Labor Reactions to Credit Deterioration: Evidence from LinkedIn Activity*

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Abstract

We examine worker reactions to firms' credit deterioration using anonymized networking activity on LinkedIn. In the weeks immediately following a negative credit event, connection activity increases at affected firms across the credit rating distribution, pointing to costs beyond those originating from bankruptcy. Heightened networking activity is associated with contemporaneous and future departures, especially at highly-rated firms. Other negative events like missed earnings and equity sell recommendations do not trigger similar reactions. Overall, our results indicate that the latent build-up of connections triggered by credit deterioration represents a source of fragility for firms.

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Economists have long speculated that deteriorating financial conditions, or the prospect thereof, may prompt workers to contemplate leaving their firms, materially impacting firms' operations (see, e.g., Opler and Titman, 1994). In an economy where intangible capital represents a growing fraction of firms' capital (Peters and Taylor, 2017), workers' reactions to firms' financial conditions represent a potential source of fragility.[1] Beyond acute financial distress, however, we have little evidence for how workers respond to changes in their firms' financial conditions.

In this paper, we study how workers respond to their firm's credit deterioration across levels of firms' ex ante financial health. A growing body of evidence focused on firms nearing bankruptcy shows that there are labor costs to financial distress (Baghai et al., 2018; Brown and Matsa, 2016), and that labor considerations influence firms' ex-ante capital structure decisions (Matsa, 2018). A common thread is that credit deterioration adversely impacts workers through the risk of bankruptcy. The evidence on firms with strong financials is sparse. Should we expect a muted response to credit deterioration at firms distant from default?

Credit deterioration may trigger different concerns for workers depending on proximity to bankruptcy. Close to bankruptcy, firms may cut wages and ultimately lay off workers to stave off liquidation or reorganization. Workers may also be affected through other actions taken by the firm to avoid bankruptcy, such as liquidating assets and forgoing profitable investment opportunities. Anticipating these risks, workers may actively seek outside opportunities when the likelihood of default becomes material (Graham et al., 2019). We refer to this channel as the *bankruptcy risk channel*.

For firms with strong credit ratings, a minor deterioration in credit standing would only marginally increase the probability of default, and we would not expect the bankruptcy

[1] Workers not only constitute a firm's human capital, but are also integral to maintaining other forms of intangible capital, including organizational capital, intellectual property, and corporate culture.

risk channel to hold much sway. Workers may, however, still think strategically about their long-term opportunities, and revise their expectations downward in response to credit deterioration. To advance within an organization, workers often need to make firm-specific human capital investments to acquire skills and knowledge regarding its operations, relevant technologies, or organizational structure (Becker, 1962; Hashimoto, 1981; Carmichael, 1983). Building this human capital may increase worker-firm productivity, but it may not lead to a proportional increase in the worker's human capital *outside* of the firm. Perceived changes in opportunities within the firm can therefore adversely impact workers' incentives to make such investments, and may even motivate workers to search for new jobs. We refer to this channel broadly as the *human capital risk channel*.

Our work innovates on the existing literature in several ways. First, we show that employees respond to credit deterioration across the entire distribution of credit ratings, including at both investment grade and non-investment grade firms. Credit deterioration motivates workers to explore outside options, even when the threat of bankruptcy is remote, lending support to the the human capital risk channel. Second, we find that credit news triggers reactions not only in workers who leave, but also in those who initially remain at the firm. In contrast to previous studies that focus on realized employee moves, we study actions that precede departures: new connections initiated on LinkedIn, a professional networking platform. Greater connection activity by workers who initially remain is associated with higher future departure rates. This suggests that the latent build-up of connections triggered by credit deterioration represents a source of fragility for firms. Third, our empirical setting allows us to draw a tight link between labor and credit-related news. High frequency data on connection activity enables us to better isolate reactions to specific events and understand the dynamics of how credit deterioration affects workers. We show there is minimal abnormal activity in the weeks prior to credit news, but that connections start rising within a week following credit events.

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. 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.[2] To account for unobservable factors, such as seasonalities in sectoral labor markets and firm-specific economic conditions, we adjust for 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. Specifically, we find the propensity for workers to initiate new connections (or “connection rate”) at affected firms sharply increases in the weeks following a downwatch announcement, at both investment grade and non-investment grade firms.

Increased connection-making is associated with employees leaving, not only in the year of the credit event, but also in future years. The dynamics differ between investment grade and non-investment grade firms. At highly-rated firms, increased connection activity is driven by individuals who choose to leave in the same or the following year, with relatively fewer connections made by individuals who stay more than two years. At non-investment grade firms, those who leave and those who stay react at similar rates. This supports the idea that the dominant motive to seek outside options depends on the distance to default. Close to default, the bankruptcy risk channel appears to dominate: all employees take actions to insure themselves against the risk of layoffs. Further from default, however, the human capital risk channel dominates: workers with more valuable outside opportunities plan their

[2]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. In the Appendix, we show that our results are similar when using downgrades rather than downwatches.

exit more aggressively.

Departures at investment grade firms appear more likely to be voluntary. We do not directly observe whether moves are voluntary; instead, we examine the career advancement of individuals who leave (e.g., whether they move from an entry-level position to manager or vice versa). A worker whose seniority is lower at their new job than at the one they left ("demoted") is more likely to have moved involuntarily. A worker whose new position is of higher seniority than the one they left ("promoted") is more likely to have moved voluntarily. Close to default, the increase in connection activity is similar across promoted and demoted workers. Far from default, connection activity is more pronounced for workers moving to promoted positions.

Is there something special about credit deterioration, relative to other negative events? As a benchmark, we examine reactions to other economically significant disclosure events that signal negative information, including missed earnings and equity sell recommendations. If workers are reacting to signals of economic deterioration, then we should observe significant reactions following the disclosure of bad performance. Our evidence broadly suggests a "specialness" to credit events. We find no significant networking activity following missed earnings or equity sell recommendations, which are typically followed by stock market reactions at least as large as the reactions to credit events.

In the intensive margin, we also find evidence that reactions to credit deterioration are informationally driven. Within the subset of downward credit watch events in our sample, we further categorize events into "sudden events," or credit watches that are triggered by revelation of new information, and "slow events," which reflect increasing credit risk as a result of slow-moving macroeconomic conditions. We find a stronger reaction in the weeks following sudden events, which supports the idea that learning takes place through credit rating agency disclosures.

Our results suggest a feedback effect between financial and labor factors. First, we find significant network activity by workers who eventually leave their firm in future years. 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.

A closer look at the cross-section of reactions further points to loss of human capital. In addition to general heightened activity and turnover, we find that reactions are strongest among more senior workers. Senior workers need to make more consequential firm-specific investments, and may be more sensitive to changes in opportunities within the firm. The stronger reaction of senior workers suggests that credit deterioration can damage a firm's organizational capital by thinning mid- and high-level ranks.

Finally, we provide suggestive evidence that labor reactions to credit deterioration are tied to real implications for firms. We cannot verify the direction of the relation with our event-study approach because data on firm decision-making is much slower-moving than employee connection-making. Nonetheless, we show that firms that experience stronger labor responses to negative credit events see larger spikes in turnover and larger drops in profitability. These effects start in the same year as the credit events and last up to one year afterward. Our results expand on the link between labor and finance: firms face labor repercussions to their financial decisions not only when they are close to distress, but also when they are financially healthy.

Our paper contributes to a growing literature that studies the interaction between labor and capital structure. Existing studies have identified several channels through which financial distress can impact workers' welfare. For example, the threat of distress can impact workers' bargaining power and wages (Matsa, 2010; Benmelech et al., 2012; Graham et al., 2019). Distress may also lead to competitors poaching key employees (Opler and Titman, 1994), affect product quality through its impact on managerial incentives (Phillips and Sertsios, 2013), and worsen firms' abilities to attract talent (Brown and Matsa, 2016). Baghai et al. (2018) find that talented workers choose to leave firms as they near bankruptcy, and

Babina (2017) finds that higher-quality workers tend to leave distressed firms to become entrepreneurs. Prior work largely focuses on firms close to or in financial distress. In contrast, we show that labor responds to news of credit deterioration even when distress is not immediately on the horizon; indeed, the human capital risk channel motivates workers even at well-rated firms. Our weekly data also allow us to show that workers start reacting immediately, and that the effect is robust to controlling for slow-moving firm trends.

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). Our paper provides an additional motive for this relationship, and supports a broader view of when labor should be a consideration for firms' capital structure decisions.

Our paper also contributes to a literature that studies the role of social networks in labor markets. With 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). Studies have documented significant referral and neighborhood effects in labor market dynamics (Bayer et al., 2008), as well as increased search activity and job flows leading up to takeover announcements and poor stock returns (Agrawal and Tambe, 2019; Agrawal et al., 2020), and in response to downturns (Bernstein et al., 2020). This suggests that workers' investments in expanding and strengthening their networks could directly impact labor market dynamics. Our paper shows explicit evidence of this dynamic 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 provide evidence for a new driver of network formation: the credit deterioration of employers.

I. Data

A. LinkedIn Network Data

Our main data source is LinkedIn, an online professional networking platform which began in 2003 and currently has over 722 million global users. We obtain 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 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 a given week.

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. Table I presents summary statistics. In figures, connection rates are weekly and cumulative. In regression tables, connection rates are annualized (i.e., we multiply the weekly rate by 52) to allow for easier comparison with other annual outcomes.

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 I also presents summary statistics for employment information. The average firm in our sample has 14% of employees leaving in year y.

We group seniority levels into three categories: S1 represents entry-level employees, as well as a small fraction of unpaid and training individuals; S2 represents mid-level employees in more senior and manager-level positions; and S3 is the most senior group, representing anyone from a director or VP-level position to executives and owners. S1 employees represent 26% of our sample; S2 employees, 54%; and S3 employees, 20%.

B. Sample Construction

We manually match LinkedIn data with Compustat. Using Compustat as an intermediate dataset provides some 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.

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 ("downwatch") or downgrades the issuer. We compare rating events with missed or "low" earnings, equity sell recommendations ("down-recs"), and other important corporate events.

Our 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. Appendix B provides more details about our data.

To dampen the effects of outliers, we winsorize continuous variables at the 1 and 99% levels. Table I 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 II counts the number of ratings, recommendations, and earnings events in the sample at weekly and yearly frequencies. In Figures I and II, we plot the share of downwatches and downgrades that are preceded or followed by other negative events. More than half of the downwatches in our sample occur in the same week as a downgrade or are followed by a downgrade in the next 12 weeks. On the other hand, downgrades are far more likely than downwatches to be preceded by other negative credit events and missed earnings. In the Appendix, we show that our results are robust to isolating downwatches from other events by considering only downwatches that are neither preceded nor followed by other credit events.

II. Empirical Approach

We use an event-study framework to measure the effect of credit deterioration news on each firm's connection rate. Our baseline regressions are based on a generalized difference-in-differences (DiD) approach, with which we compare the 12 weeks following an event to the rest of the year. We report weekly estimates as well as an average estimate over the 12 weeks following a downwatch. Results are also robust to using shorter windows. We include week, or week-by-industry, fixed effects to absorb time components, including pre- and post-periods. We also include firm, or firm-by-year, fixed effects to absorb static differences between firms that experience credit deterioration and those that do not. Looking at the total connection rate following a downwatch, our most saturated specification for firm i in industry $j(i)$, week t, and year $y(t)$ is the following:

$$(\text{Connection-Making Rate})_{it} = \beta(\text{Post-Downwatch})_{it} + \gamma_{j(i)t} + \theta_{iy(t)} + \epsilon_{it}. \tag{1}$$

We look within firm-year at a weekly frequency to alleviate concerns about confounding economic trends. The identifying assumption for this approach is that within the year, the exact week that a firm is placed on negative watch is quasi-random with respect to employees'

LinkedIn activity.

To support this assumption, we adapt a common approach in finance and report event-study graphs for all regressions that show the evolution of connection rates from 12 weeks before to 12 weeks after the event. The graphs center on the week prior to the event and cumulate left for the pre-period and right for the post-period. Specifically, we estimate "abnormal" new connections in downwatched firms for each week relative to the week before the event, removing variation that can be explained with week-by-industry, firm-by-year, or other relevant fixed effects. From the center of the graph to the left, we cumulate the "abnormal" new connections estimates from 1 to 12 weeks before the event to understand pre-downwatch activity. We then repeat the exercise toward the right to understand behavior in the post-period. All regression tables corresponding to figures can be found in Section *A*.

For example, in Figure III, we do this for total connections initiated. In the periods preceding the downwatch, the cumulative abnormal connection rate is close to zero. Starting in the week of the downwatch, we see an immediate increase in connection rates, which is sustained up to 12 weeks after.

In our baseline approach, we use Driscoll-Kraay standard errors with a five week lag (Driscoll and Kraay, 1998; Hoechle, 2007). For later regressions at an annual frequency, we double-cluster by firm and year. We prefer Driscoll-Kraay standard errors in our weekly regressions because they allow for serial correlation to degrade for observations that are further apart. Results are very similar when we use double-clustered standard errors.

III. Negative Credit Events and Connection Rates

We examine whether workers increase their networking activity following the announcement of a downwatch for their firm. Table III reports DiD estimates with different fixed effects. The estimates represent the average effect in the 12 weeks following the event relative to the rest of the year. The third column corresponds to the specification used in

Figure III, with week-by-industry and firm-by-year fixed effects. As the figure shows, connection rates start to increase immediately after a downwatch, and our results do not depend on the 12-week window used in Table III.

The results show a consistent pattern, with smaller estimates for specifications including progressively more granular fixed effects. Following a downwatch, affected firms experience a statistically significant increase in the connection rate of their workers. Our estimates indicate that weekly connection rates are 2.7% to 4.6% higher than average in the 12 weeks following a downwatch. This is equivalent to moving a firm from the 50th percentile of the connection rate distribution to the 60th-65th percentile, after removing fixed effects.

