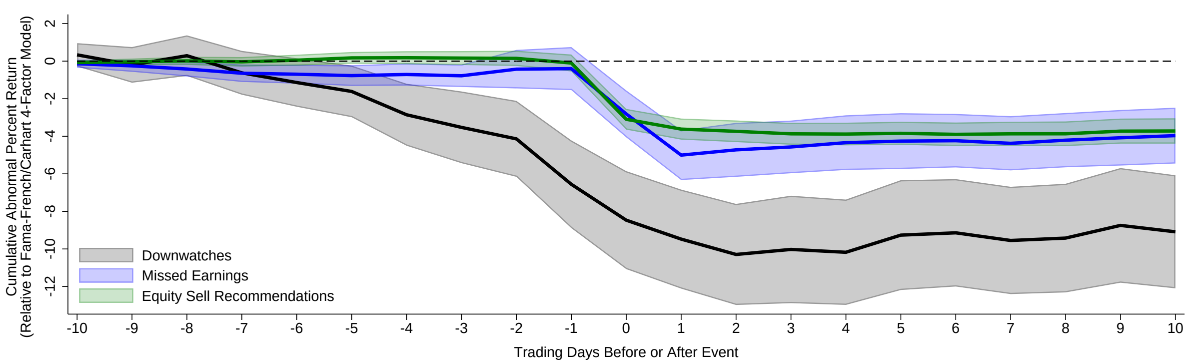
(a) All Firms



(b) Investment Grade



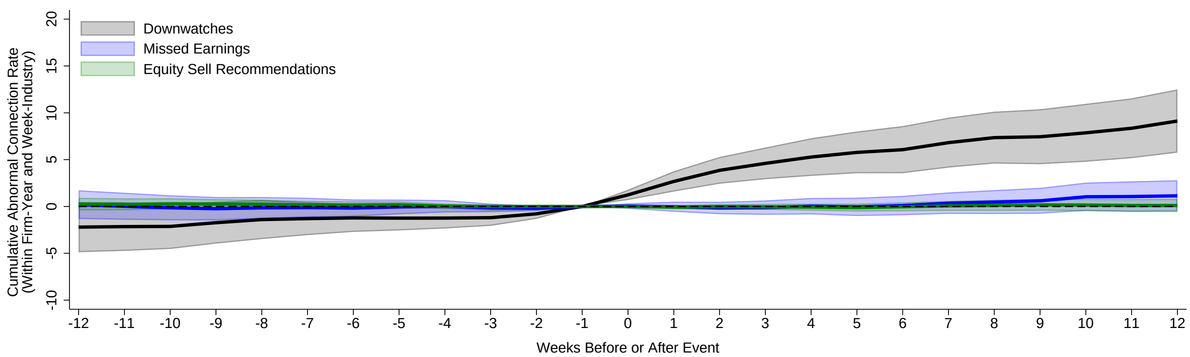
(c) Below Investment Grade



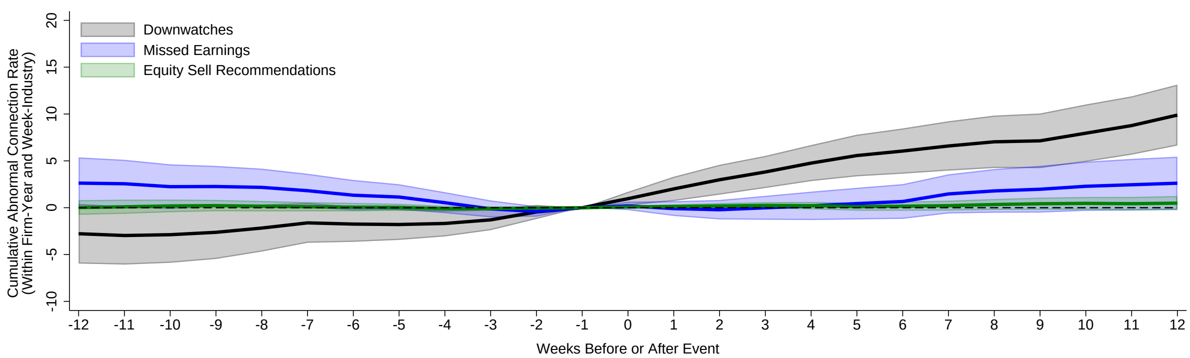
This figure shows the cumulative abnormal return by trading day around downwatches, missed earnings, and equity sell recommendations for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. For each stock-event, we use at most 300 trading days of valid return data starting 360 trading days before the event to estimate the Carhart (1997) four-factor model. We skip stock-events with fewer than 50 valid returns in this period. Starting 10 trading days before the event, we compute the stock's abnormal returns relative to this estimated model, and accumulate up through 10 trading days after the event. The shaded area shows the 95% confidence interval based on standard errors computed from the cross-section of cumulative abnormal returns.

Figure 8: Connections Initiated by Week from Downwatches and Other Events

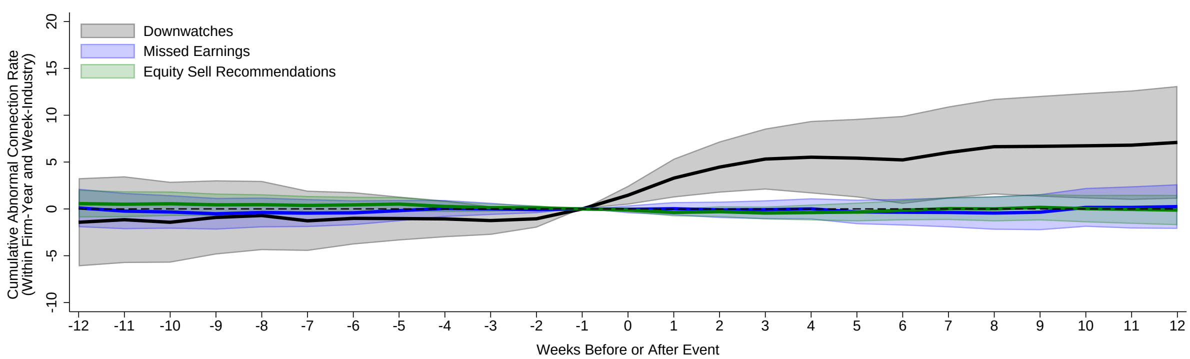
(a) All Firms



(b) Investment Grade



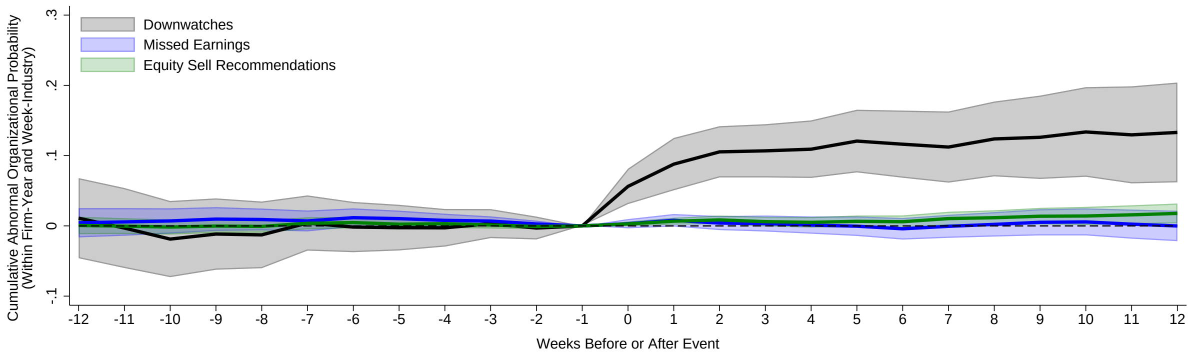
(c) Below Investment Grade



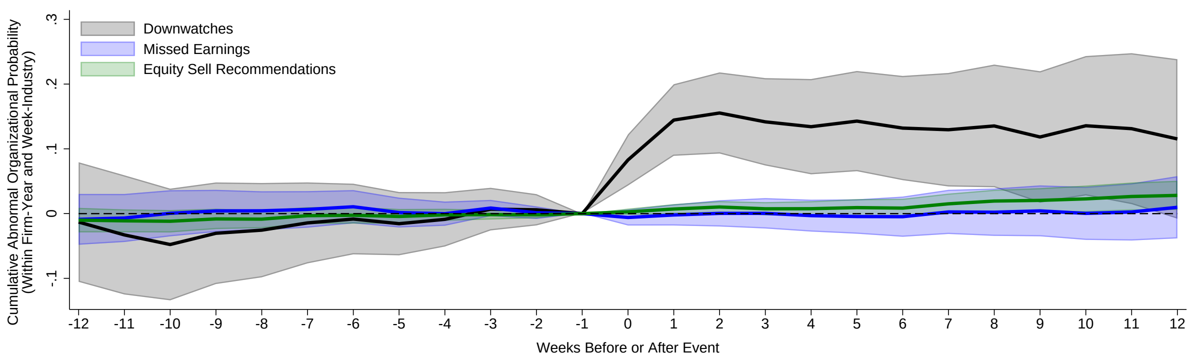
This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch event $e = 1$, a missed earnings event $e = 2$, and an equity sell recommendation event $e = 3$ for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. The unit of analysis is firm-week. Abnormal is what is left over after removing firm-year and week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{e,S} = \sum_{s=-12}^{S} \hat{\beta}_{e,s}$ from model (13). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Figure 9: Organizational Announcement by Week from Downwatches and Other Events