Our results hold with firm-by-year fixed effects, which suggests that these differences are not driven by lower frequency factors regarding the economic conditions and outlook of the affected firms. A concern could be that workers' networking behavior varies by industry. In particular, firm-level networking activity could be driven by seasonal patterns of sector-specific labor market dynamics. To account for this, we include week-by-industry fixed effects. Across our specifications, we find a strong positive relationship between downwatch disclosures and workers' networking activity. In the Appendix, we show that this relationship holds also for downgrades, and in particular, for "unexpected" downgrades—those not preceded by downwatches or other events.[3]

Our focal question is whether workers react to credit deterioration at all firms, including those with strong credit ratings. If labor reactions to credit deterioration are primarily driven by bankruptcy-related costs borne by workers, we should expect that our results arise predominantly from firms near or in financial distress. Through the bankruptcy risk channel, workers observing a downward credit event may form new connections in an effort to expand outside opportunities as their firm's default risk becomes more material.

To test this prediction, we group firms into three bins by ex ante rating at the start of the

[3]See Table DXI and Figure D1 for results for downgrades and unexpected downgrades.

year: highly rated (A or better), investment grade (BBB- to A-), and below investment grade (BB+ or worse). When rating agencies disagree, we use the higher rating as a tie breaker, but this does not affect results. Among the sample of firms that experience a downwatch, roughly 15% are highly rated firms, 40% are other investment grade firms, and 45% are below investment grade.

Figure IV shows connection activity after downwatches, broken down into each group of credit ratings. We find that all firms experience heightened connections rates after credit deterioration, including highly rated firms. Labor reactions are slightly stronger for below investment grade firms immediately following the downwatch, but connection activity at highly rated and other investment grade firms quickly catches up. This shows workers react to news about credit deterioration despite their firm being distant from imminent financial distress.

We propose the following channel, which we refer to as the human capital risk channel, to explain this phenomenon. For a long-term work-firm match to be productive, a worker may need to make investments in firm-specific human capital. These investments include acquiring firm-specific knowledge or information regarding the underlying operations, technologies, organizational structure, and culture of the firm. Workers considering such investments must base their decisions on the long-term expected value of this human capital, which increases their productivity within the firm, but may not lead to a proportional increase in their human capital outside of the firm. Changes in expectations regarding opportunities within the firm can adversely impact workers' incentives to make such firm-specific investments and may motivate workers to seek outside options. The human capital risk channel thus predicts that workers would react to changes in a firm's financial conditions even if the firm is distant from default.

Our results offer evidence that the relationship between labor and finance is broader than previously documented. The results are consistent with both the bankruptcy risk and the human capital risk channels; we explore this in further detail in Section IV.

IV. Motives for Network Formation

Our results show a robust and significant increase in networking activity following negative credit news, across the distribution of credit ratings. What motivates workers to respond to financial deterioration? We explore possible explanations below. These explanations are distinct but not necessarily mutually exclusive, and we try to understand their relative importance in different settings.

A. Bankruptcy Risk and Human Capital Risk Channels

Workers' networks form the basis for outside options, and new connections improve the set of future opportunities when workers choose to leave their current firm. Indeed, existing studies have shown that workers' networks may directly impact current and future labor market outcomes (e.g. Montgomery, 1991; Calvo-Armengol and Jackson, 2004). If workers perceive their firm's credit deterioration to be a negative signal about future opportunities—within or outside of the firm—they may want to shore up their network as a way of offsetting potential losses.

Networking acts a form of precautionary action in anticipation that a worker may want to move firms or re-enter the labor market. 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 as part of brushing up their profile. Even casual networking can help improve future opportunities, as it expands the worker's second- and third-degree connections, and increases their visibility and credibility within the platform. In this way, expanding one's network may improve the outcome of future job searches.

Why a firm's credit deterioration triggers networking can, however, depend on the firm's condition. A prominent channel operates through the costs borne by workers near or during bankruptcy. Studies have found that workers at firms under financial distress tend to experience both pecuniary and non-pecuniary negative outcomes, including wage cuts, worsening working conditions, and unemployment (Matsa, 2010; Benmelech et al., 2012; Graham et al., 2019). As a consequence, financial distress pushes workers to pursue outside opportunities (Baghai et al., 2018). In our context, at firms where credit deterioration reflects material increases in bankruptcy risk, workers may cultivate outside opportunities through networking activity in anticipation of the real possibility of a job move, whether voluntary or not.

However, even at firms far from distress, credit deterioration appears to signal relevant information for workers, evidenced by heightened networking activity. As introduced in Section III, we argue that a second channel, hinging on human capital risk, operates in addition to the bankruptcy risk channel.

Workers may continuously evaluate the long-term value of remaining at a firm when they are required to make firm-specific human capital investments. These investments may be in the firm's operations, technologies used by the firm, or organizational structure. While building this human capital may be vital for worker-firm productivity, it may not lead to a proportional increase in the individual's human capital outside of the firm. As a result, credit deterioration could result in downward revisions in expectations about the firm's long-term prospects and opportunities. Even absent the risks associated with bankruptcy, credit deterioration could thus prompt workers to form outside connections, especially for those interested in leveraging their network in their next career move.

Of course, workers who face bankruptcy risk also take into account the risks that credit deterioration poses to their human capital. For both channels, credit deterioration signals potential concerns and prompts workers to initiate connections as a way of exploring outside opportunities. However, the existing literature emphasizes the risks born from bankruptcy. Distinguishing between the two channels is important to explain workers' response to credit deterioration outside of material financial distress. The mechanism through which workers are impacted differs across the two channels. Under the human capital risk channel, workers respond to the perceived value of within-firm human capital; under the bankruptcy risk channel, workers respond to expected costs from bankruptcy.

These distinctions yield different predictions in the cross-section. Under the bankruptcy risk channel, we expect everyone to react. Whether or not they wish to leave, workers connect to insure themselves against the risk of incurring costs from financial distress. In contrast, the human capital risk channel emphasizes the tradeoff for workers with favorable outside opportunities. Reactions may thus be limited to individuals with better outside opportunities, and to those who are more actively considering leaving.

To shed light on the underlying motive, we use matched employment histories to compare the connection activity of workers who are no longer employed at the firm in the next calendar year ("leaving") with the activity of workers who are still employed by the firm in the following year ("staying"). We augment Specification (1):

$$\begin{aligned}(\text{Connection-Making Rate})_{igt} = \beta_1(\text{Post-Downwatch})_{it} + & \\ + \beta_2(\text{Post-Downwatch})_{it} \times \text{Leaving}_g + & \\ + \gamma_{j(i)gt} + \theta_{igy(t)} + \epsilon_{igt} & \end{aligned} \tag{2}$$

where Leaving_g is an indicator for the group of workers no longer at the firm in the following calendar year.[4] With Specification (2), we can isolate the contribution to connection activity made by workers who are leaving relative to those who are staying.

The top panel in Figure V shows our results. Consistent with the idea that connections are formed to improve outside options, we find that workers who end up leaving their firm contribute more to the reaction following a downwatch. In the bottom panels, we compare

[4] "Bad control" problems can arise when regressions include time-varying controls that respond to the treatment (Angrist and Pischke, 2008). Leaving_g is constant and there is no composition change in the leaving group between the pre- and post-periods.

investment grade firms (BBB- or better) with those that are below investment grade (BB+ or worse). We find that connection-making rates for leaving workers are highest at highly rated firms. In contrast, 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 is consistent with different underlying motives at each end of the credit rating spectrum. For firms in or near financial distress, all workers may be affected, and workers may be forming connections out of necessity to minimize the costs of potentially losing their jobs. For highly rated firms, workers may be making strategic decisions regarding their long-term career choices. Indeed, in subsection B we show that among employees leaving investment grade firms, connection-making is driven by those moving to positions of equal or higher seniority, while among employees leaving junk firms, connection-making is driven more by those leaving to positions of lower seniority.

More generally, the increased connection activity in both leaving and staying groups points to a precautionary motive: some of the activity may lead to new positions, and some may not. If workers are driven by concerns about the long-term prospects of their firm, then we should expect connection activity to be associated with more distant future departures as well. To address this, we create an additional category of workers who leave in the year after a credit event. This allows us to 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.

Figure VI shows the results for the full sample in panel (a), for investment grade firms in panel (b), for and below-investment grade firms in panel (c). In the full sample, all three categories display 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. In other words, connection activity in the weeks immediately following negative credit news is associated with departures a year later. Panels (b) and (c) show that the differentiation is driven by investment grade firms. At firms with below-investment grade ratings, responses are nearly identical for staying and leaving employees. This further points to different underlying motives depending on the proximity to bankruptcy. Above investment grade, reactions are driven by those with better outside opportunities. As financial distress becomes a serious prospect, that distinction fades.

Moreover, these results carry an important implication for firms, especially those above investment grade. Even if workers do not leave their firms immediately as a response to credit news, the connections prompted by credit deterioration could broaden outside options of workers, and facilitate future moves when the outlook of the firm fails to improve. These delayed departures represent a fragility for firms that is not apparent in immediate departures after credit deterioration, but instead manifests in a lagged fashion. We revisit this point in Section V.

B. Alternative Explanations

In this section, we explore other possible explanations for the increased networking activity following negative credit watches.

Our results indicate a relation between networking activity and departures. This opens the possibility that negative credit events may coincide with layoffs at the firm. If that was the case, then increased networking activity would also reflect job search efforts by recently unemployed workers, rather than just strategic reactions to worsening financial conditions.

Figures V and VI show that, although employees leaving in the event year respond the most, employees who stay or leave in the future also increase their connection activity. Therefore, direct layoffs alone cannot explain all of our results. We also show in Figure VII that connection rates are similar among employees who are likely to be leaving on a voluntary or involuntary basis. We infer that a departure is more likely to be voluntary if the seniority of the departing individual's next position is higher than that of the departed position, and that a departure is more likely to be involuntary if the next position is of lower seniority. Connection-making responses to downwatches are similar for workers leaving to positions of higher, lower, and same seniority, indicating that the response is not limited to layoffs.

A related concern may be that firms are not directly laying off workers, but encouraging them to leave by offering enticing exit packages, for example, or by announcing plans for future layoffs. Certainly, we would expect both actions to spur employees to look elsewhere and eventually leave. To an extent, these events also fit into the idea of worse long-term opportunities at the firm, to which workers respond by exploring outside opportunities. However, the difference lies in whether the employee responses we observe are desired by the firm, or whether they represent costs that the firm would want to avoid.

Overall, we believe the employee responses we document represent costs for the firm rather than desired outcomes, for several reasons. First, connection activity is associated with departures to higher-seniority positions, especially at investment grade firms. This suggests that departures are voluntary, and that the departing individuals are talented enough to garner promotions elsewhere. Second, our analysis focuses on downwatches. Downwatches represent revisions on outlooks, but they do not directly impact the cost of capital, as they stop short of changing firms' ratings. It would be unlikely for firms with strong ratings to respond to revisions in credit outlooks by reorganizing their labor force, especially by pushing out workers with attractive outside options. Third, we show evidence in subsection D that connection activity is more pronounced for sudden news. In contrast, we would expect firms to encourage exits in reaction to broader persistent issues, rather than in response to sudden developments. Lastly, we see significant connection responses even from workers who remain for several years, indicating that not all reactions can come from workers who are pushed out.[5]

[5]Table AII shows results by leaving status at years $y + 2$ and $y + 3$. Estimates become noisier as we condition on narrower groups of individuals, but we continue to see increased connections even among

Another plausible reason for increased connection activity could be that negative credit events lead to new or renewed emphasis on certain tasks. 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. It could also reflect efforts by the firm to scout new employees. All of these activities could then lead to additional connections.

In this case, connection activity should be higher among employees who *stay* with the firm, as it represents employees doing their job well. This is contrary to what we observe in Figures V and VI. Heightened connection-making among employees who eventually leave suggests that our core result cannot be explained by employees in certain occupations increasing networking activity to support their firms. In the Appendix, we show that connection-making responses are spread across many different occupations, not only executives or sales representatives.[6]

C. "Specialness" of Credit Deterioration Events

So far, we have focused primarily on negative credit events indicative of credit deterioration. Naturally, credit rating disclosures often coincide with and are triggered by signals of worsening economic outlook of the firm. This opens the possibility that workers may generally tend to increase their connection activity in response to *any* negative news about the firm. An interesting and relevant question is whether reactions to credit news differ from reactions to other significant forms of negative economic news about firms.

We consider two types of events that communicate negative economic news, but not credit deterioration per se. The first is a substantial negative deviation from consensus earnings. We view missed earnings as fairly salient events that reflect the firm's economic condition,

workers staying at $y + 3$.

[6] See Figure D7a for results by occupation and Figure D7b for results dropping one occupation at a time.

and report results in Figure VIII.[7] As documented in past studies, markets show a sharp and timely negative reaction to negative earnings surprises. This market reaction is within the same order of magnitude as the market reaction to downwatches, with a cumulative abnormal return (CAR) of about -4% (see Figure IX).[8] Running Specification (1) with negative earnings surprises, we find a fairly tightly estimated zero: workers do not appear to change their networking activity following a negative earnings surprise.

We also do not see a run-up of activity in the 12 weeks prior to a missed earning, indicating that workers do not react in anticipation of the event either. This is interesting given the well-documented importance of missed earnings in the literature and the clear negative market reaction. We believe this reflects a different set of concerns for rank-and-file employees relative to shareholders. In particular, this suggests that, with regards to networking activity, workers care more about negative financial news than they do about other negative economic news such as missed earnings.

The second type of event we consider is a "sell" recommendation for equity.[9] Like missed earnings, these represent negative economic news about the firm and trigger negative reactions on the part of shareholders. However, workers do not appear to increase networking activity much following these events (Figure VIII). We conclude that workers perceive credit deterioration as worse for their prospects than equity and accounting underperformance.

Another possibility is that workers respond to negative media coverage of their firms, which includes news about negative credit events. In Appendix C we study data from RavenPack, an aggregator of news stories, to track news coverage of firms at the time of credit events. We find that negative stories are correlated with connection-making activity

[7] As described in Appendix B, we define missed earnings events as a week in which an earnings report's consensus error is less than the 10th percentile for that year.

[8] 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.

[9] We describe how we construct this variable in Appendix B.

but do not drive the response to credit events.

D. Information Content of Credit Rating Agency Signals

Our results so far show that workers systematically increase their networking activity in the same week that credit rating agencies (S&P and Moody's) issue negative signals about the firm's credit condition. An interesting question is 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 the 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 X 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.

V. Implications for Firms

Having established that workers increase their connection activity in response to firms' credit deterioration, we turn our attention to implications for firms. We first discuss employee outcomes and then consider the effect on other real outcomes for the firm.