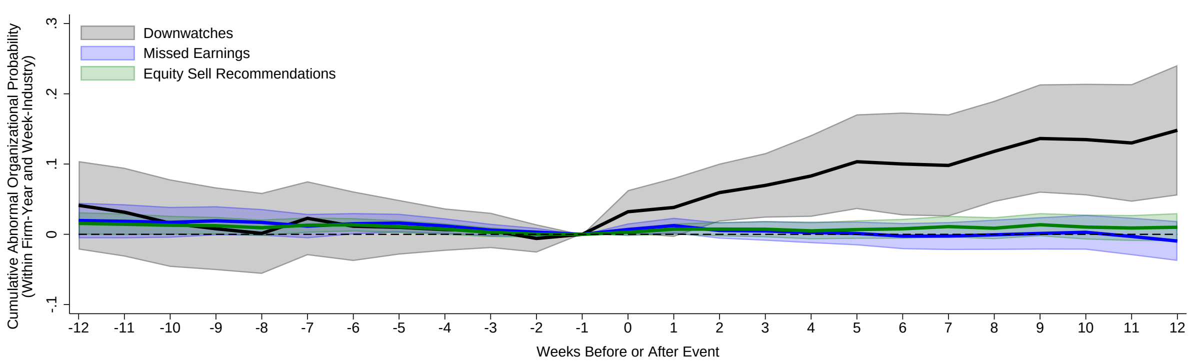
(a) All Firms



(b) Investment Grade



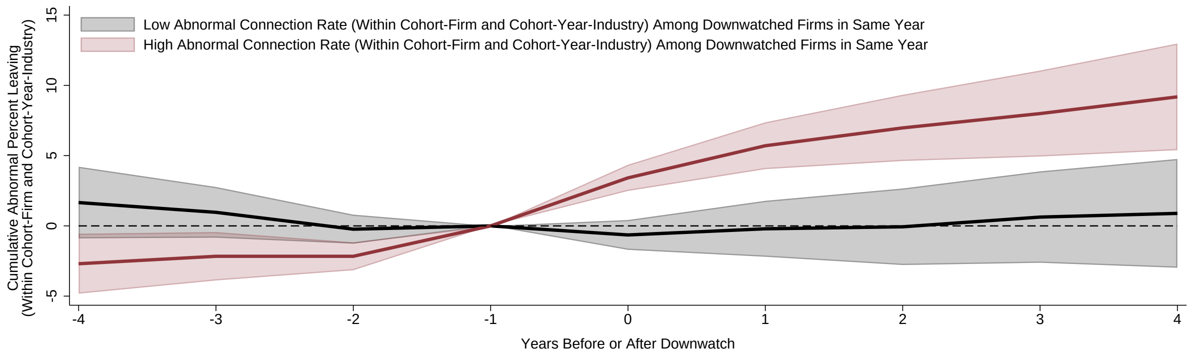
(c) Below Investment Grade



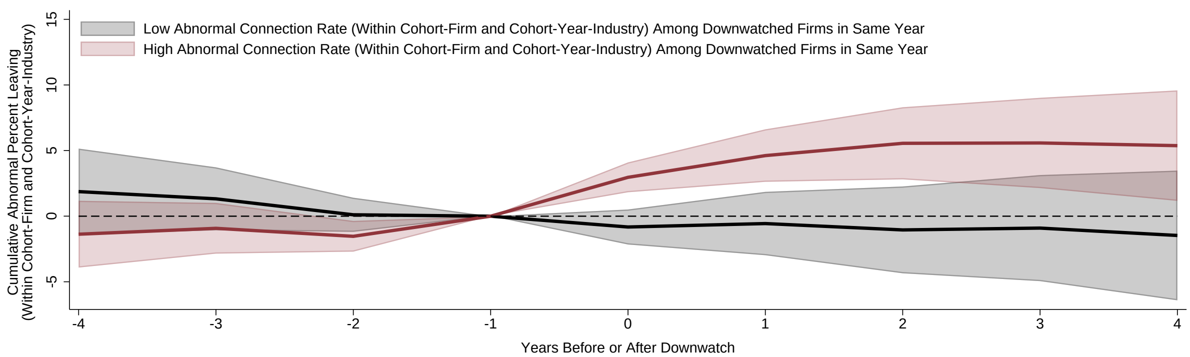
This figure shows the cumulative abnormal probability of organizational restructuring announcements by week relative to the week before a downwatch event $e = 1$, a missed earnings event $e = 2$, and an equity sell recommendation event $e = 3$ for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. Organizational restructuring announcements from Capital IQ include seeking to sell/divest, discontinued operations/downsizing, business reorganizations, and spin-offs/split-offs. The unit of analysis is firm-week. Abnormal is what is left over after removing firm-year and week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{e,S} = \sum_{s=-12}^{S} \hat{\beta}_{e,s}$ from model (13) with a reorganization indicator on the left hand side. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Figure 10: Departure Rate by Year from Downwatch, by High vs. Low Connection Rate

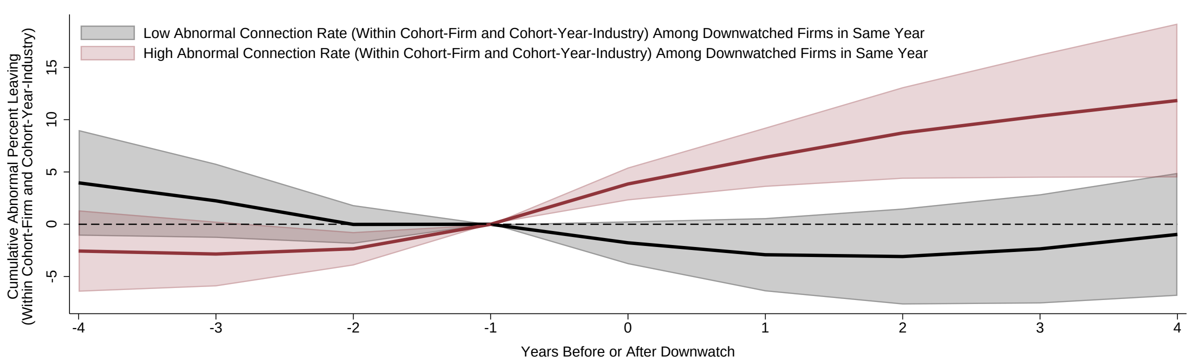
(a) All Firms



(b) Investment Grade



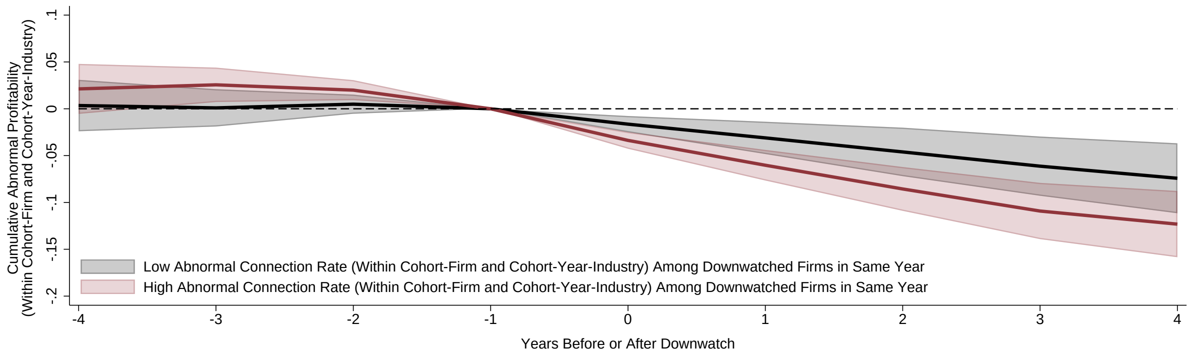
(c) Below Investment Grade



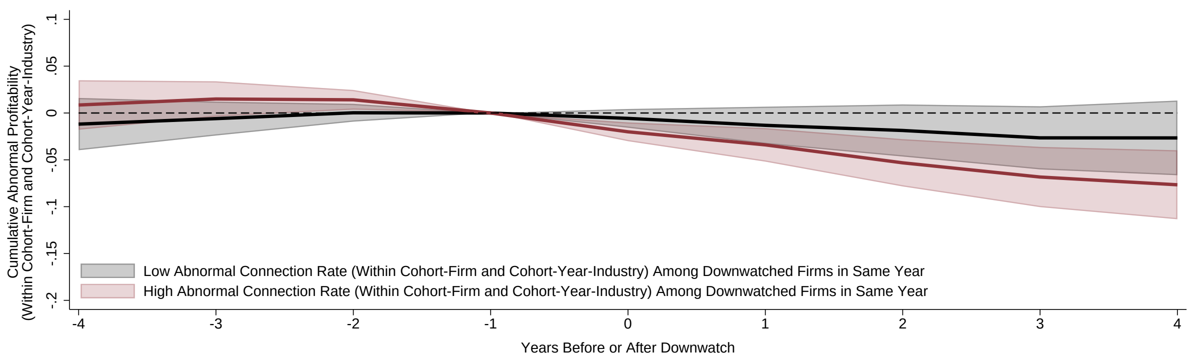
This figure shows the cumulative abnormal departure rate by year relative to the year before a downwatch for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better at the start of the year. The bottom panel is for firms with BB+ credit ratings or worse at the start of the year. Percent leaving is the percent of employees on LinkedIn who are no longer employed at the company in the next calendar year. We define two different downwatch events: event $e = 1$ are those for which the downwatched firm in that year had an abnormal connection rate below the median, and event $e = 2$ are those above the median. The unit of analysis is firm-year. Abnormal is what is left over after removing firm and year-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{e,S} = \sum_{s=-4}^{S} \hat{\beta}_{e,s}$ from estimating model (15) with the "stacked" approach of Gormley and Matsa (2011). The shaded area shows the 95% confidence interval using standard errors that are clustered by firm.

Figure 11: Profitability by Year from Downwatch, by High vs. Low Connection Rate

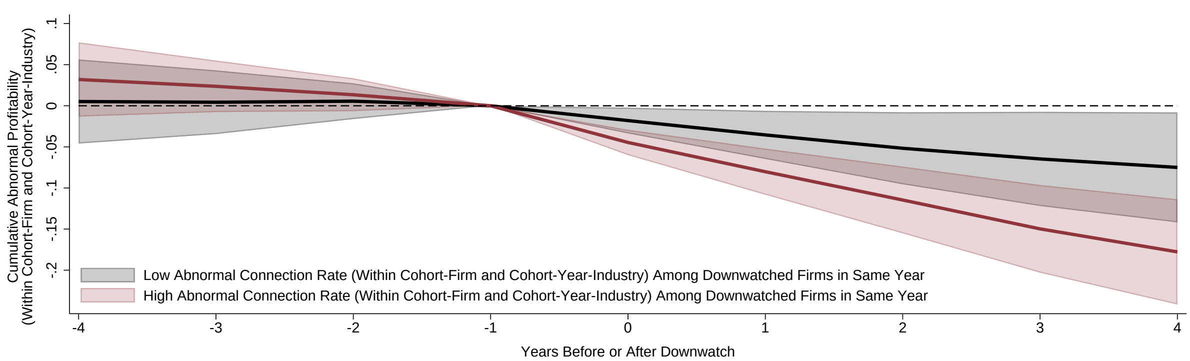
(a) All Firms



(b) Investment Grade



(c) Below Investment Grade



This figure shows cumulative abnormal profitability by year relative to the year before a downwatch for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better at the start of the year. The bottom panel is for firms with BB+ credit ratings or worse at the start of the year. Profitability is annual operating income before depreciation scaled by last year's assets. We define two different downwatch events: event $e = 1$ are those for which the downwatched firm in that year had an abnormal connection rate below the median, and event $e = 2$ are those above the median. The unit of analysis is firm-year. Abnormal is what is left over after removing firm and year-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{e,S} = \sum_{s=-4}^{S} \hat{\beta}_{e,s}$ from estimating model (15) with the "stacked" approach of Gormley and Matsa (2011). The shaded area shows the 95% confidence interval using standard errors that are clustered by firm.

Online Appendix

A. Event Data

In this appendix, we provide more details about how we construct the various events that we use throughout the paper.

A1. Credit Events

Data on downwatches and downgrades are from Moody's Default and Recovery Database (DRD) and S&P's entity ratings dataset. For each issuer, we identify the weeks in which either agency takes a credit action. Issuers in the S&P data are identified by GVKEY. We use the CRSP-Compustat crosswalk to map 6-digit CUSIPs in the DRD to GVKEYs at the date of the credit action.

A2. Earnings Surprises

We construct earnings surprises from Institutional Brokers Estimate System (IBES) data. Following Chiang, Dai, Fan, Hong, and Tu (2019), we define a quarterly earnings report's consensus error as the actual earnings minus the median consensus value, scaled by the CRSP stock price 20 days before the earnings announcement. We define a missed earnings event as a week in which the consensus error of an earnings report is less than the 10th percentile among all earnings reports in our sample during the same year.

As an alternative measure of earnings surprise, we follow Chiang et al. (2019) and compute the fraction of forecasts that miss on the same side (FOM). We identify earnings reports with FOM $= -1$ (i.e., the actual earnings number was worse than all analysts' forecasts). We report results for earnings with FOM = -1 in Appendix B.

IBES data identifies firms by CUSIP. We map these to GVKEYs with the CRSP-Compustat crosswalk at the date of the earnings report.

A3. Equity Sell Recommendations

We also construct equity sell recommendation events from the IBES data, again mapping CUSIPs to GVKEYs with the CRSP-Compustat crosswalk at the date of the event.

Recommendations take on values from 1 (strong buy) to 5 (strong sell). When an analyst's recommendation for the firm's stock increases (i.e., gets worse) by more than one value, we call this an equity sell recommendation. One-point changes are much more frequent but are associated with much smaller connection-making responses on average. We call changes of more than two values strong equity sell recommendations, and report results for these more rare events in Appendix B.

A4. Organizational Restructuring

Organizational restructuring announcements come from the Capital IQ Key Developments dataset. For each firm, identified by GVKEY, we identify the weeks in which there is one of the following announcements: seeking to sell/divest, discontinued operations/downsizing, business reorganizations, or spin-offs/split-offs.

A5. Mergers

To be sure that our results are not driven by mergers, we discard all events that occur within two weeks of a merger announcement, closing, or cancellation. To identify these merger-related events, we use the Capital IQ Key Developments dataset, in which firms are already identified by GVKEY.

Without this filtering, the connection-making response to some events such as upwatches are driven by the change in issuer rating that would occur mechanically post-merger. Although this effect is certainly interesting, it is not our focus in this paper.

A6. Additional Filtering

To ensure that our results are not driven by prior events, we filter out downwatches preceded by other downwatches or downgrades in the 12 weeks prior. Similarly, to ensure that our results comparing downwatches with other events are not being driven by contemporaneous credit events, we filter out missed earnings and equity sell recommendations that coincide with any negative or positive credit event in the 12 weeks prior, the week of, or the 12 weeks after.