A. Employee Outcomes

One obvious implication of our results is that firms may lose employees who ramp up their networking activity in response to credit deterioration. Figures V and VI already indicate that connection activity is associated with departures, and Figure VII shows that this includes employees who find promotions elsewhere. In this section, we show that credit deterioration is 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.[10] Table IV shows that connection-making is unconditionally predictive of higher departure rates, as are downwatches. Since employment histories are annual, the results in Table IV are also at an annual level.

We create an annual version of event studies to understand the dynamics in years leading up to and following credit events. We examine firms that experience a negative credit event (downgrade or downwatch) in year y and use total initiated connections in year y divided by the number of LinkedIn profiles at the beginning of the year as an annual measure of connection-making. High connection-making firms are those with year y connections above median. Figure XI shows that firms with higher connection-making rates in the year of a credit event experience much higher departure rates that year and the following year. Along with Figure VI, the results tie future departures to employees' reaction to credit deterioration.

It is hard to estimate the cost of potential lost productivity from those employees who

[10]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.

stay but are looking for alternatives. However, 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 US rely mostly on older data, yet direct and indirect hiring costs are similarly estimated at about 8 weeks of wage payments (Dolfin, 2006).

B. Cross-sectional Patterns: Who Connects?

Who reacts the most to credit events? To examine this, we turn to the cross-section of worker attributes. We examine whether there are significantly different reactions by workers of different seniority levels.

We may expect more senior workers to respond more strongly or weakly to credit rating events depending on several factors. On one hand, senior workers may have greater and timelier access to information about the true underlying financial conditions of the firm. While deteriorating financial conditions could motivate greater networking activity by senior workers, this activity would not necessarily follow the arrival of credit rating events, which are more indicative of information revelation outside of the firm.

On the other hand, the financing conditions of the firm may be directly impacted by credit rating agencies' disclosures (Boot et al., 2005). Senior workers' compensation is more likely to be contingent on the performance and financial health of the firm, so greater seniority may come with a greater reaction following a downwatch. More senior workers may also be more sophisticated in their understanding of what a downwatch or a downgrade represents for the firm.

To analyze whether there are significant differences in reactions to credit deterioration between workers of different seniority, we first split each firm-week observation into two observations: one for entry-level employees, and another for all employees more senior than that. On average, entry-level employees represent 26% of a firm's employees in our sample.

We show these results in Figure XII. Both senior and junior workers show increased connection-making after the credit event, but we find that senior-level workers drive the networking reaction.

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 54% of a firm's employees in our sample, and most senior, 20%.

We report results in Figure XIII. Broadly speaking, the estimates support a monotonic relationship between seniority and the intensity of reactions to downwatches: the increase in connection activity following a downwatch event is higher as we go up in seniority, although the difference is not always statistically significant. We know from the summary statistics in Table I that baseline connection rates increase with seniority. Our specification includes fixed effects interacted with seniority to account for that baseline difference. When we compute the implied increase relative to group means, the total implied increase remains increasing in seniority.

The results indicate that credit deterioration events trigger reactions among some of the firm's most valuable and hard to replace employees. In the Appendix, we show that skilled employees also seem to react more strongly than other employees. To the extent that this activity indicates an increase in potential future departures, the results indicate potentially large labor costs.

C. Firm Outcomes

Finally, we investigate whether labor responses to credit events appear to have any relationship with other firm outcomes, such as profitability. We cannot verify the direction of this relationship with our weekly event-study approach because data on firm decision-making is much slower-moving than employee connection-making. Instead, we use annual event studies comparing high- and low-connection-making firms, similar to our analysis of departure rates in Figure XI.

Figure XIV shows that firms with above-median connection activity in response to credit events have significantly worse profitability in the year of the credit event, relative to other firms that experience negative credit events but whose employees react less strongly. There is no divergence in years prior to the credit event, but high connection-making firms continue to lag behind their counterparts in the year following the credit event, after which they catch up.

VI. Conclusion

We examine labor reactions to firm financial news. We show that workers systematically respond to signals of credit deterioration, even when the firm is far from default. We argue that in addition to the bankruptcy risk channel that has been the focus of the existing literature, there is a human capital risk channel that can tie human capital to the firm's credit condition even when bankruptcy is not on the horizon. When a firm's credit condition deteriorates, even if it is still financially healthy, workers may perceive that internal opportunities are diminished, increasing the attractiveness of exploring outside opportunities. We find evidence consistent with the existence of both channels.

The networking activity triggered by negative credit events results in a latent build-up of connections that represents a source of fragility for firms. We find connection activity especially increases among workers who eventually leave, not just in the year of the event but also for those who leave in subsequent years. In financially healthy firms, connections are especially associated with departures to higher-seniority positions, consistent with voluntary departures of valuable employees. Reactions are also strongest for senior workers, who represent an essential segment of the firm's organizational and human capital. Indeed, credit events followed by stronger reactions also correspond to larger drops in profitability in following years. These results suggest that credit deterioration could lead to a negative feedback loop between financial conditions of the firm and its intangible capital.

Our findings shed new light on how and when workers respond to worsening financial conditions at their firm. We learn that workers react even when the firm is far from bankruptcy. Other economic news, like missed earnings and equity sell recommendations, do not trigger an equivalent response. Taken together, our results suggest that there is 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.

References

Agrawal, Ashwini K and David A Matsa, "Labor unemployment risk and corporate financing decisions," *Journal of Financial Economics*, 2013, *108* (2), 449–470.

_ **and Prasanna Tambe**, "Takeovers and endogenous labor reallocation," *Available at SSRN 3369831*, 2019.

_ **, Isaac Hacamo, and Zhongchen Hu**, "Information Dispersion Across Employees and Stock Returns," *Kelley School of Business Research Paper*, 2020, (18-47).

Angrist, Joshua D and Jörn-Steffen Pischke, *Mostly harmless econometrics: An empiricist's companion*, Princeton university press, 2008.

Babina, Tania, "Destructive Creation at Work: How Financial Distress Spurs Entrepreneurship," Technical Report, US Census Bureau, Center for Economic Studies 2017.

Baghai, Ramin, Rui Silva, Viktor Thell, and Vikrant Vig, "Talent in distressed firms: Investigating the labor costs of financial distress," *Available at SSRN 2854858*, 2018.

Bayer, Patrick, Stephen L Ross, and Giorgio Topa, "Place of work and place of residence: Informal hiring networks and labor market outcomes," *Journal of Political Economy*, 2008, *116* (6), 1150–1196.

Becker, Gary S, "Investment in human capital: A theoretical analysis," *Journal of political economy*, 1962, *70* (5, Part 2), 9–49.

Benmelech, Efraim, Nittai K Bergman, and Ricardo J Enriquez, "Negotiating with labor under financial distress," *The Review of Corporate Finance Studies*, 2012, *1* (1), 28–67.

Berk, Jonathan B, Richard Stanton, and Josef Zechner, "Human capital, bankruptcy, and capital structure," *The Journal of Finance*, 2010, *65* (3), 891–926.

Bernstein, Shai, Richard R Townsend, and Ting Xu, "Flight to safety: How economic downturns affect talent flows to startups," Technical Report, National Bureau of Economic Research 2020.

Blatter, Marc, Samuel Muehlemann, and Samuel Schenker, "The costs of hiring skilled workers," *European Economic Review*, 2012, *56* (1), 20–35.

Boot, Arnoud WA, Todd T Milbourn, and Anjolein Schmeits, "Credit ratings as coordination mechanisms," *The Review of Financial Studies*, 2005, *19* (1), 81–118.

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

Calvo-Armengol, Antoni and Matthew O Jackson, "The effects of social networks on employment and inequality," *American economic review*, 2004, *94* (3), 426–454.

Carmichael, Lorne, "Firm-specific human capital and promotion ladders," *The Bell Journal of Economics*, 1983, pp. 251–258.

Chiang, Chin-Han, Wei Dai, Jianqing Fan, Harrison Hong, and Jun Tu, "Robust Measures of Earnings Surprises," *The Journal of Finance*, 2019, *74* (2), 943–983.

Correia, Sergio, "Linear Models with High-Dimensional Fixed Effects: An Efficient and Feasible Estimator," Technical Report 2017. Working Paper.

Dolfin, Sarah, "An examination of firms' employment costs," *Applied Economics*, 2006, *38* (8), 861–878.

Driscoll, John C and Aart C Kraay, "Consistent covariance matrix estimation with spatially dependent panel data," *Review of economics and statistics*, 1998, *80* (4), 549–560.

Graham, John R, Hyunseob Kim, Si Li, and Jiaping Qiu, "Employee costs of corporate bankruptcy," Technical Report, National Bureau of Economic Research 2019.

Hashimoto, Masanori, "Firm-specific human capital as a shared investment," *The American Economic Review*, 1981, *71* (3), 475–482.

Hoechle, Daniel, "Robust Standard Errors for Panel Regressions with Cross–sectional Dependence," *Stata Journal*, 2007, *7* (3), 281–312.

Matsa, David A, "Capital structure as a strategic variable: Evidence from collective bargaining," *The Journal of Finance*, 2010, *65* (3), 1197–1232.

_ , "Capital structure and a firm's workforce," *Annual Review of Financial Economics*, 2018, *10*, 387–412.

Montgomery, James D, "Social networks and labor-market outcomes: Toward an economic analysis," *The American economic review*, 1991, *81* (5), 1408–1418.

Muehlemann, Samuel and Mirjam Strupler Leiser, "Hiring costs and labor market tightness," *Labour Economics*, 2018, *52*, 122–131.

Opler, Tim C and Sheridan Titman, "Financial distress and corporate performance," *The Journal of finance*, 1994, *49* (3), 1015–1040.

Peters, Ryan H and Lucian A Taylor, "Intangible capital and the investment-q relation," *Journal of Financial Economics*, 2017, *123* (2), 251–272.

Phillips, Gordon and Giorgo Sertsios, "How do firm financial conditions affect product quality and pricing?," *Management Science*, 2013, *59* (8), 1764–1782.

Table I: Summary Statistics

	Mean	SD	25th	50th	75th	Count
Weekly LinkedIn Variables						
Employees on LinkedIn	2,841	5,785	234	803	2,502	652,455
S1 Share (Entry)	0.260	0.100	0.190	0.252	0.324	652,455
S2 Share (Mid-Level)	0.534	0.102	0.478	0.544	0.602	652,455
S3 Share (Most Senior)	0.203	0.118	0.117	0.177	0.263	652,455
Leaving Share	0.141	0.067	0.099	0.130	0.170	652,455
Leaving Next Year Share	0.116	0.058	0.081	0.107	0.139	586,519
Initiated Connections	1,239	2,535	73	307	1,087	652,455
Connection-Making Rate	0.413	0.240	0.237	0.384	0.545	652,455
S1 (Entry)	0.286	0.218	0.136	0.245	0.380	645,204
S2 (Mid-Level)	0.396	0.244	0.219	0.367	0.526	647,937
S3 (Most Senior)	0.647	0.433	0.333	0.593	0.874	645,757
Staying	0.385	0.228	0.219	0.355	0.506	651,921
Leaving	0.582	0.412	0.288	0.522	0.791	639,899
Staying Next Year	0.344	0.211	0.191	0.315	0.457	585,316
Leaving Next Year	0.469	0.352	0.222	0.417	0.638	573,620
Yearly LinkedIn Variables						
Employees on LinkedIn	2,989	6,067	253	855	2,625	12,911
Leaving Employees	423	865	33	120	376	12,911
Leaving Share	0.146	0.069	0.103	0.134	0.176	12,911
S1 (Entry)	0.198	0.099	0.137	0.184	0.246	12,787
S1/S2 (Senior)	0.127	0.065	0.086	0.116	0.155	12,887
Yearly Compustat Variables						
Total Employees	27,838	53,402	2,241	7,600	26,734	12,793
Assets (Dollars, Billions)	39.050	136.389	1.975	5.295	18.415	12,905
Profitability	0.123	0.089	0.069	0.114	0.168	12,243

This table presents summary statistics for our sample. All observations are at the firm-time level. S1 employees correspond to entry-level, unpaid or training employees. S2 employees include senior and manager-level employees. S3 employees include directors, VPs, and executives. Profitability is annual operating income before depreciation scaled by last year's assets.

Table II: Event Counts

	Weekly	Yearly
Downwatches	898	743
Upwatches	324	311
Downgrades	2,242	1,559
Upgrades	2,045	1,723
Downrecs	7,380	4,630
Uprecs	7,056	4,547
Low Earnings	2,274	1,711
High Earnings	2,449	1,872

This table presents counts for the events in our sample. Please refer to Section B for event definitions or Appendix B for more detail.

Table III: Connections Initiated After Downwatches

	Annualized Connection-Making Rate		
Downwatch	0.978***	0.710***	0.585***
	(0.133)	(0.113)	(0.115)
Firm Effects	1,744		
Week Effects	507	507	
Firm-Year Effects		12,849	12,783
Week-Industry Effects			37,054
R^2 (Percent)	66.4	79.6	80.9
Observations	635,851	635,839	632,539

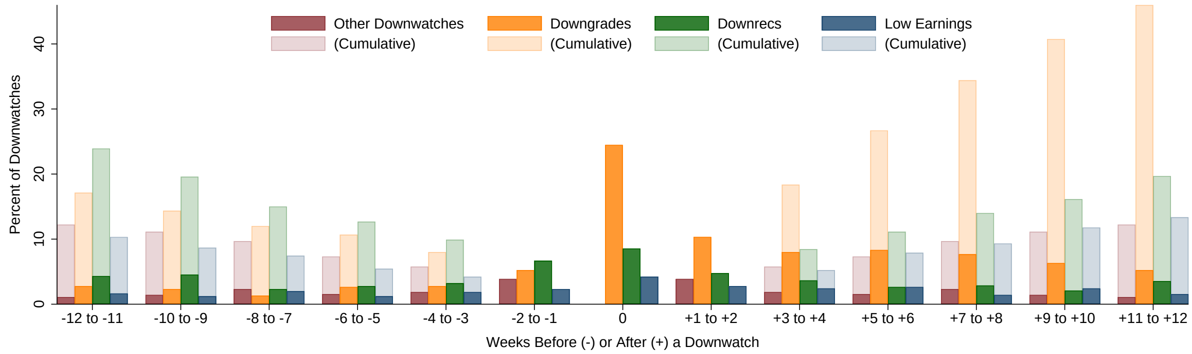
This table provides estimates of new connections initiated in the 12 weeks following downwatch events. Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

Table IV: Departure Rates and Connection Rates

	Percent Leaving	
Connection-Making Rate	0.180***	0.196***
	(0.018)	(0.021)
Firm Effects	1,649	1,642
Year Effects	10	
Year-Industry Effects		731
R^2 (Percent)	55.6	60.7
Observations	12,813	12,747

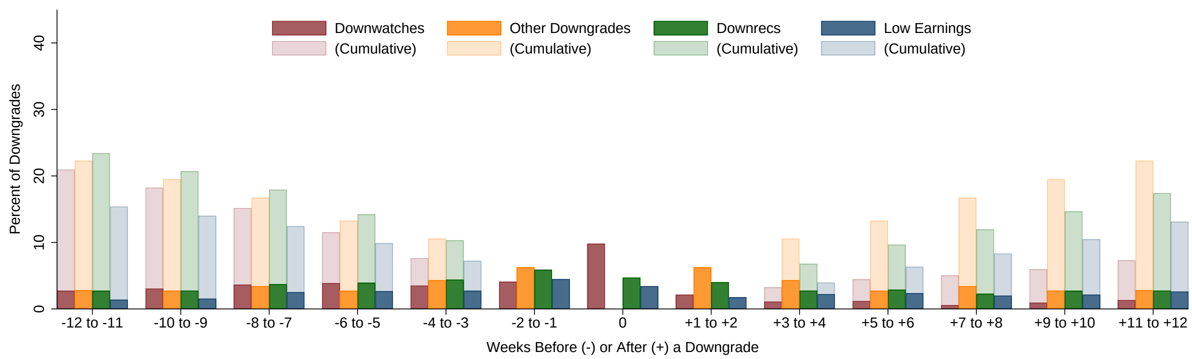
This table provides estimates of the relationship departure rates and connection rates. Standard errors in parentheses are double-clustered by firm and year.

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



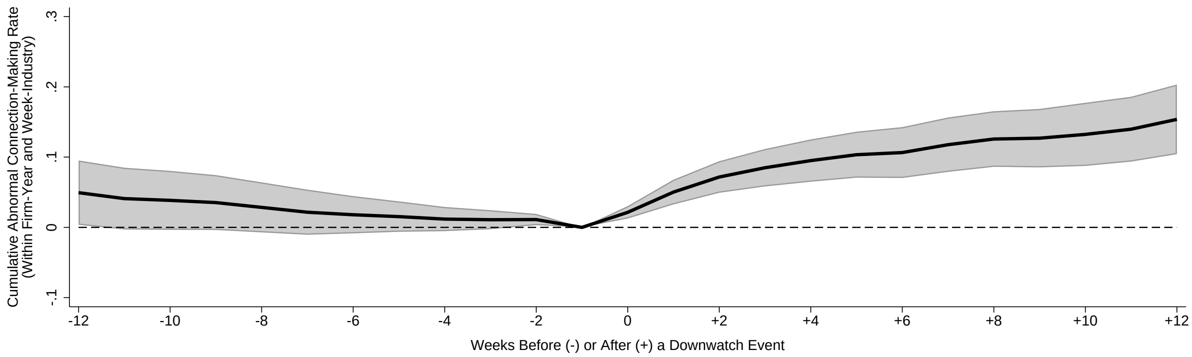
In the weeks before and after the downwatches in the sample, this figure shows the share that are preceded or followed by other downwatches, downgrades, downrecs, and low earnings events. The lighter bars accumulate these percentages outwards.

Figure II: Percent of Downgrades Preceded or Followed by Other Events



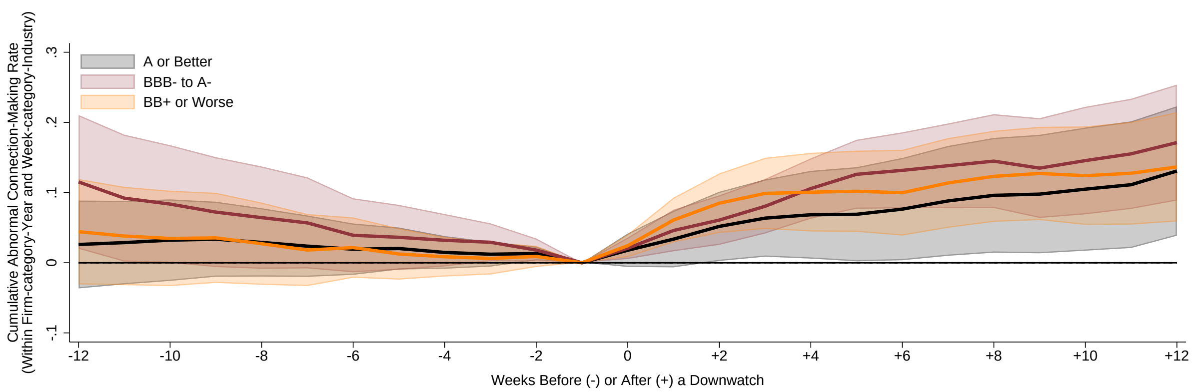
In the weeks before and after the downgrades in the sample, this figure shows the share that are preceded or followed by other downwatches, downgrades, downrecs, and low earnings events. The lighter bars accumulate these percentages outwards.

Figure III: Connections Initiated by Week from Downwatch



This figure shows the cumulative "abnormal" new connection rate by week relative to a downwatch event. Abnormal is what is left over after removing firm-year and week-NAICS3 fixed effects. Analogous estimates for this specification are in column three of Table III. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a 5 week lag.

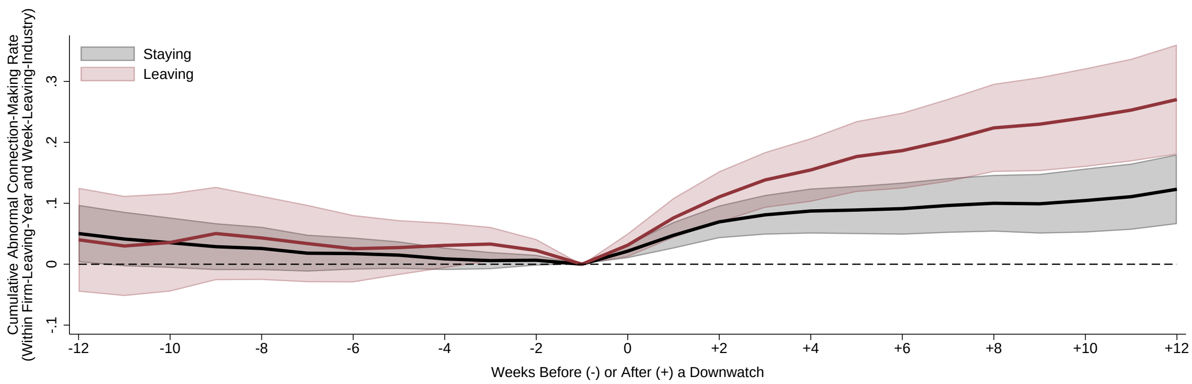
Figure IV: Connections Initiated by Week from Downwatch, by Credit Rating



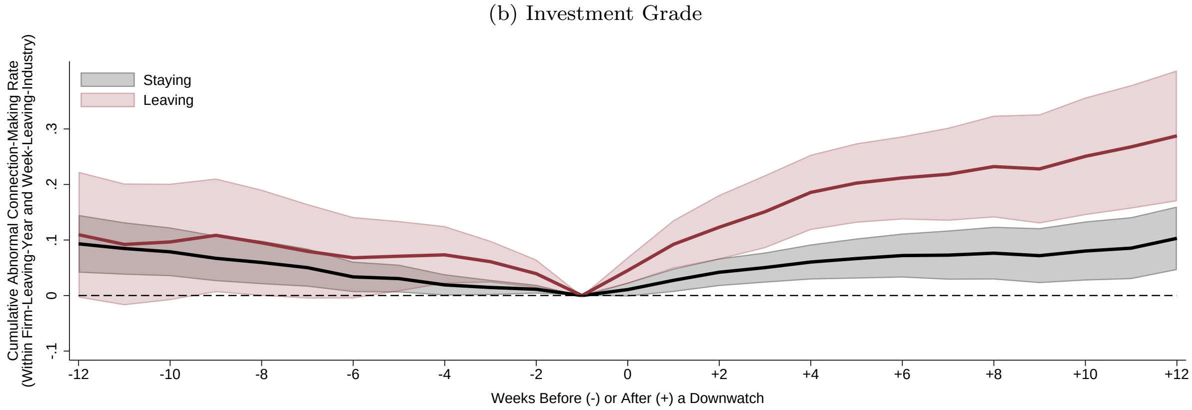
This figure shows the cumulative "abnormal" new connection rate by week relative to a downwatch event. Abnormal is what is left over after removing firm-year-rating and week-NAICS3-rating fixed effects. Analogous estimates for this specification are in column two of Table AI. We separate firms into highly rated (A or better), just investment grade (BBB- to A-), and below investment grade (BB+ or worse). Rating categories are ex ante, assigned at the start of the year. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors.

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

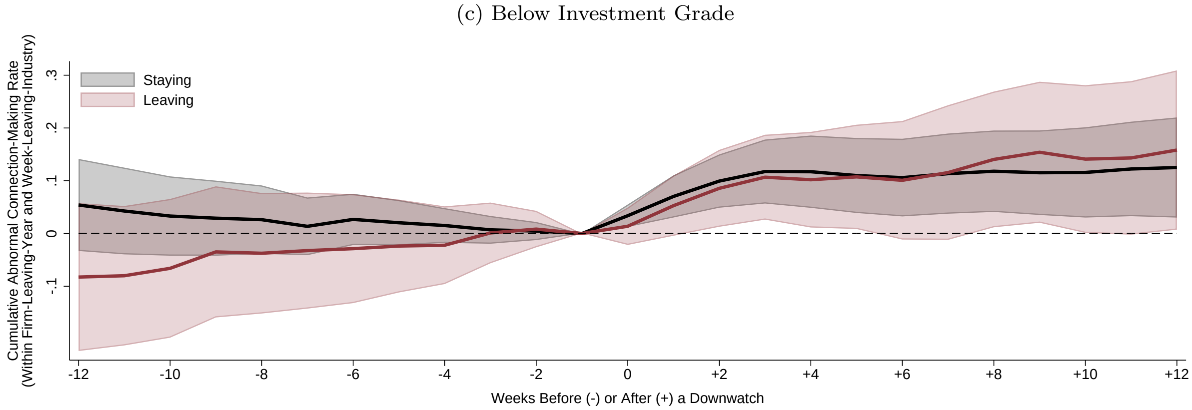
(a) All Firms



(b) Investment Grade



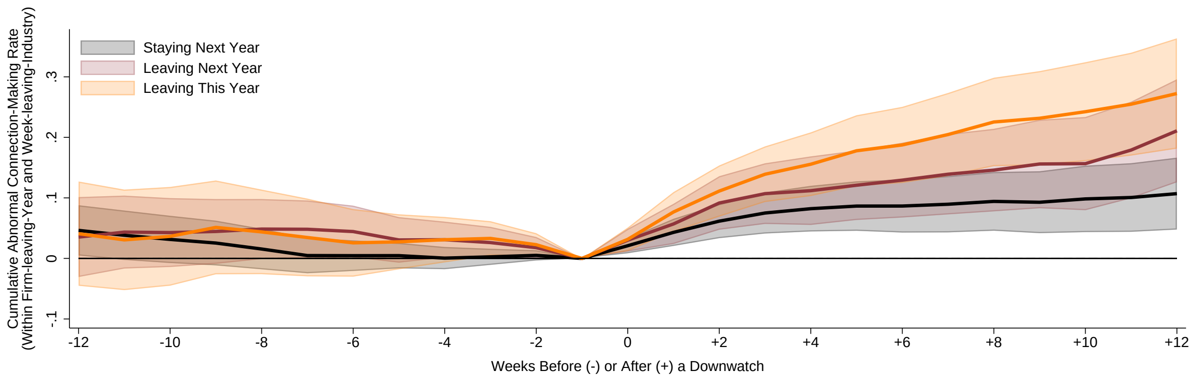
(c) Below Investment Grade



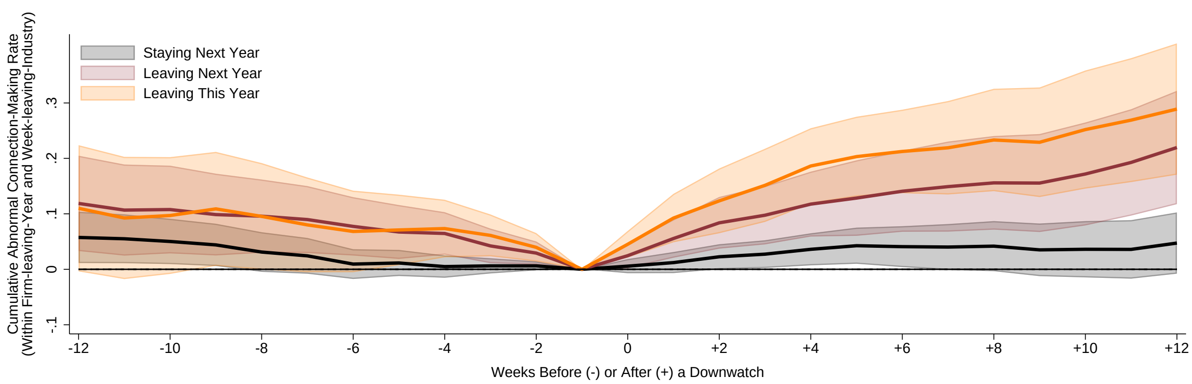
This figure shows the cumulative "abnormal" new connection rate by week relative to a downwatch event for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Rating categories are ex ante, assigned at the start of the year. Abnormal is what is left over after removing firm-year-leaving and week-NAICS3-leaving fixed effects. Analogous estimates for the specification in the top panel are in column two of Table AII. Leaving is an annual fixed indicator for no longer employed by the firm in the next calendar year. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a 5 week lag.