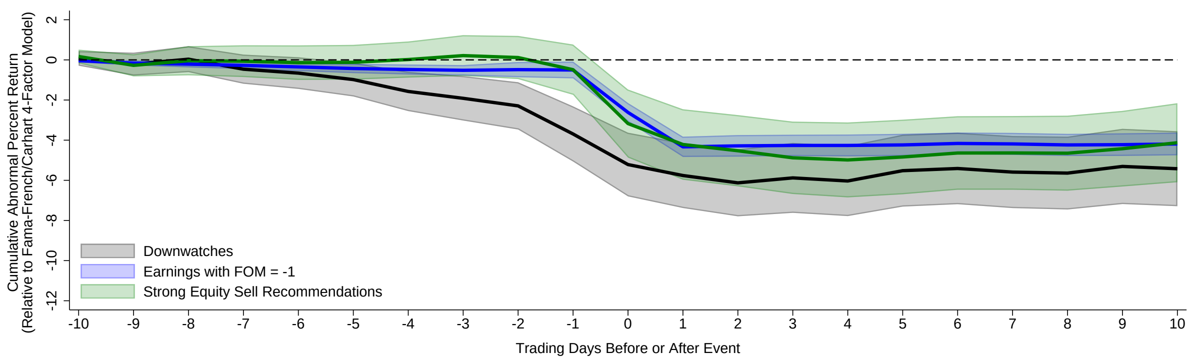
B. Alternative Events

In this appendix, we verify that our results in Section 5.3 about other events is robust to different definitions of missed earnings and equity sell recommendations. Instead of earnings with a consensus error less than the 10th percentile, we consider earnings for which the actual number was worse than all analysts' forecasts (FOM = -1 using the terminology of Chiang et al., 2019). Instead of one-point changes in the five-point equity recommendation scale, we consider strong equity sell recommendations associated with at least two-point changes.

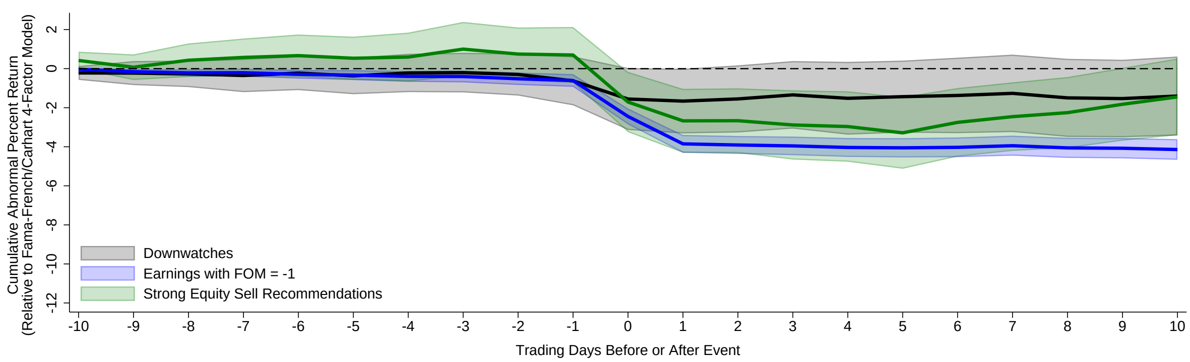
The market reaction for earnings with FOM = -1 and strong equity sell recommendations are similar, with a cumulative abnormal return (CAR) of about -4%, a percentage point stronger than for the baseline event definitions (Figure B1 and Table B1). Connection-making responses are also similarly small, except for strong equity sell recommendations for investment grade firms, for which the response is about half that of a downwatch (Figure B2 and Table B2). Consistent with this, earnings with FOM = -1 and strong equity sell recommendations generally do not come with a higher probability of subsequent organizational restructuring, with again the exception of strong equity sell recommendations for investment grade firms (Figure B3 and Table B3).

Figure B1: Market Response by Trading Day to Downwatches and Other Events

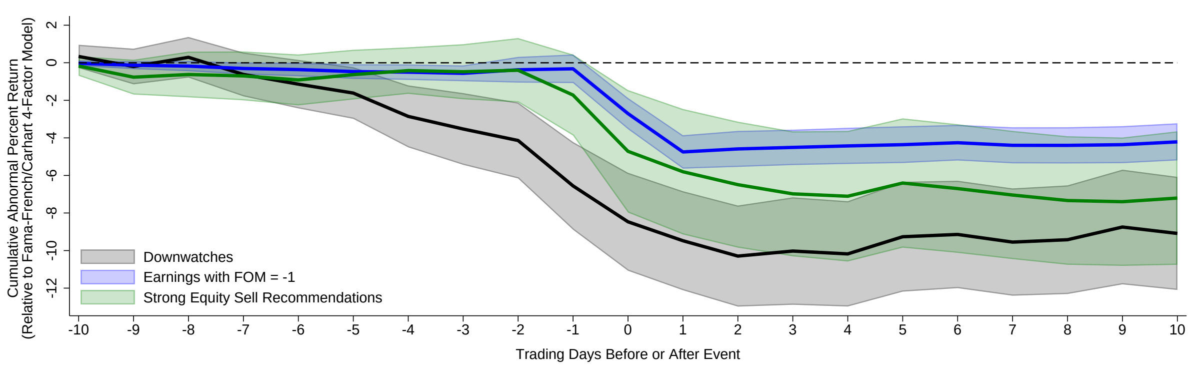
(a) All Firms



(b) Investment Grade



(c) Below Investment Grade



This figure replicates Figure 7 with alternate definitions of missed earnings and equity sell recommendations.

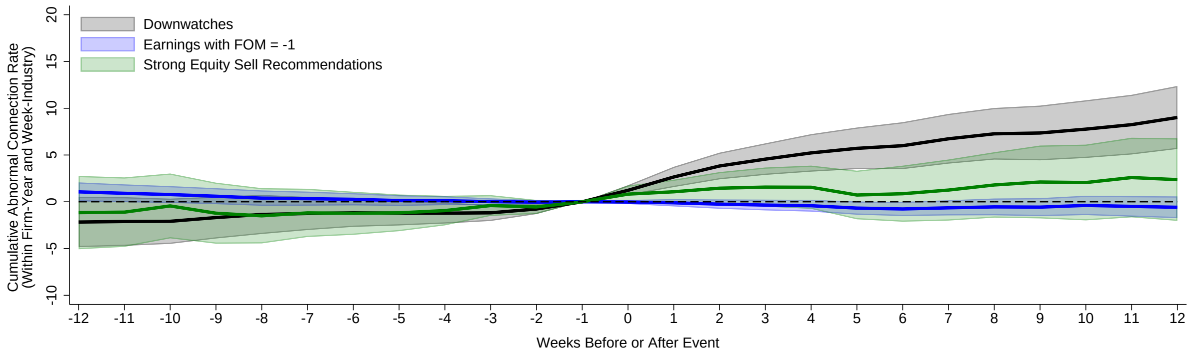
Table B1: Market Response to Downwatches and Other Events

	Cumulative Abnormal Return		
Downwatch	-5.42***	-1.40	-9.09***
	(0.95)	(1.03)	(1.54)
Earnings with FOM = -1	-4.19***	-4.14***	-4.21***
	(0.29)	(0.27)	(0.50)
Strong Equity Sell Recommendation	-4.13***	-1.45	-7.20***
	(1.00)	(1.00)	(1.81)
Sample of Firms	All	IG	Below IG
Downwatches	478	226	248
Earnings with FOM = -1	2,416	1,140	1,235
Strong Equity Sell Recommendations	185	100	83

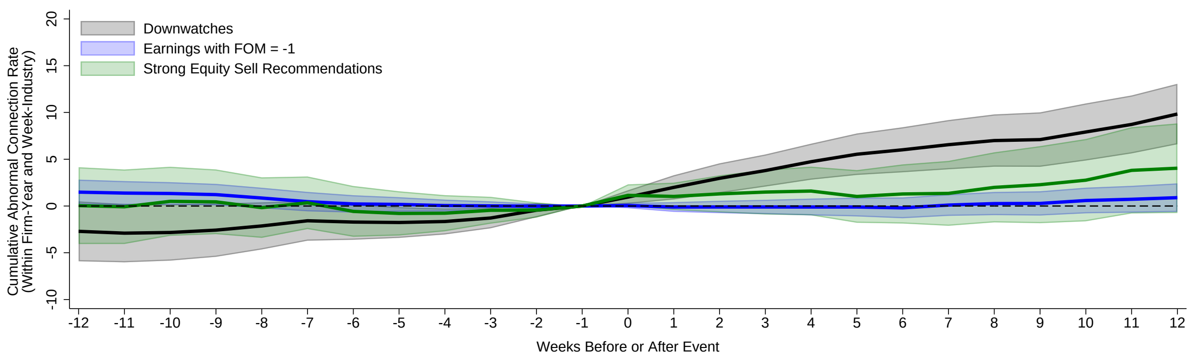
This table replicates Table 8 with alternate definitions of missed earnings and equity sell recommendations.

Figure B2: Connections Initiated by Week from Downwatches and Other Events

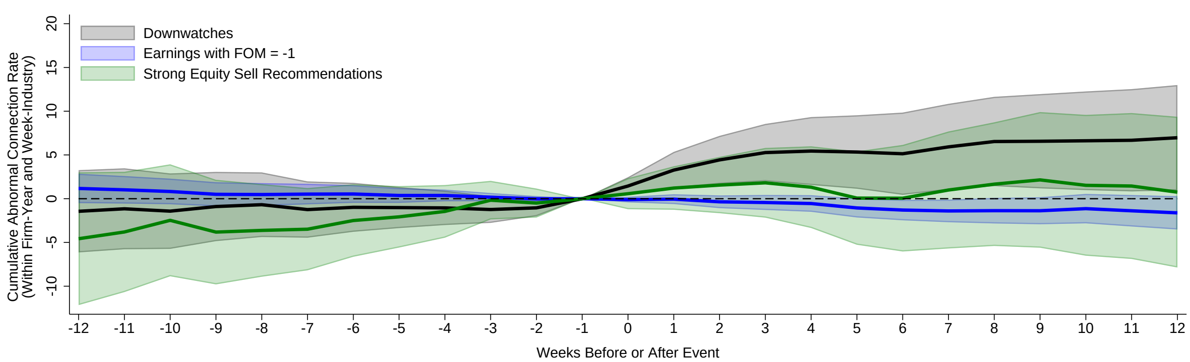
(a) All Firms



(b) Investment Grade



(c) Below Investment Grade



This figure replicates Figure 8 with alternate definitions of missed earnings and equity sell recommendations.

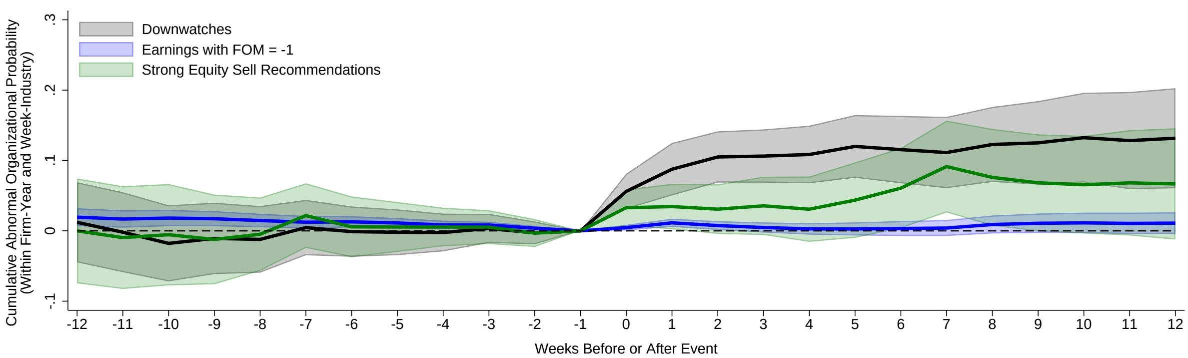
Table B2: Connections Initiated After Downwatches and Other Events

	Connection Rate		
Downwatch	9.01***	9.83***	6.97**
	(1.72)	(1.65)	(3.07)
Earnings with FOM = -1	-0.59	0.89	-1.62*
	(0.59)	(0.78)	(0.97)
Strong Equity Sell Recommendation	2.37	4.04*	0.75
	(2.25)	(2.44)	(4.40)
Mean Connection Rate	21.51	21.45	21.56
Sample of Firms	All	IG	Below IG
Firm-Year Fixed Effects	12,838	6,697	5,878
Week-Industry Fixed Effects	37,942	26,220	33,932
Pre-trend p-value for Downwatches	0.316	0.252	0.665
Pre-trend p-value for Earnings with FOM = -1	0.548	0.153	0.654
Pre-trend p-value for Strong Equity Sell Recommendations	0.180	0.432	0.222
R^2	0.809	0.830	0.804
Adjusted R^2	0.793	0.812	0.774
Observations	649,065	338,269	288,465
Firms	1,740	880	980
Weeks	519	519	519
Downwatches	649	302	331
Earnings with FOM = -1	4,006	1,698	2,176
Strong Equity Sell Recommendations	272	147	112

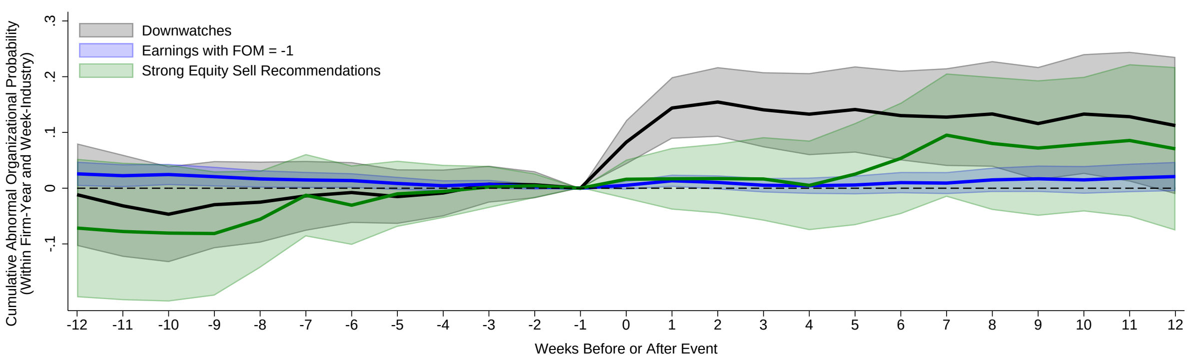
This table replicates Table 9 with alternate definitions of missed earnings and equity sell recommendations.

Figure B3: Organizational Announcements by Week from Downwatches and Other Events

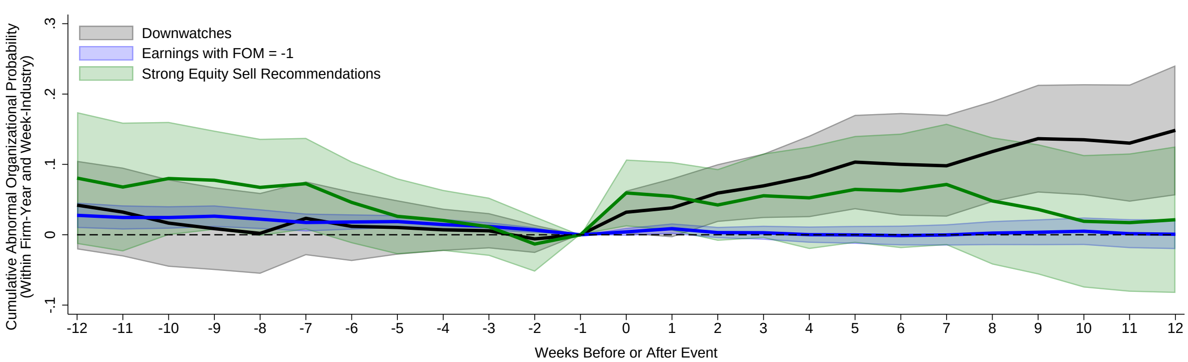
(a) All Firms



(b) Investment Grade



(c) Below Investment Grade



This figure replicates Figure 9 with alternate definitions of missed earnings and equity sell recommendations.

Table B3: Organizational Announcements After Downwatches and Other Events

	Organizational Announcement		
Downwatch	0.132***	0.112*	0.148***
	(0.036)	(0.063)	(0.047)
Earnings with FOM = -1	0.011	0.021	0.001
	(0.008)	(0.013)	(0.011)
Strong Equity Sell Recommendation	0.067*	0.071	0.021
	(0.040)	(0.075)	(0.053)
Mean Outcome	0.018	0.024	0.011
Sample of Firms	All	IG	Below IG
Firm-Year Fixed Effects	12,838	6,697	5,878
Week-Industry Fixed Effects	37,942	26,220	33,932
Pre-trend p-value for Downwatches	0.027	0.187	0.012
Pre-trend p-value for Earnings with FOM = -1	0.027	0.177	0.003
Pre-trend p-value for Strong Equity Sell Recommendations	0.105	0.221	0.000
R^2	0.156	0.184	0.195
Adjusted R^2	0.085	0.097	0.068
Observations	649,065	338,269	288,465
Firms	1,740	880	980
Weeks	519	519	519
Downwatches	649	302	331
Earnings with FOM = -1	4,006	1,698	2,176
Strong Equity Sell Recommendations	272	147	112

This table replicates Table 10 with alternate definitions of missed earnings and equity sell recommendations.

C. Heterogeneous Treatment Effects

In this appendix, we discuss the implications of heterogeneous treatment effects for our weekly event-studies. Under staggered adoption with an absorbing treatment, Sun and Abraham (2020) show how a two-way fixed effects estimator of β_s in (9) can be written as a weighted average of treatment effects for different relative event times s and cohorts of events. The concern is that when treatment effects are heterogeneous, weights for relative event times other than s can be nonzero, and weights for some cohorts can be negative, potentially impeding both the validity of pre-trend tests and the interpretation of estimates.

Intuitively, persistent treatment effects from other relative periods and cohorts may not cancel out, "contaminating" estimates. In our setting, downwatch treatments are sparse and connection-making treatment effects are short-lived, so we do not expect contamination to be a large concern. However, we are unaware of any econometric result that formalizes this intuition in our setting with multi-way fixed effects, non-absorbing treatments, and dynamic treatment effects. So we verify that our estimates remain essentially unchanged when using the "stacked" approach of Gormley and Matsa (2011), which to some degree is robust to treatment effects that vary by cohort (Gardner, 2022).[26]

The idea is to transform the data into a two-group (treated and control) and two-period (pre and post) design, stacked by cohort. For each week with a downwatch, we construct a cohort c of treated firms that experience a downwatch and control firms that do not. Each cohort is a year-long panel of 26 weeks before the event through 25 weeks after. We explicitly eliminate contaminating treatment effects by dropping control firm-weeks that are within a 12 week radius of another downwatch. Our model for the stacked specification is

$$r_{cit} = \alpha_{c,i,y(t)} + \gamma_{c,t,j(i)} + \sum_{s=-12}^{12} \beta_s \cdot z_{c,i,t-s} + \varepsilon_{cit}. \tag{C1}$$

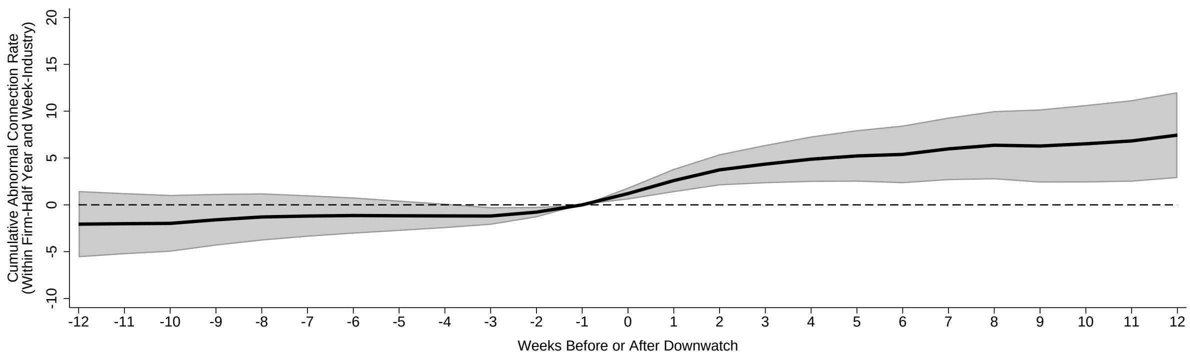
Following standard practice, we allow the fixed effects to differ by cohort c. This has a side-effect of adjusting for higher-frequency firm-specific trends. Since each cohort is a year-long panel and downwatches are approximately uniformly spread throughout the calendar year, allowing firm-by-year fixed effects to vary by cohort is similar to including firm-by-half year fixed effects in our baseline specification.

Accordingly, in Figure C1 and Table C1 we compare our baseline specification with these additional fixed effects to estimates from the stacked specification. After stacking, it is straightforward to estimate the stacked model with a differenced regression analogous to the one in (10). Since the time dimension within each cohort is short, we do not use Driscoll-Kraay standard errors and instead cluster by both firm and year in both sets of results. Results are nearly identical. If anything, the point estimate obtained with the stacked approach is slightly larger with a smaller standard error. Compared with our baseline estimates in Figure 2 and Table 3, the point estimate is slightly smaller because we are adjusting for higher-frequency firm-specific trends.

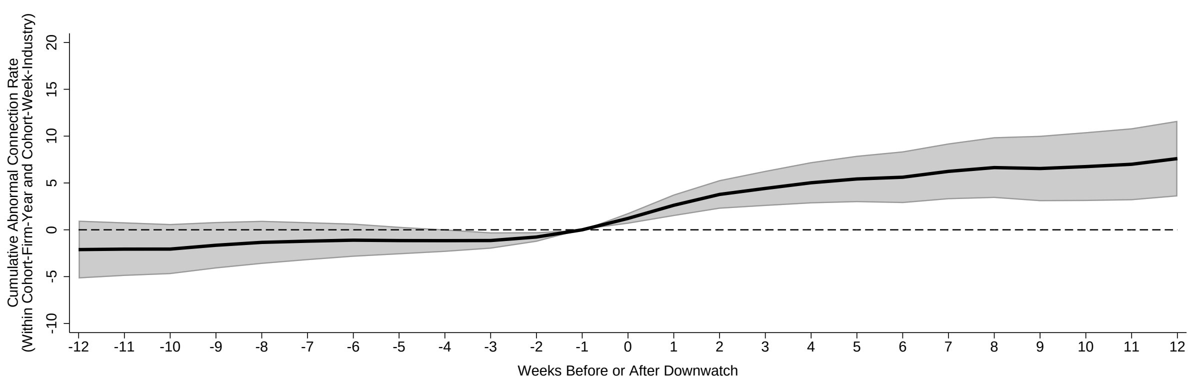
[26]We do not consider the interaction-weighted estimator of Sun and Abraham (2020). Our setting has many cohorts, so estimating separate dynamic effects for each event week requires more than 16 thousand regressors, 100 gigabytes of memory, and two days of computing time.

Figure C1: Connections Initiated by Week from Downwatch, Stacked Approach

(a) Not Stacked



(b) Stacked



This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch using two estimation approaches. The top panel uses our baseline approach with firm-half year fixed effects instead of firm-year, and with double clustered instead of Driscoll-Kraay standard errors. The bottom panel uses the stacked approach of Gormley and Matsa (2011). The unit of analysis is firm-week. In the top panel, abnormal is what is left over after removing firm-half year and week-industry fixed effects; in the bottom panel, after removing cohort-firm-year and cohort-week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_S = \sum_{s=-12}^{S} \hat{\beta}_s$ from model (9) for the top panel (with firm-half year fixed effects) and from model (C1) for the bottom panel. The shaded area shows the 95% confidence interval using standard errors clustered by firm and week.