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

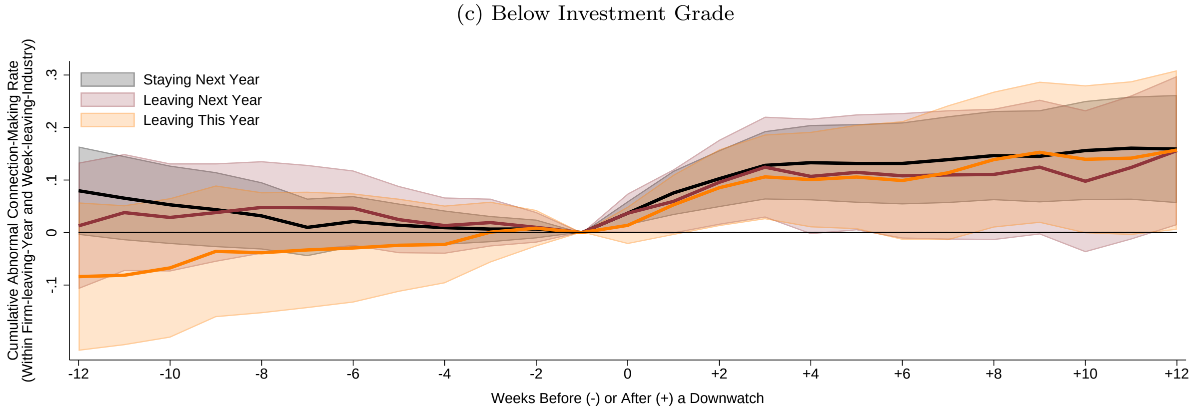
(a) All Firms



(b) Investment Grade



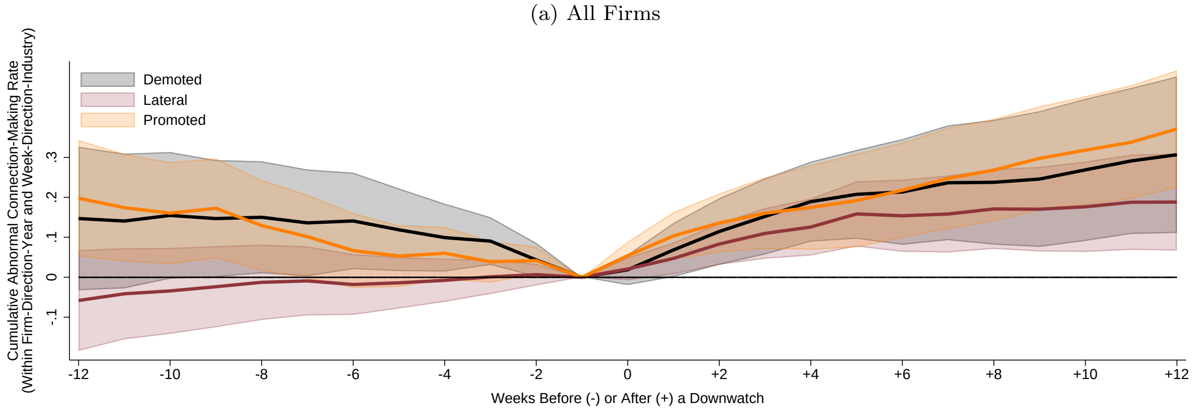
(c) Below Investment Grade



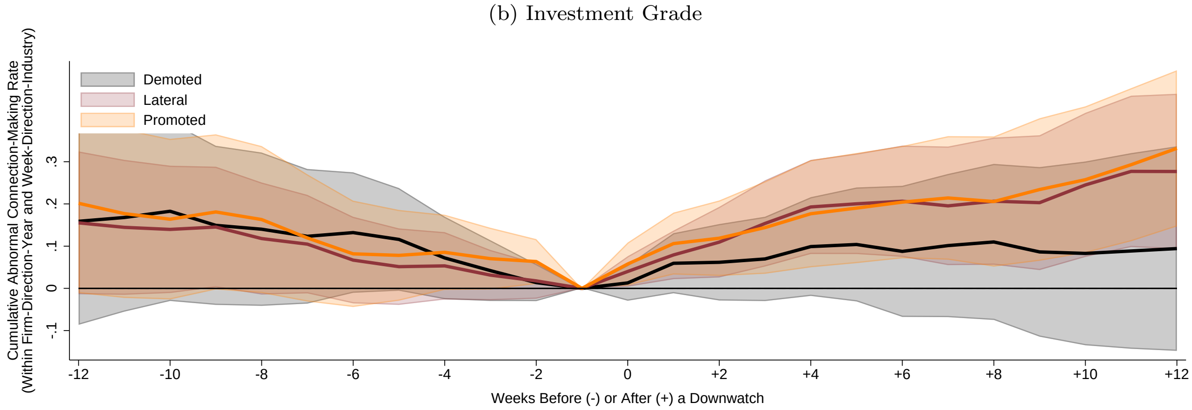
This figure shows the cumulative "abnormal" new connection rate by week relative to a downwatch event for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Rating categories are ex ante, assigned at the start of the year. Abnormal is what is left over after removing firm-year-timing and week-NAICS3-timing fixed effects. Analogous estimates for the specification in the top panel are in column two of Table AIII. Leaving This Year is an annual fixed indicator for no longer employed by the firm in the next calendar year, and Leaving Next Year is an annual fixed indicator for no longer employed by the firm in two calendar years. Staying Next Year covers the remainder. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a 5 week lag.

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

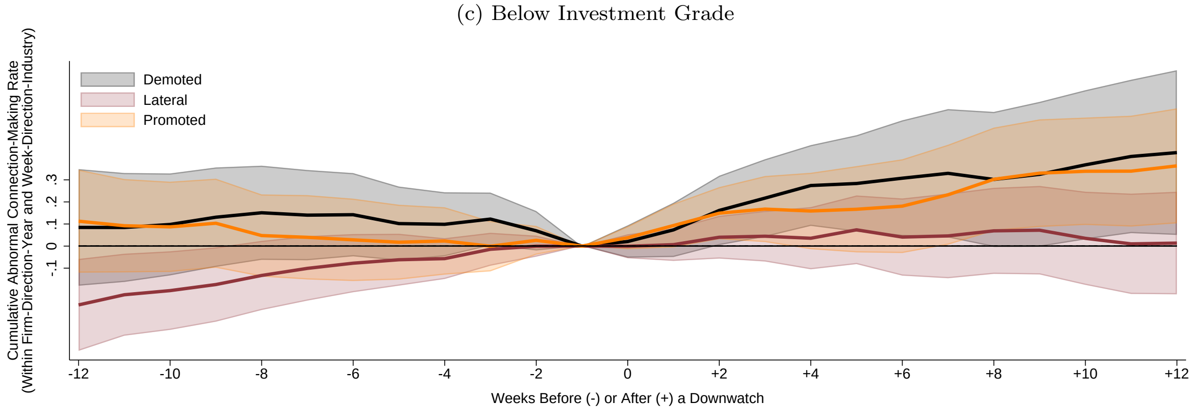
(a) All Firms



(b) Investment Grade



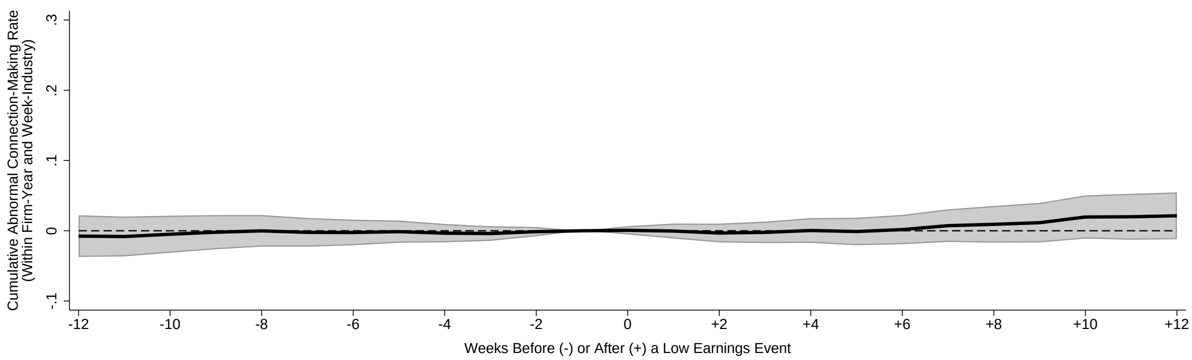
(c) Below Investment Grade



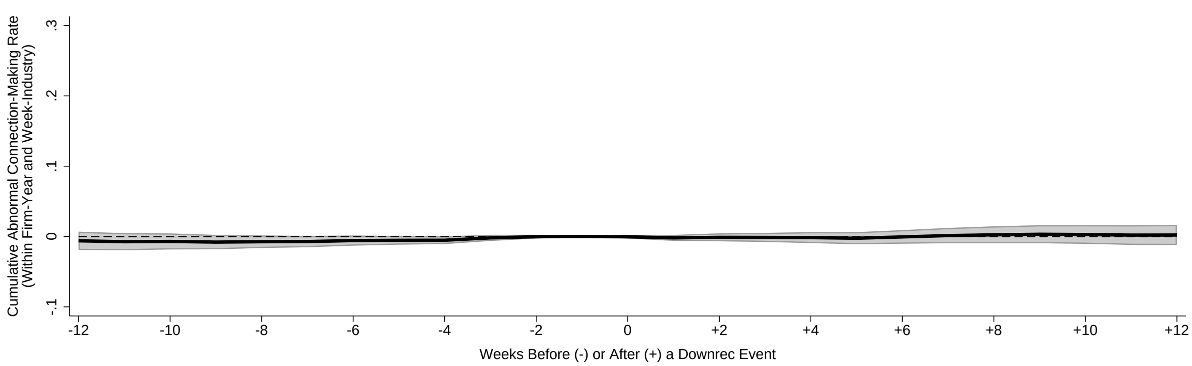
This figure shows the cumulative "abnormal" new connection rate by week relative to a downwatch event for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Rating categories are ex ante, assigned at the start of the year. Abnormal is what is left over after removing firm-year-group and week-NAICS3-group fixed effects. Analogous estimates for the specification in the top panel are in column two of Table AIV. Promoted refers to employees moving to a more senior position during the calendar year; lateral to a position of same seniority; and demoted to a position of lower seniority. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a 5 week lag.

Figure VIII: Connections Initiated by Week from Other Events

(a) Missed Earnings (Bottom Decile)



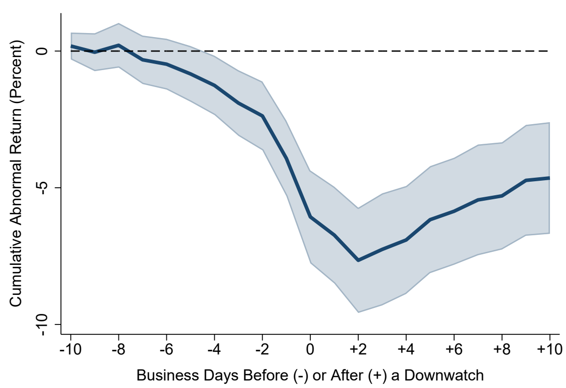
(b) Equity Sell Recommendations



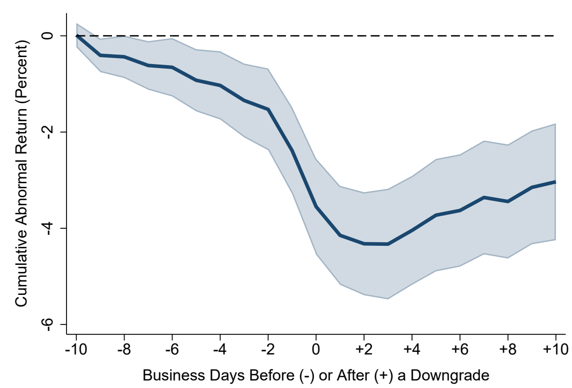
This figure shows the cumulative "abnormal" new connection rate by week relative to event, where the events in the top panel are missed earnings and in the bottom panel are equity sell recommendations. Abnormal is what is left over after removing firm-year and week-NAICS3 fixed effects. Analogous estimates for this specification are in columns three and six of Table AVI. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors.

Figure IX: Market Response to Credit and Other Events

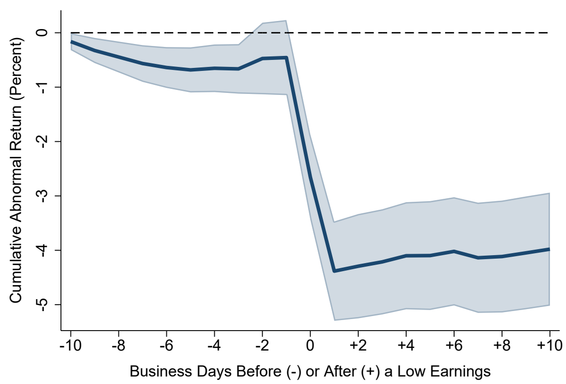
(a) Downwatches



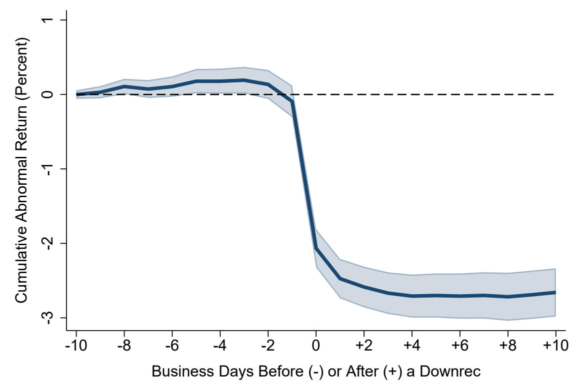
(b) Downgrades



(c) Missed Earnings (Bottom Decile)