Table C1: Connections Initiated After Downwatches, Stacked Approach

	Connection Rate	
Downwatch	7.44***	7.60***
	(2.34)	(2.06)
Mean Connection Rate	21.51	20.47
Stacked	No	Yes
Firm-Half Year Fixed Effects	25,338	
Week-Industry Fixed Effects	37,942	
Cohort-Firm-Year Fixed Effects		656,886
Cohort-Week-Industry Fixed Effects		1,055,793
Pre-trend p-value	0.249	0.172
R^2	0.825	0.823
Adjusted R^2	0.806	0.804
Observations	649,046	17,516,432
Firms	1,740	1,740
Weeks	519	519
Downwatches	649	649

This table provides estimates of new connections initiated in the 12 weeks following downwatches using two estimation approaches. The first column uses our baseline approach with firm-half year fixed effects instead of firm-year, and with double clustered instead of Driscoll-Kraay standard errors. The second column uses the stacked approach of Gormley and Matsa (2011). The unit of analysis is firm-week. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{12} = \sum_{s=-12}^{12} \hat{\beta}_s$ from model (9) for the first column (with firm-half year fixed effects) and from model (C1) for the second column. Standard errors in parentheses are clustered by firm and week. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

D. Responses by Seniority

In this appendix, we examine how the cross-section of reactions varies by employee seniority. We may expect more senior workers to respond more strongly or weakly to credit rating events depending on several factors. On the one hand, senior workers may have greater and timelier access to information about the true underlying financial conditions of the firm. If this is the case, we should see less of a response from senior workers to the arrival of information they already anticipated.

On the other hand, senior workers' compensation may be more contingent on the performance and financial health of the firm, so senior workers may react more to downwatches. More senior workers may also be more sophisticated in their understanding of what a downwatch represents for the firm.

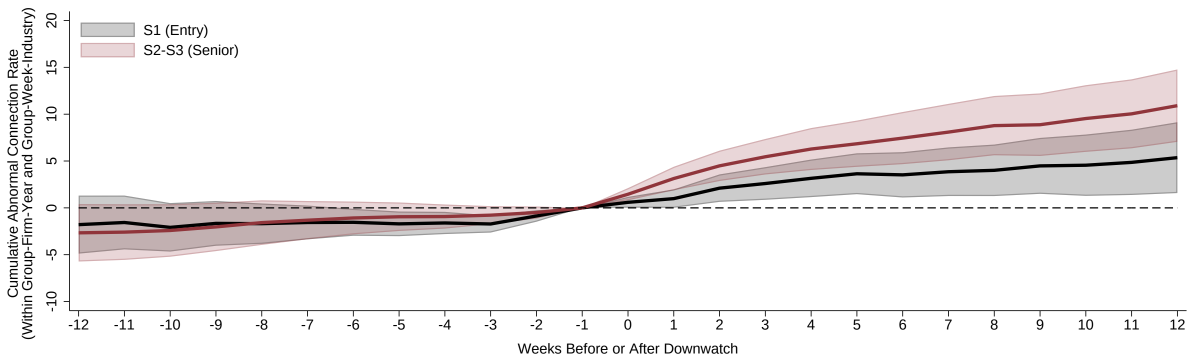
To analyze whether there are significant differences in reactions to credit deterioration between workers of different seniority, we first create two groups of employees: one for entry-level employees, and another for all employees more senior than that. On average, entry-level employees represent 27% of a firm's employees in our sample. Figure D1 and Table D1 show that both senior and junior workers increase connection-making after the credit event, but senior-level workers connect the most.

We then split our senior group into two: mid-level (S2) and most senior (S3). Mid-level (S2) covers workers higher than entry-level and through manager level, while most senior (S3) covers directors, VPs, and executives. On average, mid-level employees represent 53% of a firm's employees in our sample, and most senior, 20%.

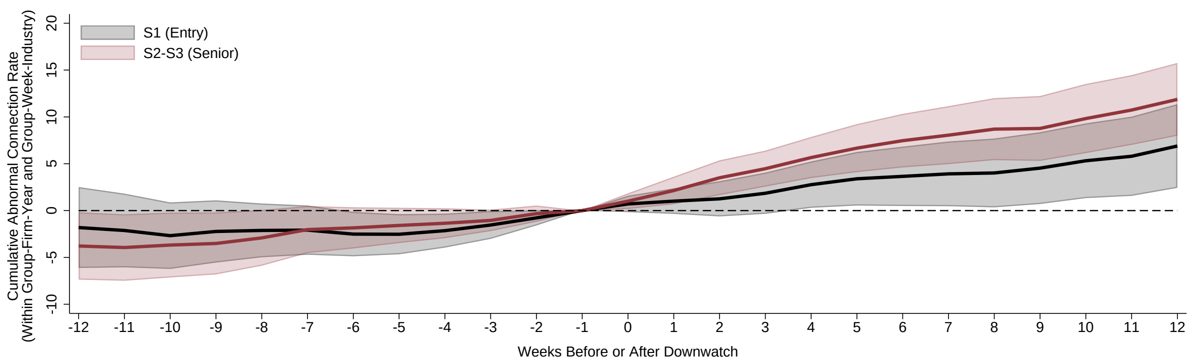
We report results in Figure D2. Reactions seem to be driven by both the mid-level and most senior groups, but the difference between them is not statistically significant (Table D1).

Figure D1: Connections Initiated by Week from Downwatch, by Entry/Senior

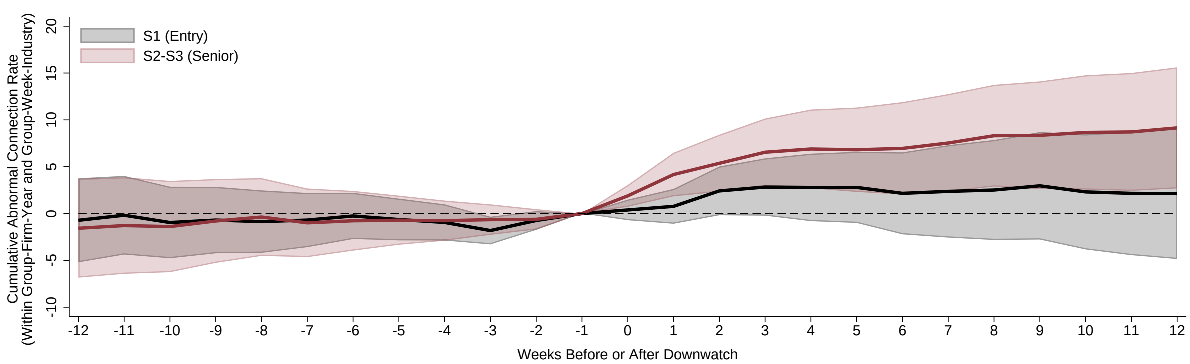
(a) All Firms



(b) Investment Grade



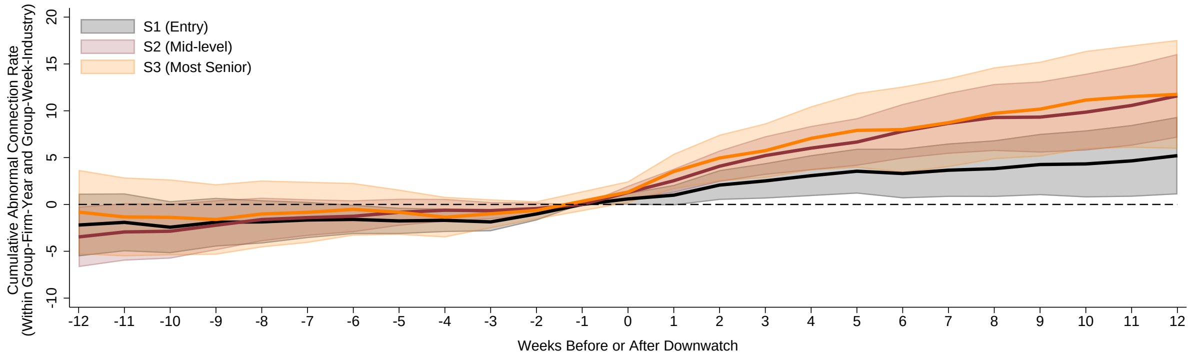
(c) Below Investment Grade



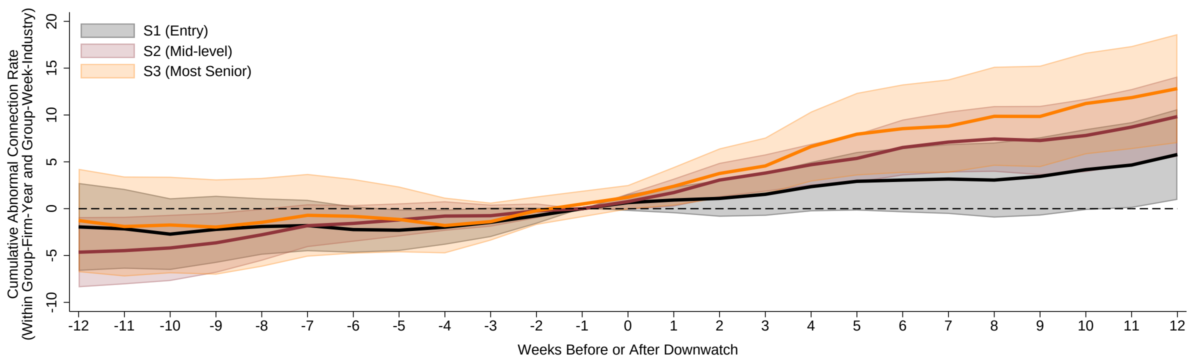
This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. We split employees into two groups: group $g = 1$ denoted S1 are entry-level, unpaid, or training employees, while group $g = 2$ denoted S2-S3 are everyone else. The unit of analysis is group-firm-week. Abnormal is what is left over after removing group-firm-year and group-week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{g,S} = \sum_{s=-12}^{S} \hat{\beta}_{g,s}$ from model (12). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Figure D2: Connections Initiated by Week from Downwatch, by Seniority

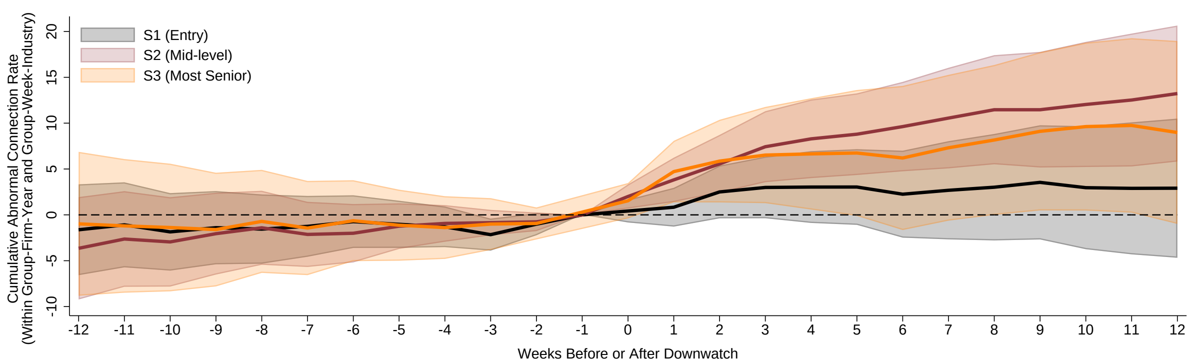
(a) All Firms



(b) Investment Grade



(c) Below Investment Grade



This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. We split employees into three groups: group $g = 1$ denoted S1 includes to entry-level, unpaid or training employees; group $g = 2$ denoted S2 includes senior and manager-level employees; and group $g = 3$ denoted S3 includes directors, VPs, and executives. The unit of analysis is group-firm-week. Abnormal is what is left over after removing group-firm-year and group-week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{g,S} = \sum_{s=-12}^{S} \hat{\beta}_{g,s}$ from model (12). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Table D1: Connections Initiated After Downwatches, by Seniority