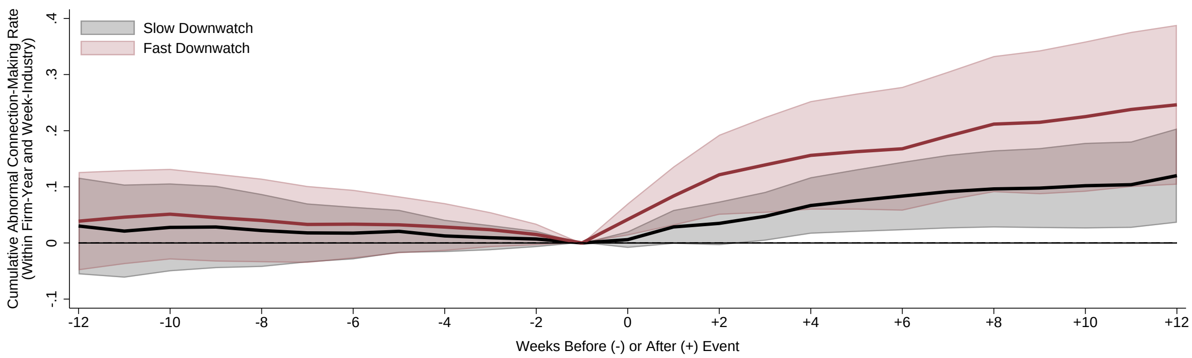


(d) Equity Sell Recommendations



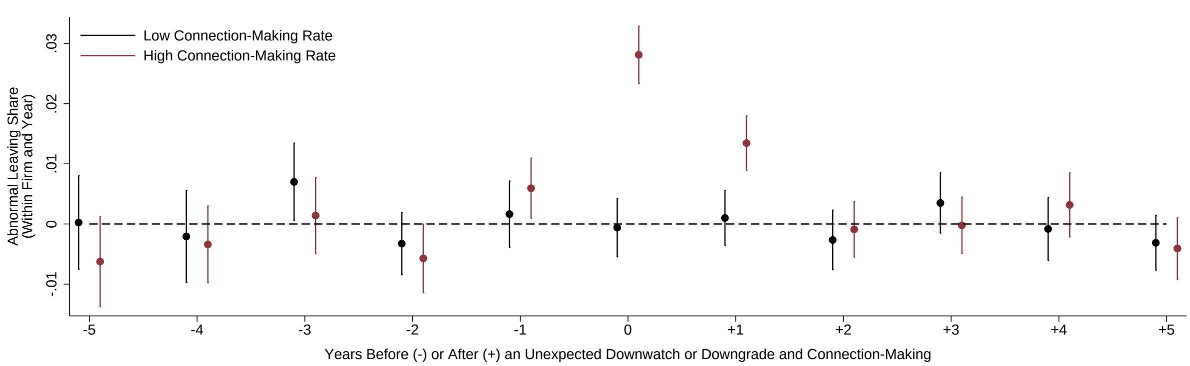
This figure shows Cumulative Abnormal Returns (CAR) plots for four types of events. CAR are estimated using the four-factor Fama-French model.

Figure X: Connections Initiated by Week from Downwatch, "Slow" vs. "Fast" News



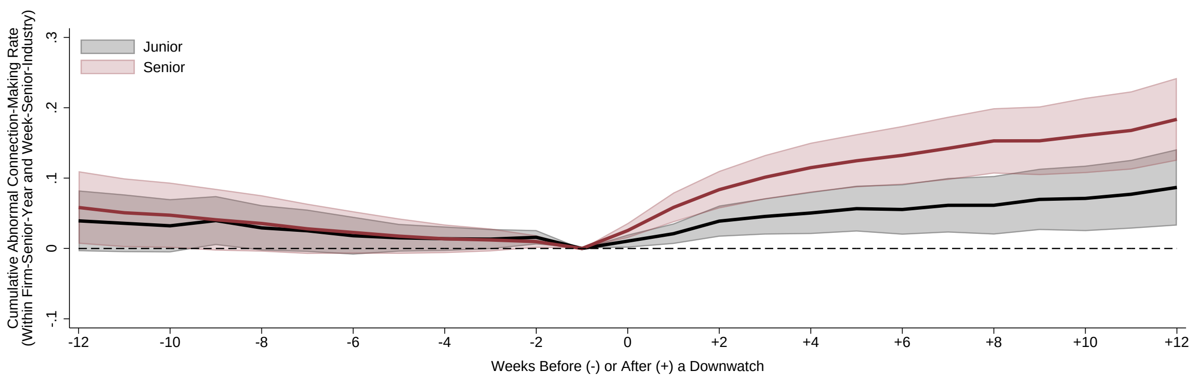
This figure shows the cumulative "abnormal" new connection rate by week relative to two subsets of downwatch events: "slow" downwatches, which occur following gradually unfolding events (e.g., declining performance), and "fast" downwatches, which occur following an event that happens more quickly (e.g., a sudden layoff announcement). We manually categorize S&P downwatches using the text of S&P research updates. Abnormal is what is left over after removing firm-year and week-NAICS3 fixed effects. Analogous estimates for this specification are in column three of Table AV. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a 5 week lag.

Figure XI: Leaving Share by Year from Credit Event, by High vs. Low Connection Response



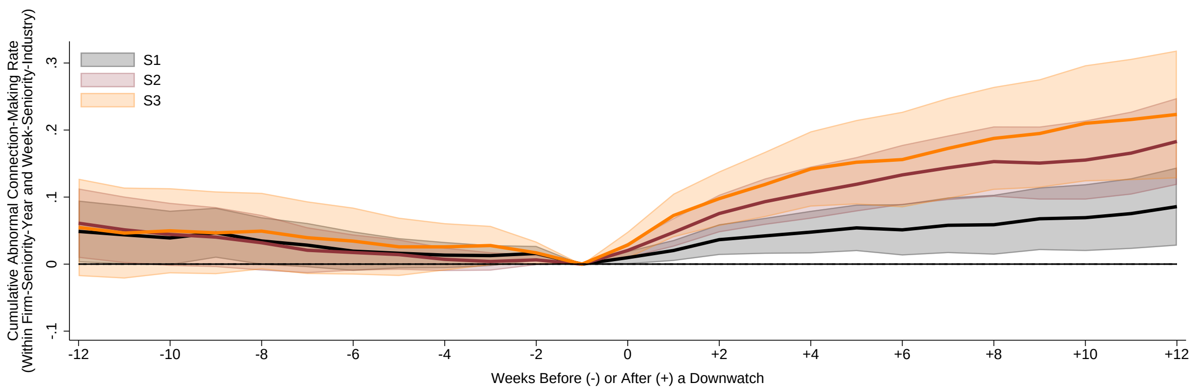
This figure shows the "abnormal" leaving share by year relative to a credit event in year y. Credit events include both downwatches and downgrades, but we exclude firms that experienced prior credit events in years leading up to y. Abnormal is what is left over after removing firm and year fixed effects. The bars represent 95% confidence intervals using standard errors that are double-clustered by firm and year.

Figure XII: Connections Initiated by Week from Downwatch, by Employee Seniority



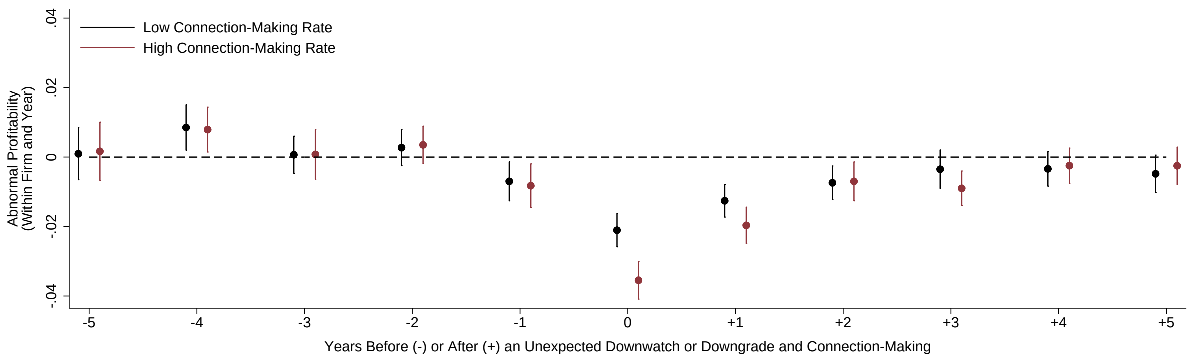
This figure shows the cumulative "abnormal" new connection rate by week relative to a downwatch event. Abnormal is what is left over after removing firm-year-seniority and week-NAICS3-seniority fixed effects. Analogous estimates for this specification are in column two of Table AVII. Junior employees are entry-level, unpaid or training employees (S1). Senior employees are everyone else (S2 and S3). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a 5 week lag.

Figure XIII: Connections Initiated by Week from Downwatch, by Employee Seniority (3 Levels)



This figure shows the cumulative "abnormal" new connection rate by week relative to a downwatch event. Abnormal is what is left over after removing firm-year-senior and week-NAICS3-senior fixed effects. Analogous estimates for this specification are in column two of Table AVIII. S1 are entry-level, unpaid or training employees. S2 are senior and manager-level employees. S3 employees include directors, VPs, and executives. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a 5 week lag.

Figure XIV: Profitability by Year from Credit Event, by High vs. Low Connection Response



This figure shows profitability by year relative to a credit event in year y. Profitability is annual operating income before depreciation scaled by last year's assets. Credit events include both downwatches and downgrades, but we exclude firms that experienced prior credit events in years leading up to y. Abnormal is what is left over after removing firm and year fixed effects. The bars represent 95% confidence intervals using standard errors that are double-clustered by firm and year.

A. Regression Tables

In this appendix, we provide regression tables for the various plots of cumulative "abnormal" new connection rates in the main paper.

Table AI: Connections Initiated After Downwatches, by Credit Rating

	Annualized Connection-Making Rate	
Downwatch	0.768***	0.601***
	(0.195)	(0.207)
Downwatch × BBB- or Worse	-0.097	-0.060
	(0.244)	(0.267)
Downwatch × BB+ or Worse (Junk)	-0.198	-0.052
	(0.209)	(0.229)
Firm-Year Effects	12,783	
Week-Industry Effects	37,054	
Firm-Group Effects	1,985	
Week-Group Effects	1,521	
Firm-Group-Year Effects		12,783
Week-Group-Industry Effects		37,054
R^2 (Percent)	81.0	81.9
Observations	632,539	614,114

This table provides estimates of new connections initiated in the 12 weeks following downwatch events. We separate firms into highly rated (A or better), just investment grade (BBB- to A-), and below investment grade (BB+ or worse). Rating categories are ex ante, assigned at the start of the year. Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

Table AII: Connections Initiated After Downwatches, by Departure Status

	Annualized Connection-Making Rate							
Downwatch	0.211	0.408***	0.401***	0.379***	0.333**	0.410***	0.446***	0.414***
	(0.144)	(0.134)	(0.154)	(0.127)	(0.160)	(0.131)	(0.143)	(0.137)
Downwatch × Leaving	1.135***	0.739***	0.389	0.435**	0.050	-0.093	0.236	0.294
	(0.215)	(0.224)	(0.252)	(0.178)	(0.261)	(0.163)	(0.227)	(0.203)
Leaving	y	y	$y+1$	$y+1$	$y+2$	$y+2$	$y+3$	$y+3$
Firm-Year Effects	12,846		11,525		10,184		8,819	
Week-Industry Effects	39,647		35,709		31,653		27,493	
Firm-Leaving Effects	3,471		3,380		3,285		3,166	
Week-Leaving Effects	1,014		912		808		704	
Firm-Leaving-Year Effects		25,336		22,705		20,018		17,270
Week-Leaving-Industry Effects		74,072		66,916		59,443		51,952
R^2 (Percent)	65.8	72.3	62.6	69.5	60.1	66.7	56.9	63.5
Observations	1,258,154	1,252,908	1,125,928	1,121,404	988,746	984,861	848,484	845,432

This table provides estimates of new connections initiated in the 12 weeks following downwatch events. In the first two columns, Leaving is an annual fixed indicator for the group of employees no longer at the firm in the next calendar year ($y+1$). In the next two columns, the population is limited to workers employed at the firm in years y and $y+1$, and Leaving is an annual fixed indicator for the group of employees no longer at the firm in the following calendar year ($y+2$). We repeat the same process for years $y+2$ and $y+3$. Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

Table AIII: Connections Initiated After Downwatches, by Departure Timing

	Annualized Connection-Making Rate	
Downwatch	0.173	0.389***
	(0.158)	(0.132)
Downwatch × Leaving This Year or Next	0.453	0.483**
	(0.282)	(0.195)
Downwatch × Leaving This Year	0.970***	0.283
	(0.307)	(0.258)
Firm-Year Effects	12,811	
Week-Industry Effects	39,279	
Firm-Leaving Effects	5,111	
Week-Leaving Effects	1,419	
Firm-Leaving-Year Effects		35,267
Week-Leaving-Industry Effects		103,934
R^2 (Percent)	60.6	69.4
Observations	1,749,027	1,742,271

This table provides estimates of new connections initiated in the 12 weeks following downwatch events. Leaving This Year is an annual fixed indicator for no longer employed by the firm in the next calendar year, and Leaving This Year or Next also includes those who are no longer employed by the firm in two calendar years. Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

Table AIV: Connections Initiated After Downwatches, by Departure Type

	Annualized Connection-Making Rate	
Downwatch	1.255***	1.034**
	(0.449)	(0.453)
Downwatch × Lateral/Promoted	-0.361	-0.202
	(0.532)	(0.489)
Downwatch × Promoted	0.248	0.647
	(0.503)	(0.395)
Firm-Year Effects	12,564	
Week-Industry Effects	39,515	
Firm-Group Effects	5,133	
Week-Group Effects	1,521	
Firm-Group-Year Effects		36,328
Week-Group-Industry Effects		110,045
R^2 (Percent)	42.1	57.3
Observations	1,800,547	1,792,378

This table provides estimates of new connections initiated in the 12 weeks following downwatch events. Promoted refers to employees moving to a more senior position during the calendar year; lateral, to a position of same seniority; and the remainder, demoted, to a position of lower seniority. Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

Table AV: Connections Initiated After Downwatches, "Slow" vs. "Fast" News

	Annualized Connection-Making Rate		
Slow Downwatch	1.230***	0.554***	0.496***
	(0.269)	(0.156)	(0.171)
Fast Downwatch	0.909***	0.980***	0.839***
	(0.337)	(0.266)	(0.281)
Firm Effects	1,744		
Week Effects	507	507	
Firm-Year Effects		12,849	12,783
Week-Industry Effects			37,054
R^2 (Percent)	66.4	79.6	80.9
Observations	635,851	635,839	632,539

This table provides estimates of new connections initiated in the 12 weeks following two subsets of downwatch events: "slow" downwatches, which occur following gradually unfolding events (e.g., declining performance), and "fast" downwatches, which occur following an event that happens more quickly (e.g., a sudden layoff announcement). We manually categorize S&P downwatches using the text of S&P research updates. Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

Table AVI: Connections Initiated After Missed Earnings and Equity Sell Recommendations

	Annualized Connection-Making Rate					
Low Earnings	0.005	0.080	0.068			
	(0.080)	(0.062)	(0.063)			
Downrec				0.223***	0.007	-0.011
				(0.042)	(0.032)	(0.032)
Firm Effects	1,744			1,744		
Week Effects	507	507		507	507	
Firm-Year Effects		12,849	12,783		12,849	12,783
Week-Industry Effects			37,054			37,054
R^2 (Percent)	66.4	79.6	80.9	66.4	79.6	80.9
Observations	635,851	635,839	632,539	635,851	635,839	632,539

This table provides estimates of new connections initiated in the 12 weeks following missed earnings and equity sell recommendation ("downrec") events. Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

Table AVII: Connections Initiated After Downwatches, by Employee Seniority and Skill

	Annualized Connection-Making Rate			
Downwatch	0.250*	0.327**	0.341***	0.412***
	(0.147)	(0.133)	(0.130)	(0.127)
Downwatch × Category	0.517***	0.370**	0.459**	0.323**
	(0.175)	(0.144)	(0.187)	(0.133)
Category	Senior	Senior	Skilled	Skilled
Firm-Year Effects	12,847		12,847	
Week-Industry Effects	39,687		39,687	
Firm-Category Effects	3,468		3,476	
Week-Category Effects	1,014		1,014	
Firm-Category-Year Effects		25,420		25,481
Week-Category-Industry Effects		74,108		74,108
R^2 (Percent)	73.8	77.8	71.1	75.6
Observations	1,262,528	1,257,238	1,265,997	1,260,707

This table provides estimates of new connections initiated in the 12 weeks following downwatch events. Junior employees are entry-level, unpaid or training employees (S1). Senior employees are everyone else (S2 and S3). Skilled occupations are those that have more than 50% of workers holding a Bachelor's degree according to the BLS (Table DXII). Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

Table AVIII: Connections Initiated After Downwatches, by Employee Seniority (3 Levels)

	Annualized Connection-Making Rate	
Downwatch	0.184	0.311**
	(0.178)	(0.143)
Downwatch × S2/S3	0.589***	0.391**
	(0.217)	(0.162)
Downwatch × S3	0.088	0.117
	(0.258)	(0.211)
Firm-Year Effects	12,847	
Week-Industry Effects	39,687	
Firm-Seniority Effects	5,190	
Week-Seniority Effects	1,521	
Firm-Seniority-Year Effects		38,019
Week-Seniority-Industry Effects		111,162
R^2 (Percent)	71.6	77.7
Observations	1,888,429	1,880,493

This table provides estimates of new connections initiated in the 12 weeks following downwatch events. S2 are senior and manager-level employees. S3 employees include directors, VPs, and executives. Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

B. Event Data

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

B1. Credit Events

Data on downwatches, upwatches, downgrades, and upgrades 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, and we use the CRSP-Compustat crosswalk to map 6-digit CUSIPs in the DRD to GVKEYs at the date of the credit action.

B2. Earnings Surprises

We construct earnings surprises from Institutional Brokers Estimate System (IBES) data. Following Chiang et al. (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 "low" or "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. If the consensus error is greater than the 90th percentile, we call this a "high" earnings event.

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) and with FOM $= +1$ (i.e., the actual number was better than all forecasts).

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

B3. Equity Recommendations

We also construct buy/sell equity 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 a "downrec," and when it increases by more than one value, we call this an "uprec." One-point changes are much more frequent but are associated with much smaller connection-making responses on average. Changes of more than one point are rare, but are associated with larger connection-making responses.

B4. Merger Announcements

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.

C. Ravenpack

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 negative news stories. Table CIX presents summary statistics for the data.

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 negative stories are correlated with connection-making activity. Table CX shows connection activity following negative news coverage for individual firms. 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 or downgrade. Furthermore, this relationship holds after adjusting for week-by-industry and firm-by-year 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 activity, we should expect that conditioning on negative stories should drive down the impact of credit events. Table CX reports results in which we condition on negative stories and interact them with our main credit event variable. The magnitude and significance of credit events on connection-making activity remains unchanged. Furthermore, the interaction term, which estimates whether credit events coinciding with more negative news coverage exhibits larger impact, is small and not consistently significant across credit event types. This suggests that media coverage alone is unlikely to be driving workers' response to credit events.

Table CIX: Summary Statistics for RavenPack

	Mean	SD	25%	50%	75%	Count
Negative Stories	0.6	2.0	0	0	0	645,961
Compustat Employees Q1: (0, 2,297]	0.3	0.8	0	0	0	161,031
Compustat Employees Q2: (2,297, 7,750]	0.4	1.3	0	0	0	160,354
Compustat Employees Q3: (7,750, 27,276]	0.4	1.3	0	0	0	159,050
Compustat Employees Q4: (27,276, 2,300,000]	1.1	3.4	0	0	1	159,989
Same Week as a Downwatch	2.1	6.8	0	0	2	884
Same Week as a Downgrade	1.5	3.9	0	0	1	2,217
Same Week as a Downrec	1.1	3.5	0	0	1	7,308
Same Week as a Low Earnings	0.9	2.1	0	0	1	2,239

This table presents summary statistics for our RavenPack data. All observations are at the firm-week level. We identify "negative stories" with a composite sentiment score constructed by RavenPack. We report summary statistics for the number of these stories at the firm-week level, separately for firms in different quartiles of the number of Compustat-reported employees, and separately for weeks when there is a negative credit event, equity recommendation event, or earnings event.

Table CX: Connections Initiated and Negative News Coverage

	Annualized Connection-Making Rate					
Event	0.585***		0.597***	0.339***		0.314***
	(0.115)		(0.120)	(0.069)		(0.070)
Negative Stories		0.023***	0.023***		0.023***	0.021***
		(0.004)	(0.005)		(0.004)	(0.004)
Event × Negative Stories			0.001			0.032**
			(0.013)			(0.014)
Event	Downwatch	Downwatch	Downwatch	Downgrade	Downgrade	Downgrade
Firm-Year Effects	12,783	12,704	12,650	12,783	12,704	12,650
Week-Industry Effects	37,054	37,786	36,898	37,054	37,786	36,898
R^2 (Percent)	80.9	80.9	81.0	80.9	80.9	81.0
Observations	632,539	642,415	626,106	632,539	642,415	626,106

This table shows the interaction between negative news stories from RavenPack and credit events. Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

D. Additional Results

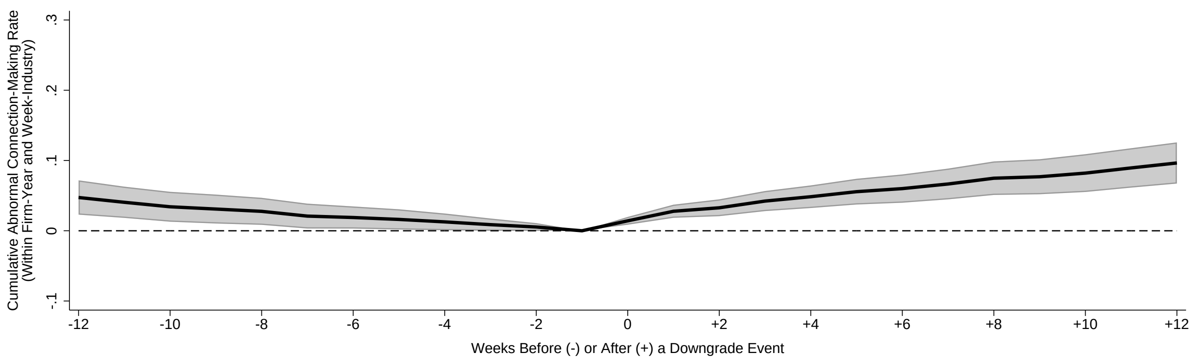
Table DXI: Connections Initiated After Downgrades

	Annualized Connection-Making Rate					
Any Downgrade	0.840***	0.381***	0.339***			
	(0.092)	(0.068)	(0.069)			
Unexpected Downgrade				0.648***	0.291***	0.259***
				(0.098)	(0.071)	(0.077)
Firm Effects	1,744			1,744		
Week Effects	507	507		507	507	
Firm-Year Effects		12,849	12,783		12,849	12,783
Week-Industry Effects			37,054			37,054
R^2 (Percent)	66.4	79.6	80.9	66.4	79.6	80.9
Observations	635,851	635,839	632,539	635,851	635,839	632,539

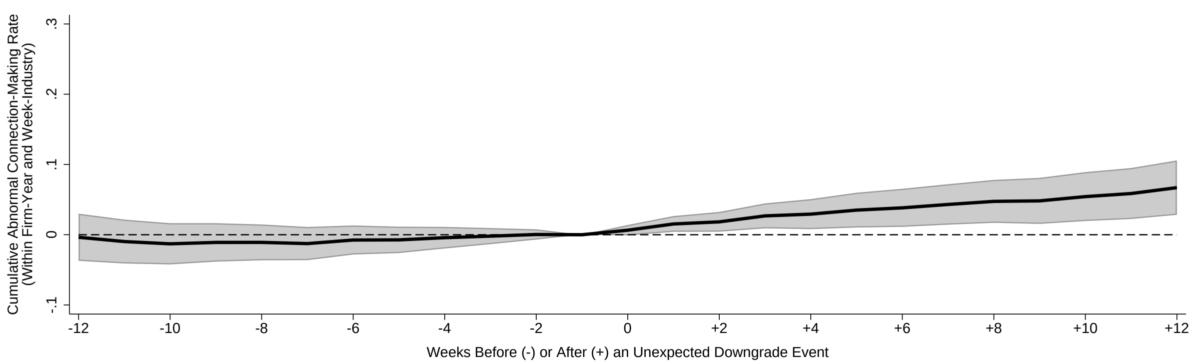
This table provides estimates of new connections initiated in the 12 weeks following downgrade events. The first three columns include all 2,242 downgrades in our sample. The last three columns discard 878 downgrades that were preceded by downwatches or other credit events in the 12 weeks before the event. Standard errors in parentheses are Driscoll-Kraay with a 5 week lag.

Figure D1: Connections Initiated by Week from Downgrade

(a) Downgrades



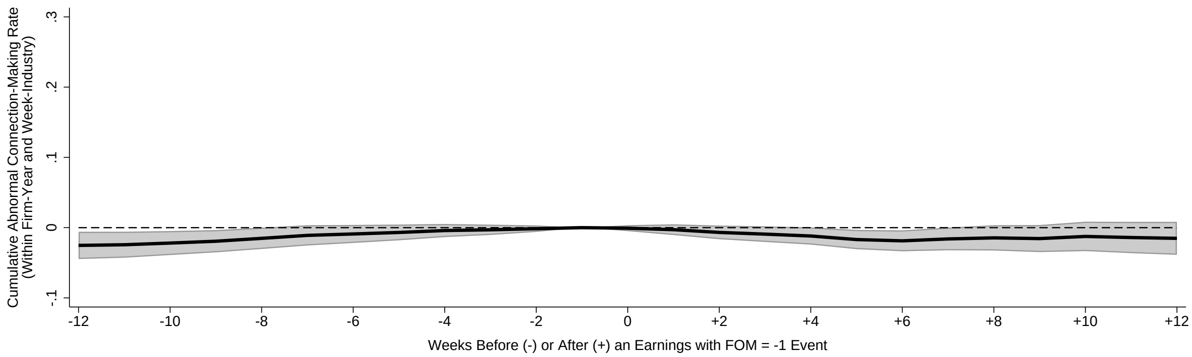
(b) Unexpected Downgrades



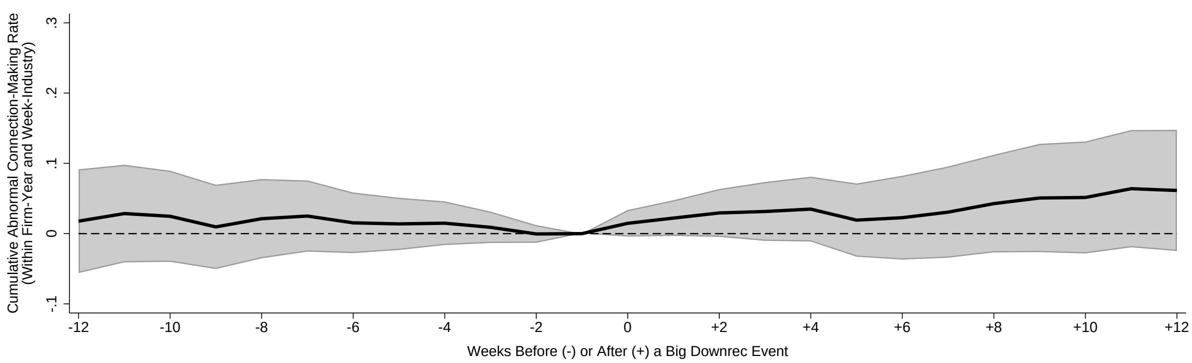
This figure shows the cumulative "abnormal" new connection rate by week relative to downgrade events. The top panel includes all 2,242 downgrades in our sample. The bottom panel discards 878 downgrades that were preceded by downwatches or other credit events in the 12 weeks before the event. Abnormal is what is left over after removing firm-year and week-NAICS3 fixed effects. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a 5 week lag.