	Connection Rate					
Downwatch	5.36***	6.90***	2.13	5.21**	5.78**	2.91
	(1.93)	(2.28)	(3.56)	(2.11)	(2.47)	(3.87)
Downwatch × S2-S3 (Senior)	5.55***	4.98*	7.02**	6.39**	4.05	10.32**
	(2.10)	(2.69)	(3.45)	(2.53)	(3.00)	(4.60)
Downwatch × S3 (Most Senior)				0.16	2.99	-4.25
				(3.10)	(3.18)	(5.07)
Mean Connection Rate for S1	14.92	15.47	14.29	15.04	15.56	14.44
Mean Connection Rate for S2-S3	23.87	23.58	24.16			
Mean Connection Rate for S2				20.79	20.68	20.89
Mean Connection Rate for S3				33.27	32.62	33.82
Sample of Firms	All	IG	Below IG	All	IG	Below IG
Group-Firm-Year Fixed Effects	25,528	13,319	11,681	38,180	19,924	17,459
Group-Week-Industry Fixed Effects	75,884	52,440	67,686	113,826	78,524	101,420
Pre-trend p-value for S1	0.014	0.212	0.106	0.017	0.316	0.184
Pre-trend p-value for S2-S3	0.878	0.408	0.895			
Pre-trend p-value for S2				0.609	0.416	0.111
Pre-trend p-value for S3				0.625	0.519	0.903
R^2	0.776	0.801	0.771	0.776	0.801	0.771
Adjusted R^2	0.76	0.78	0.74	0.76	0.78	0.73
Observations	1,289,571	672,514	572,603	1,928,727	1,006,124	855,746
Firms	1,740	880	980	1,740	880	980
Weeks	519	519	519	519	519	519
Downwatches	633	300	317	633	300	317

This table provides estimates of new connections initiated in the 12 weeks following downwatches for three samples of firms. Columns 1 and 4 are our full sample. Columns 2 and 5 are for firms with BBB- credit ratings or better. Columns 3 and 6 are for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. In Columns 1-3 we split employees into two groups: group $g = 1$ denoted S1 are entry-level, unpaid, or training employees, while group $g = 2$ denoted S2-S3 are everyone else. In Columns 4-6 we split employees into three groups: group $g = 1$ denoted S1 includes to entry-level, unpaid or training employees; group $g = 2$ denoted S2 includes senior and manager-level employees; and group $g = 3$ denoted S3 includes directors, VPs, and executives. The unit of analysis is group-firm-week. Industries are 3-digit NAICS codes. Estimates in Columns 1-3 are $\hat{\delta}_{1,12}$ and $\hat{\delta}_{2,12} - \hat{\delta}_{1,12}$, while estimates in Columns 4-6 are $\hat{\delta}_{1,12}$, $\hat{\delta}_{2,12} - \hat{\delta}_{1,12}$, and $\hat{\delta}_{3,12} - \hat{\delta}_{2,12}$ where $\hat{\delta}_{g,12} = \sum_{s=-12}^{12} \hat{\beta}_{g,s}$ from model (12). Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

E. Responses by Occupation

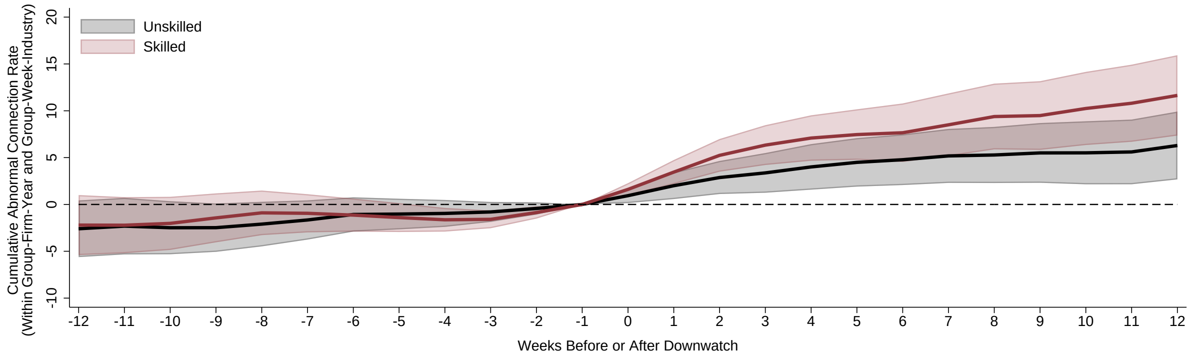
In this appendix, we examine how the cross-section of reactions varies by employee occupation. We provide evidence that more "skilled" employees seem to react more strongly than others, and that connection-making responses are spread out across many different occupations for both investment grade and below investment grade firms.

Similar to our results by seniority in Appendix D, we split each firm-week observation into two observations: one for "skilled" employees with more than 50% of workers holding a Bachelor's degree according to the Bureau of Labor Statistics (Table E2) and another for everyone else, denoted “unskilled.” We report results in Figure E1 and Table E1. Skilled employees seem to react more strongly than others, although the difference is not statistically significant for below investment grade firms.

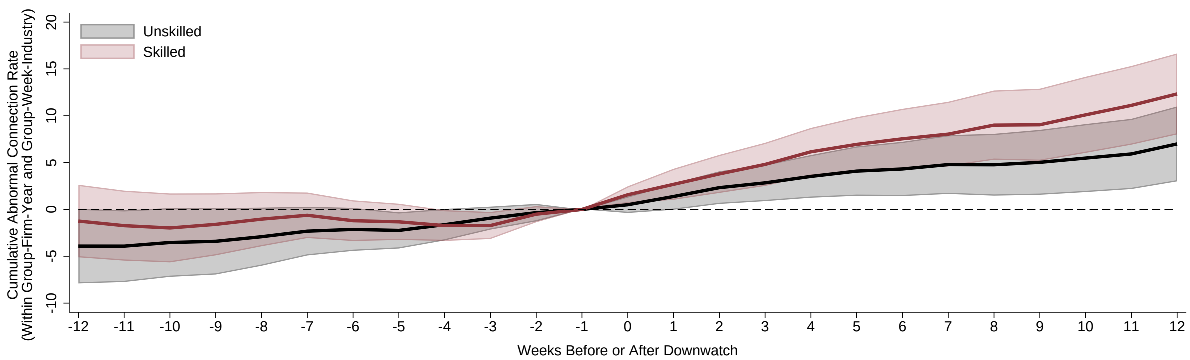
To document that connection-making responses are spread out across different occupations, we also define more granular occupation groups, breaking up the LinkedIn occupation categories into five similar groups, each of which contains 10-30% of the employees registered on LinkedIn in our sample. In Table E3 we replicate our results in Table 4 comparing the connection response for investment grade versus below investment grade firms, separately for each occupation group. We find broadly similar results for each group of occupations, suggesting that our results apply to many occupations in the firms in our sample, not just, for example, executives or sales representatives.

Figure E1: Connections Initiated by Week from Downwatch, by Employee "Skill"

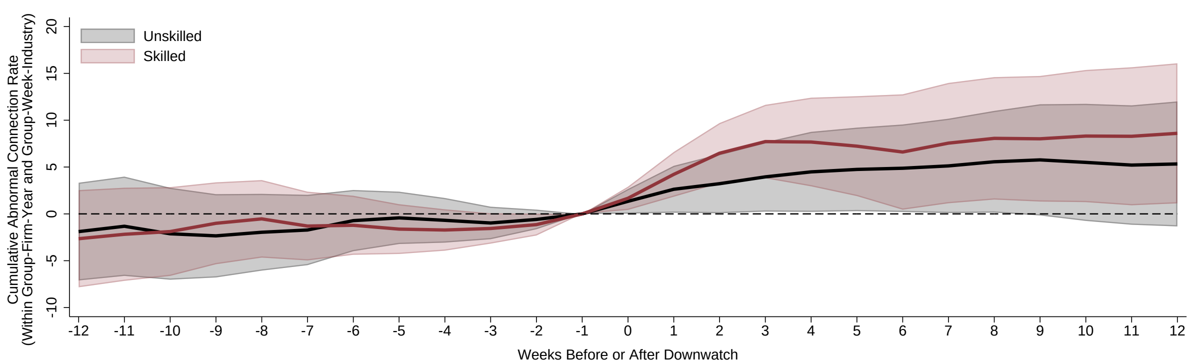
(a) All Firms



(b) Investment Grade



(c) Below Investment Grade



This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. We split employees into two groups: group $g = 1$ are in "unskilled" occupations that have less than 50% of workers holding a Bachelor's degree according to the BLS (Table E2) and group $g = 2$ are in the remaining "skilled" occupations. The unit of analysis is group-firm-week. Abnormal is what is left over after removing group-firm-year and group-week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{g,S} = \sum_{s=-12}^{S} \hat{\beta}_{g,s}$ from model (12). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Table E1: Connections Initiated After Downwatches, by Employee "Skill"

	Connection Rate		
Downwatch	6.30***	6.99***	5.33
	(1.85)	(2.04)	(3.41)
Downwatch $\times$ Skilled	5.35**	5.34*	3.27
	(2.11)	(2.74)	(3.73)
Mean Connection Rate for Unskilled	21.55	21.48	21.61
Mean Connection Rate for Skilled	21.80	21.70	21.85
Sample of Firms	All	IG	Below IG
Group-Firm-Year Fixed Effects	25,591	13,346	11,719
Group-Week-Industry Fixed Effects	75,884	52,440	67,752
Pre-trend p-value for Unskilled	0.661	0.524	0.568
Pre-trend p-value for Skilled	0.125	0.100	0.461
R^2	0.756	0.789	0.748
Adjusted R^2	0.735	0.766	0.708
Observations	1,293,439	673,964	574,903
Firms	1,740	880	980
Weeks	519	519	519
Downwatches	646	302	328

This table provides estimates of new connections initiated in the 12 weeks following downwatches for three samples of firms. Column 1 is our full sample. Column 2 is for firms with BBB- credit ratings or better. Column 3 is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks.We split employees into two groups: group $g = 1$ are in "unskilled" occupations that have less than 50% of workers holding a Bachelor's degree according to the BLS (Table E2) and group $g = 2$ are in the remaining "skilled" occupations. The unit of analysis is group-firm-week. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{1,12}$ and $\hat{\delta}_{2,12} - \hat{\delta}_{1,12}$ where $\hat{\delta}_{g,12} = \sum_{s=-12}^{12} \hat{\beta}_{g,s}$ from model (12). Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

Table E2: Educational Attainment by Occupation

SOC	Description	Percent Bachelor's or More	Years Secondary Schooling	"Skilled"	2016 Employment (Thousands)
19-0000	Life, Physical, and Social Science	81.0%	8.76	1	1,300
23-0000	Legal	80.1%	9.93	1	1,283
25-0000	Education, Training, and Library	75.2%	8.31	1	9,427
21-0000	Community and Social Services	70.7%	7.89	1	2,571
15-0000	Computer and Mathematical	68.8%	7.63	1	4,419
13-0000	Business and Financial Operations	66.8%	7.47	1	8,067
17-0000	Architecture and Engineering	64.3%	7.45	1	2,601
27-0000	Arts, Design, Entertainment, Sports, and Media	62.8%	7.22	1	2,773
29-0000	Healthcare Practitioners and Technical	56.8%	7.72	1	8,752
11-0000	Management	52.6%	6.84	1	9,533
41-0000	Sales and Related	29.8%	5.61	0	15,748
33-0000	Protective Service	26.9%	5.73	0	3,506
43-0000	Office and Administrative Support	22.8%	5.48	0	23,081
39-0000	Personal Care and Service	20.4%	5.17	0	6,420
31-0000	Healthcare Support	12.2%	5.03	1*	4,316
35-0000	Food Preparation and Serving Related	10.5%	4.45	0	13,206
53-0000	Transportation and Material Moving	9.0%	4.41	0	10,274
49-0000	Installation, Maintenance, and Repair	8.3%	4.64	0	5,905
51-0000	Production	8.2%	4.34	0	9,357
45-0000	Farming, Fishing, and Forestry	7.1%	3.47	0	1,060
37-0000	Building and Grounds Cleaning and Maintenance	6.9%	3.98	0	5,654
47-0000	Construction and Extraction	6.4%	4.12	0	6,812

*LinkedIn's classification scheme provides one category for healthcare services, so we count both healthcare support and practitioner and technical occupations as high-skilled.

Table E3: Connections Initiated After Downwatches, by Occupation Group

	Connection Rate				
Downwatch	9.15***	5.32	4.85**	10.87***	12.71***
	(2.96)	(3.76)	(2.27)	(3.54)	(2.98)
Downwatch × Below Investment Grade	0.80	6.23	-2.36	-2.48	-1.01
	(4.95)	(6.10)	(3.86)	(6.24)	(5.34)
Mean Connection Rate for Investment Grade	24.85	25.65	19.03	22.19	18.11
Mean Connection Rate for Below Investment Grade	26.45	26.52	18.97	20.59	17.64
Occupations	Business	Client-facing	Internal	PSTS	Tech
Group-Firm-Year Fixed Effects	12,456	12,273	12,443	12,224	12,314
Group-Week-Industry Fixed Effects	60,011	59,690	59,985	59,611	59,867
Pre-trend p-value for Investment Grade	0.931	0.453	0.422	0.938	0.163
Pre-trend p-value for Below Investment Grade	0.602	0.984	0.170	0.070	0.657
R^2	0.679	0.696	0.714	0.596	0.605
Adjusted R^2	0.637	0.656	0.677	0.543	0.553
Observations	620,246	610,702	619,773	607,608	612,932
Firms	1,692	1,673	1,688	1,671	1,681
Weeks	519	519	519	519	519
Downwatches for Investment Grade	298	300	299	297	300
Downwatches for Below Investment Grade	323	313	318	310	316

This table provides estimates of new connections initiated in the 12 weeks following downwatches for different occupation groups. We group LinkedIn occupation categories into five groups: "Business" includes skilled occupations related to running the business such as finance and program/project management; "Client-facing" includes less skilled occupations such as sales for which interacting outside the firm is a routine part of the job; "Internal" includes less skilled internal production occupations such as operations and HR which would not necessarily interact outside the firm as part of the job; "PSTS" stands for professional, scientific and technical services, which are more likely to be concentrated in specialized firms; and "Tech" includes Engineering and Information Technology. Each group contains 10-30% of the employees registered on LinkedIn in our sample. We split firms into two ex ante rating groups lagged by 24 weeks: group $g = 1$ is investment grade (BBB- or better) and group $g = 2$ is below investment grade (BB+ or worse). The unit of analysis is firm-week. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{1,12}$ and $\hat{\delta}_{2,12} - \hat{\delta}_{1,12}$ where $\hat{\delta}_{g,12} = \sum_{s=-12}^{12} \hat{\beta}_{g,s}$ from model (11). Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

F. Information Content of Credit Rating Agency Signals

In this appendix, we study whether workers are responding to credit rating agencies' actions themselves, or if rating agencies' actions happen to coincide with broader patterns of credit deterioration. If rating agencies' actions happen to be correlated with credit deterioration, but are not themselves a significant source of information for workers, then we should expect worker reactions to be particularly strong for "sudden" credit events: rating actions driven by sudden shifts in the economic environment.

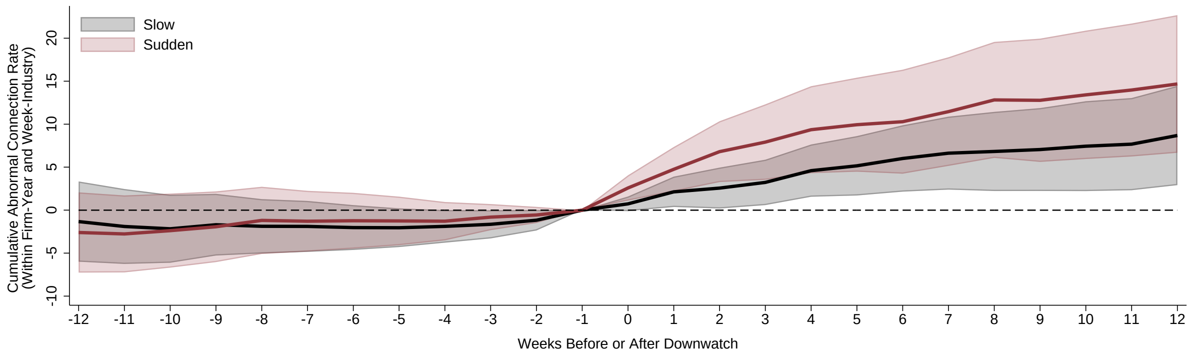
We tackle this question by using contextual information provided by S&P analysts on the rationale for downwatches. We classify our set of credit events into two groups: "slow" and "fast" credit events. "Slow" credit events correspond to an agency's actions relating to slowly worsening conditions. For example, sales have been slowly deteriorating for a firm, and an agency decides it is finally time to signal this information via a negative credit watch. In contrast, "fast" credit events are prompted by a sudden change in economic conditions that, in combination with the firm's pre-existing situation, pushes an agency to place the firm on a negative credit watch. For example, a jump in oil prices constitutes a "fast" negative credit shock for a highly-levered airline.

We find in Figure F1 and Table F1 that employees respond to both slow and fast events. The magnitude of the response is greater for fast events. This indicates that both mechanisms play a role: employees are responding to the underlying situation, but they also gain additional information from the agency's signal, even when the event could have been anticipated.

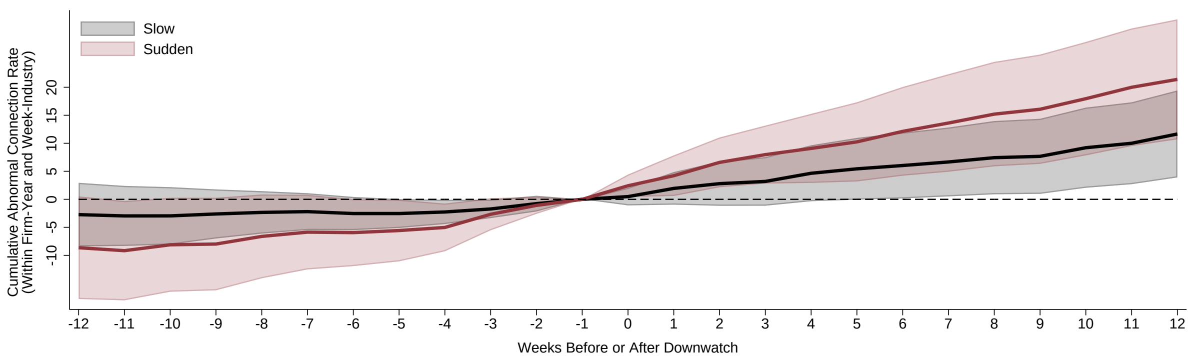
There is still a possibility that workers respond to negative media coverage of their firms, and that negative coverage especially increases around negative credit events. We tackle this possibility in Appendix G.

Figure F1: Connections Initiated by Week from Downwatch, “Slow” vs. “Sudden” News

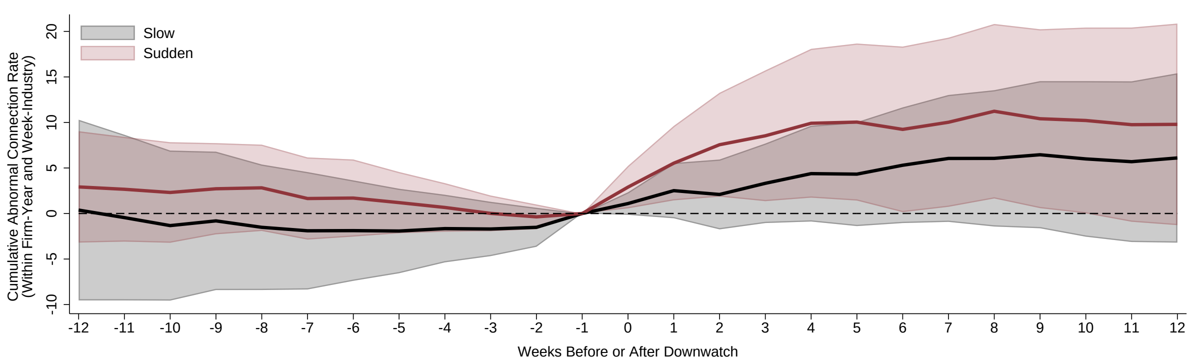
(a) All Firms



(b) Investment Grade



(c) Below Investment Grade



This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. We manually classify S&P downwatches using the text of S&P research updates to define two subsets of downwatch events: “slow” downwatch events $e = 1$, which occur following gradually unfolding events (e.g., declining performance), and “sudden” downwatch events $e = 2$, which occur following an event that happens more quickly (e.g., a sudden layoff announcement). The unit of analysis is firm-week. Abnormal is what is left over after removing firm-year and week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{e,S} = \sum_{s=-12}^{S} \hat{\beta}_{e,s}$ from model (13). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Table F1: Connections Initiated After Downwatches, "Slow" vs. "Sudden" News

	Connection Rate		
Downwatch	8.69***	11.66***	6.10
	(2.95)	(3.96)	(4.75)
Downwatch × Sudden	5.99	9.75	3.69
	(5.19)	(7.26)	(6.69)
Mean Connection Rate	21.51	21.45	21.56
Sample of Firms	All	IG	Below IG
Firm-Year Fixed Effects	12,838	6,697	5,878
Week-Industry Fixed Effects	37,942	26,220	33,932
Pre-trend p-value for Slow	0.666	0.653	0.927
Pre-trend p-value for Sudden	0.880	0.341	0.807
R^2	0.809	0.830	0.804
Adjusted R^2	0.793	0.812	0.774
Observations	649,065	338,269	288,465
Firms	1,740	880	980
Weeks	519	519	519
Slow Downwatches	200	97	96
Sudden Downwatches	169	67	97

This table provides estimates of new connections initiated in the 12 weeks following downwatches for three samples of firms. Column 1 is our full sample. Column 2 is for firms with BBB- credit ratings or better. Column 3 is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. We manually classify S&P downwatches using the text of S&P research updates to define two subsets of downwatch events: "slow" downwatch events $e = 1$, which occur following gradually unfolding events (e.g., declining performance), and "sudden" downwatch events $e = 2$, which occur following an event that happens more quickly (e.g., a sudden layoff announcement). The unit of analysis is firm-week. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{1,12}$ and $\hat{\delta}_{2,12} - \hat{\delta}_{1,12}$ where $\hat{\delta}_{e,12} = \sum_{s=-12}^{12} \hat{\beta}_{e,s}$ from model (13). Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.

G. Responses to Negative Media Coverage

We collect data from RavenPack, an aggregator of news stories, to track media coverage of firms at the time of credit events. RavenPack's data enables us to identify new negative news stories. Table G1 presents summary statistics for the data. Unsurprisingly, there are around double as many new stories about firms that are downwatched, and around three times as many new negative stories.

We restrict our attention to full articles, discard both "news flashes" and short press releases, and filter out articles with a relevance score less than 90%, which is the cutoff recommended by RavenPack. To identify which stories are "negative," we use RavenPack's Multi Classifier for Equities (MCQ) sentiment score, which takes on values of 0 (negative), 50 (neutral) or 100 (positive). This score is a composite of other sentiment scores, which discards combinations that contradict each other, with the goal of providing a consistent sentiment classification.

In general, we find that new negative stories are correlated with connection-making activity. Figure G1 and Columns 1-3 in Table G2 show connection activity following new negative news coverage. Negative stories do come with an increase in connection-making; however, the effect is an order of magnitude smaller than the effect of a downwatch. Furthermore, this relationship holds after adjusting for firm-by-year and week-by-industry fixed effects, suggesting that connection-making is driven by the arrival of stories that shed a negative light on employers.

If negative stories about firms are the primary driver of employees' connection-making response to downwatches, we should expect downwatches that come with new negative stories to have a larger connection-making response. Figure G2 and Columns 4-6 in Table G2 report results in which we estimate separate effects for downwatches that come with new negative stories in the surrounding weeks. The magnitude and significance of credit events on connection-making activity remain generally unchanged, suggesting that media coverage alone is unlikely to be driving workers' response to credit events.

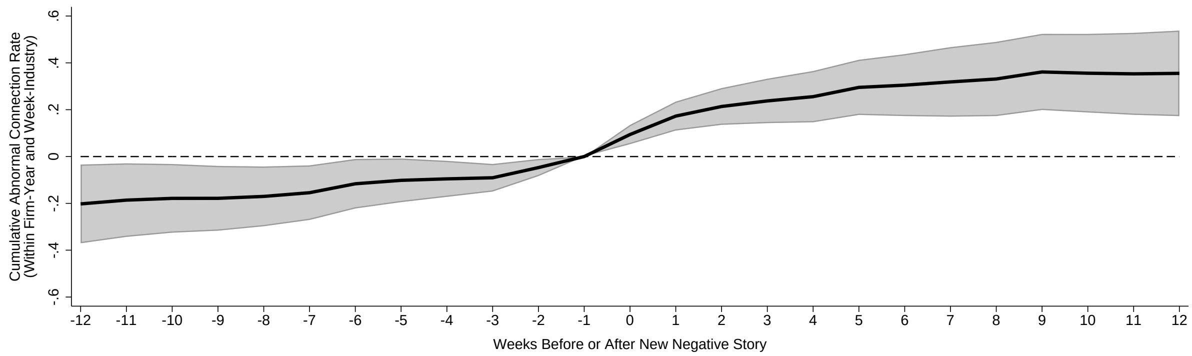
Table G1: RavenPack Summary Statistics

	Mean	SD	25th	50th	75th	Count
All Weeks						
New Stories	2.412	7.260	0	0	2	645,961
New Negative Stories	0.519	1.875	0	0	0	645,961
New Story	0.488	0.500	0	0	1	645,961
New Negative Story	0.214	0.410	0	0	0	645,961
Same Week as a Downwatch						
New Stories	5.817	15.883	0	1	5	641
New Negative Stories	1.655	5.463	0	0	2	641
New Story	0.626	0.484	0	1	1	641
New Negative Story	0.387	0.487	0	0	1	641

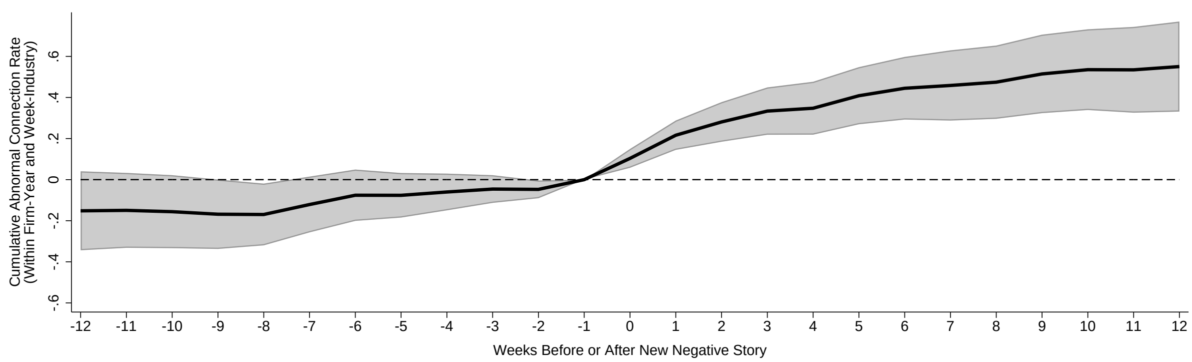
This table presents summary statistics for our RavenPack data. Observations are at the firm-week level. We classify new stories as "negative" with a composite sentiment score constructed by RavenPack. We report both total counts of stories and indicators for whether there is a story for each firm-week. We also present these summary statistics separately for firm-weeks with a downwatch.

Figure G1: Connections Initiated by Week from New Negative Story

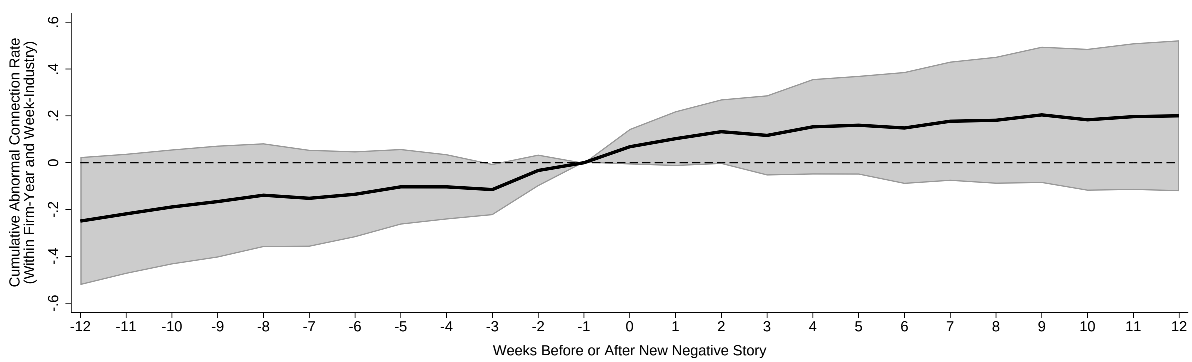
(a) All Firms



(b) Investment Grade



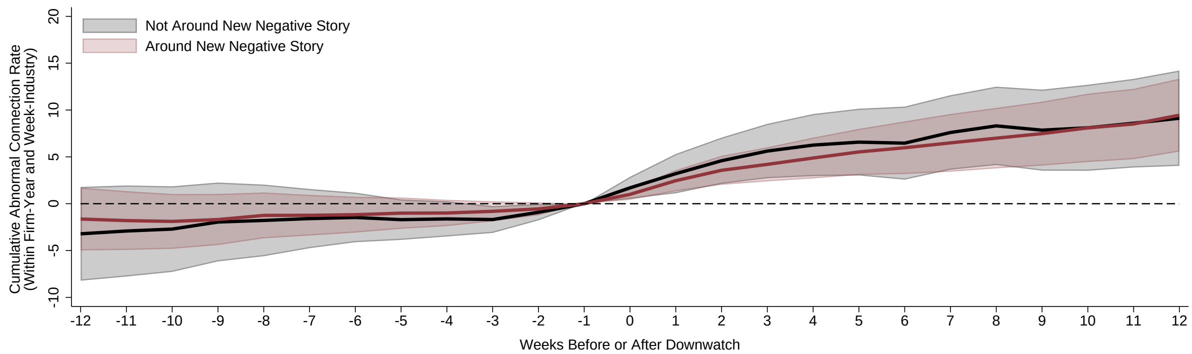
(c) Below Investment Grade



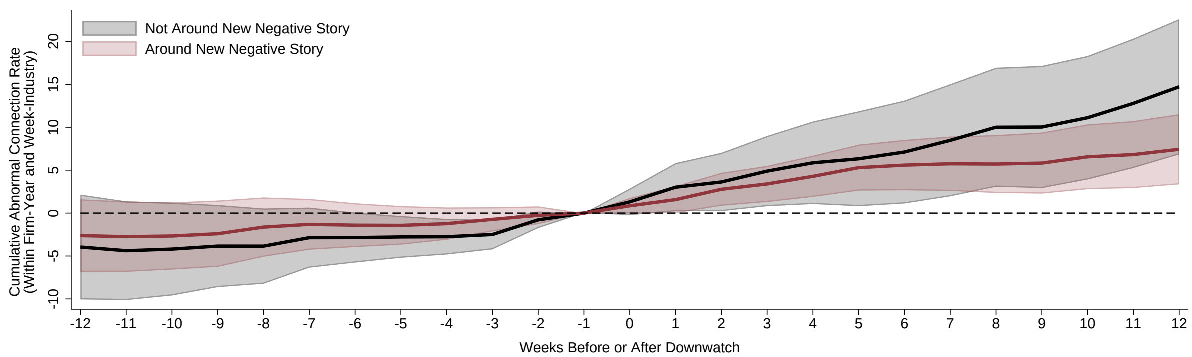
This figure shows the cumulative abnormal connection rate by week relative to the week before a new negative story for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. The unit of analysis is firm-week. Abnormal is what is left over after removing firm-year and week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_S = \sum_{s=-12}^{S} \hat{\beta}_s$ from model (9). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Figure G2: Connections Initiated by Week from Downwatch, by Media Coverage

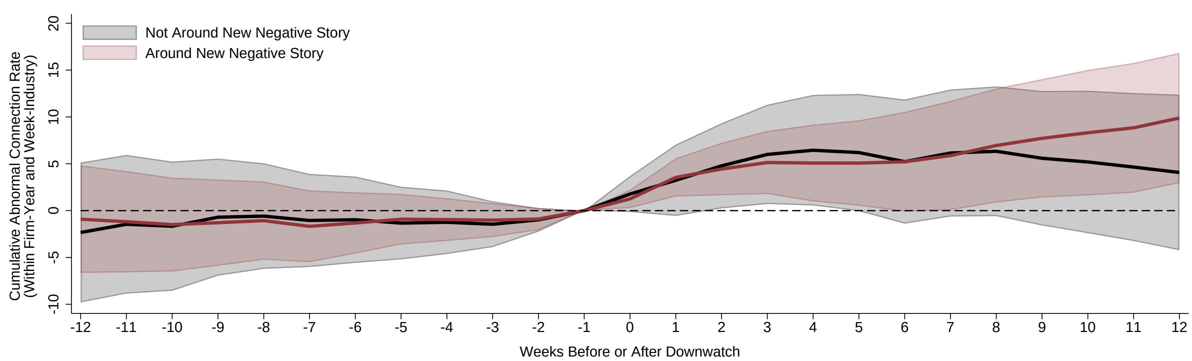
(a) All Firms



(b) Investment Grade



(c) Below Investment Grade



This figure shows the cumulative abnormal connection rate by week relative to the week before a downwatch for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. We define two subsets of downwatch events: events $e = 1$ that do not coincide with a new negative story in the week before, the week of, or the week after the downwatch, and events $e = 2$ that do coincide with a new negative story. The unit of analysis is firm-week. Abnormal is what is left over after removing firm-year and week-industry fixed effects. Industries are 3-digit NAICS codes. Estimates are $\hat{\delta}_{e,S} = \sum_{s=-12}^{S} \hat{\beta}_{e,s}$ from model (13). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a five week lag.

Table G2: Connections Initiated After New Negative Stories and Downwatches, by Media Coverage

	Connection Rate					
New Negative Story	0.36***	0.55***	0.20			
	(0.09)	(0.11)	(0.16)			
Downwatch				9.13***	14.72***	4.08
				(2.60)	(4.02)	(4.24)
Downwatch × Around New Negative Story				0.32	-7.28	5.81
				(2.98)	(4.90)	(4.72)
Mean Connection Rate	21.51	21.43	21.58	21.51	21.43	21.58
Sample of Firms	All	IG	Below IG	All	IG	Below IG
Firm-Year Fixed Effects	12,704	6,653	5,795	12,704	6,653	5,795
Week-Industry Fixed Effects	37,786	26,153	33,776	37,786	26,153	33,776
Pre-trend p-value	0.243	0.116	0.523			
Pre-trend p-value for Not Around New Negative Story				0.674	0.336	0.802
Pre-trend p-value for Around New Negative Story				0.850	0.599	0.892
R^2	0.809	0.831	0.805	0.809	0.831	0.805
Adjusted R^2	0.793	0.812	0.774	0.793	0.812	0.774
Observations	642,415	336,187	284,420	642,415	336,187	284,420
Firms	1,717	871	965	1,717	871	965
Weeks	519	519	519	519	519	519
Observations with New Negative Story	137,576	83,083	49,665			
Downwatches Not Around New Negative Story				255	98	152
Downwatches Around New Negative Story				382	198	171

This table provides estimates of new connections initiated in the 12 weeks following new negative stories and downwatches for three samples of firms. Columns 1 and 4 are our full sample. Columns 2 and 5 are for firms with BBB- credit ratings or better. Columns 3 and 6 are for firms with BB+ credit ratings or worse. Credit ratings are lagged by 24 weeks. The unit of analysis is firm-week. Industries are 3-digit NAICS codes. Estimates in Columns 1-3 are $\hat{\delta}_{12} = \sum_{s=-12}^{12} \hat{\beta}_s$ from model (9), while estimates in Columns 4-6 are $\hat{\delta}_{1,12}$ and $\hat{\delta}_{2,12} - \hat{\delta}_{1,12}$ where $\hat{\delta}_{e,12} = \sum_{s=-12}^{12} \hat{\beta}_{e,s}$ from model (13). Standard errors in parentheses are Driscoll-Kraay with a five week lag. Significance at the 10% level is denoted by *; 5%, by **; and 1%, by ***.