Figure D2: Connections Initiated by Week from Alternative Events

(a) Missed Earnings (FOM = -1)



(b) Equity Sell Recommendations (Large Changes)

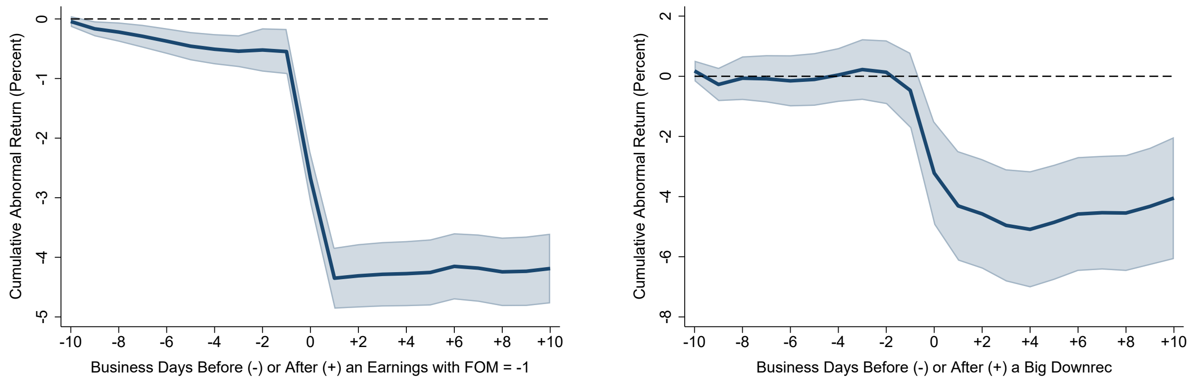


This figure shows the cumulative "abnormal" new connection rate by week relative to event, where the events in the top panel are based on an alternative measure of missed earnings and those in the bottom panel are equity sell recommendations associated with the largest one-week change in recommendation values. For more information about event definitions, please refer to Appendix B. Abnormal is what is left over after removing firm-year and week-NAICS3 fixed effects. The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors.

Figure D3: Market Response to Alternative Events

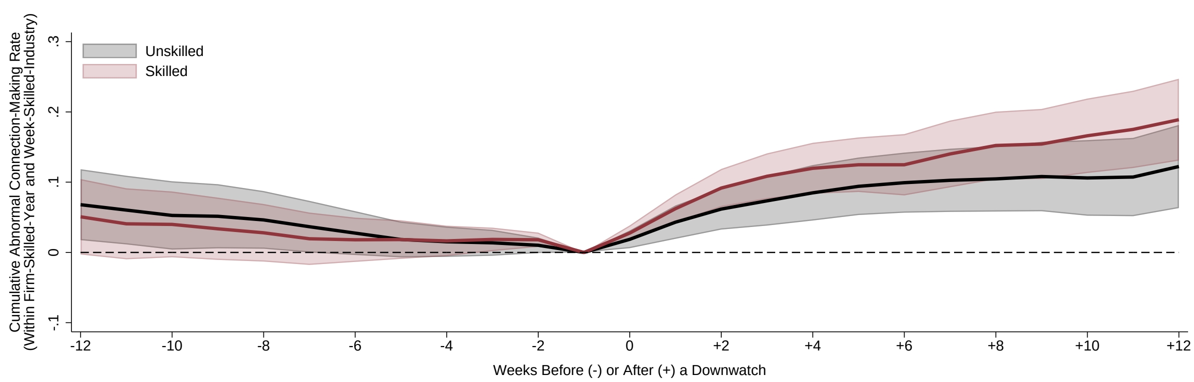
(a) Missed Earnings (FOM = -1)

(b) Equity Sell Recommendations (Large Changes)



This figure shows Cumulative Abnormal Returns (CAR) plots, where the events in the left panel are based on an alternative measure of missed earnings and those in the right panel are equity sell recommendations associated with the largest one-week change in recommendation values. For more information about event definitions, please refer to Appendix B. CAR are estimated using the four-factor Fama-French model.

Figure D4: Connections Initiated by Week from Downwatch, by Employee Skill



This figure shows the cumulative "abnormal" new connection rate by week relative to a downwatch event. Abnormal is what is left over after removing firm-year-skill and week-NAICS3-skill fixed effects. Skilled occupations are those that have more than 50% of workers holding a Bachelor's degree according to the BLS (Table DXII). The shaded area shows the 95% confidence interval using Driscoll-Kraay standard errors with a 5 week lag.

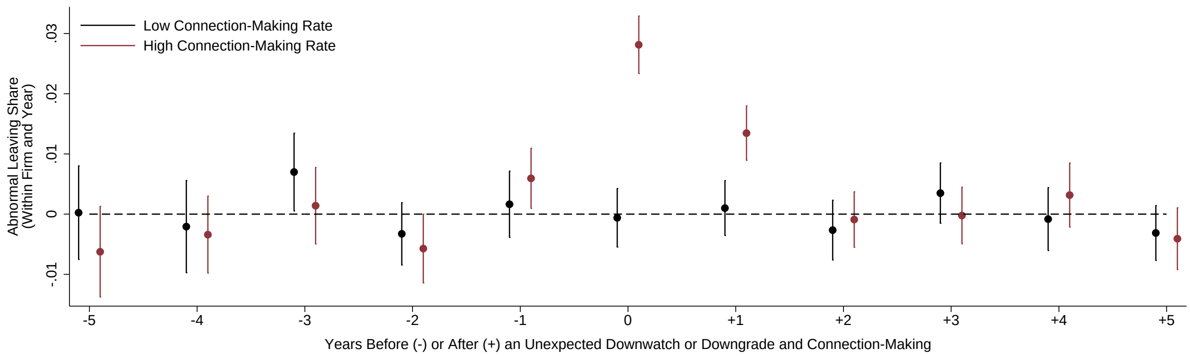
Table DXII: Educational Attainment by Occupation

SOC	Description	% bachelor's or more	Years secondary schooling	High-skilled	Total 2016 employment (000s)
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

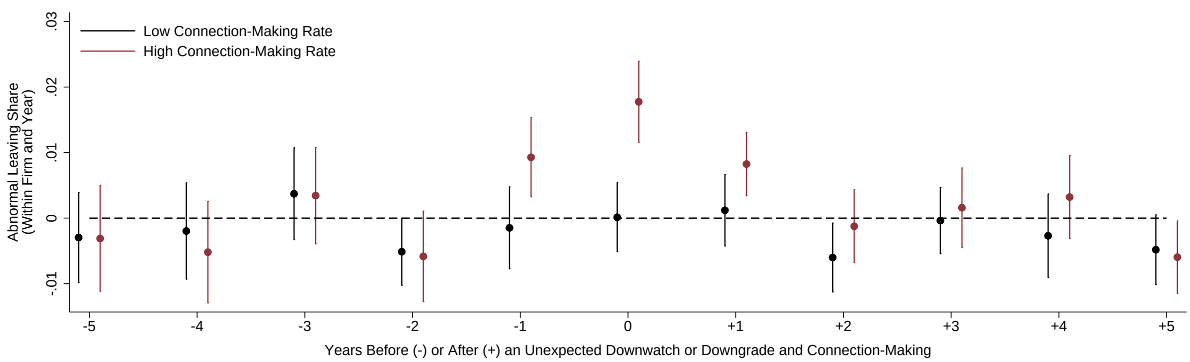
*LinkedIn's classification scheme provides one category for healthcare services, so we count both healthcare support and practitioner and technical occupations as high-skilled.

Figure D5: Leaving Share by Year from Credit Event, by High vs. Low Connection Response

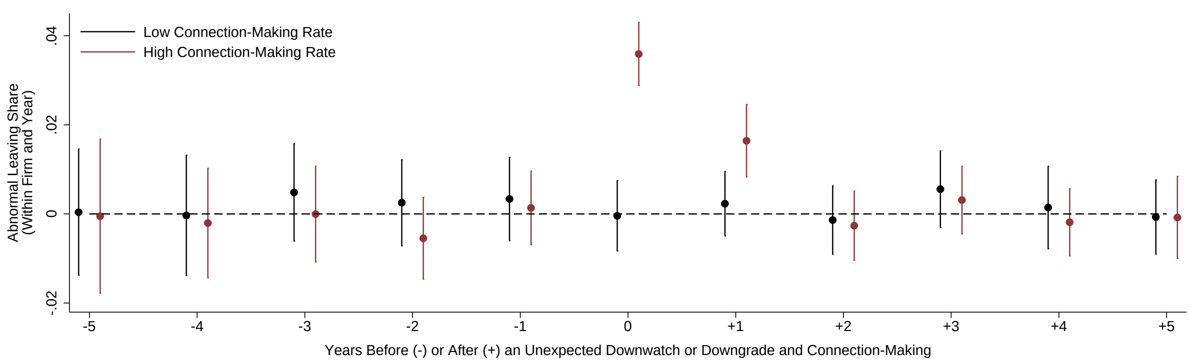
(a) All Firms



(b) Investment Grade



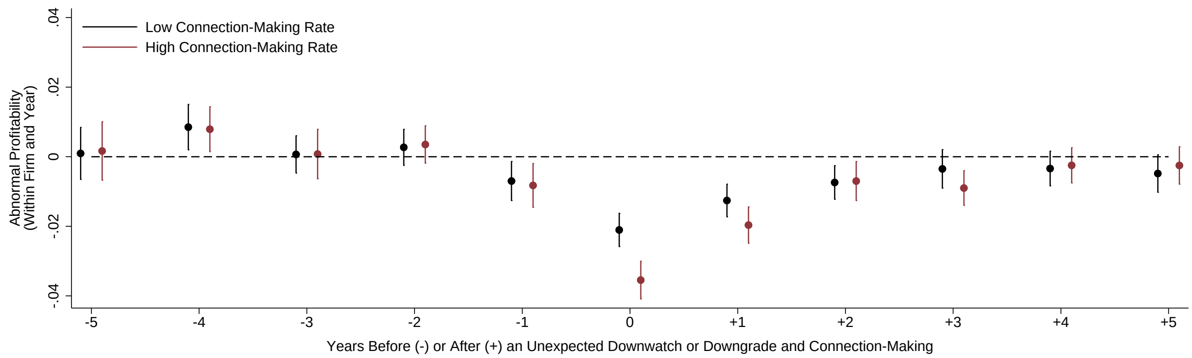
(c) Below Investment Grade



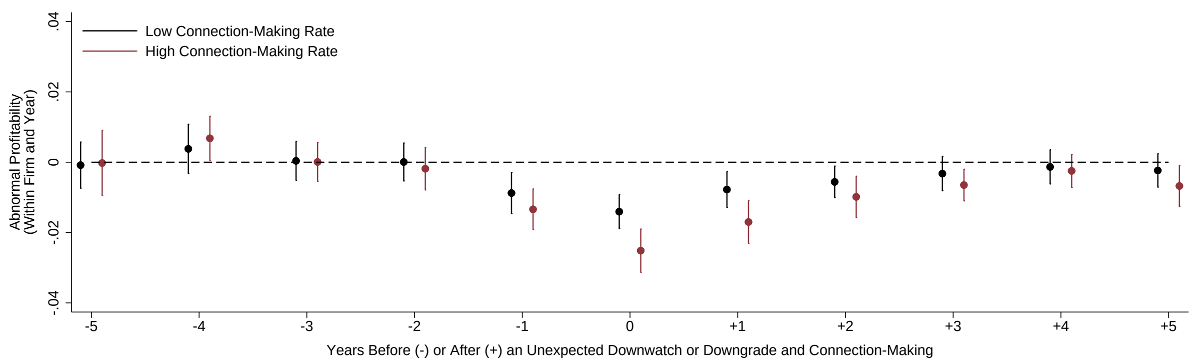
This figure shows the "abnormal" leaving share by year relative to a credit event in year y for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Rating categories are ex ante, assigned at the start of the year. Credit events include both downwatches and downgrades, but we exclude firms that experienced prior credit events in years leading up to y. Abnormal is what is left over after removing firm-year and year-NAICS3 fixed effects. The bars represent 95% confidence intervals using standard errors that are double-clustered by firm and year.

Figure D6: Profitability by Year from Credit Event, by High vs. Low Connection Response

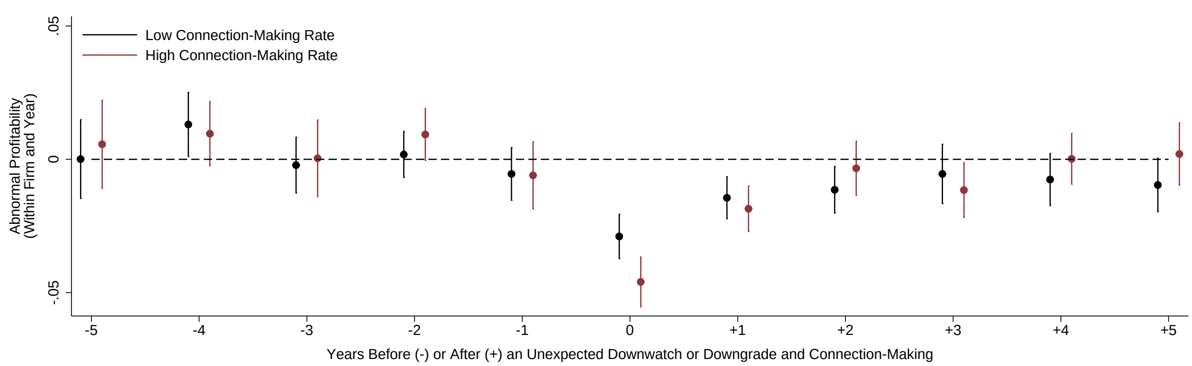
(a) All Firms



(b) Investment Grade



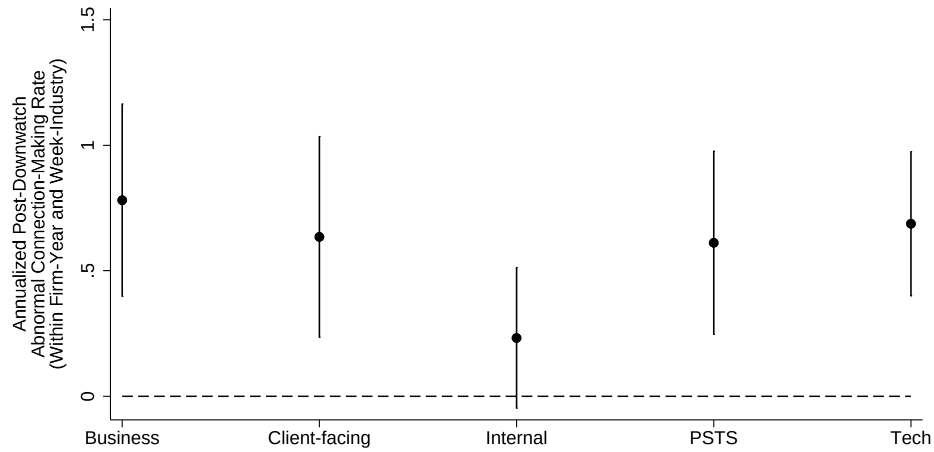
(c) Below Investment Grade



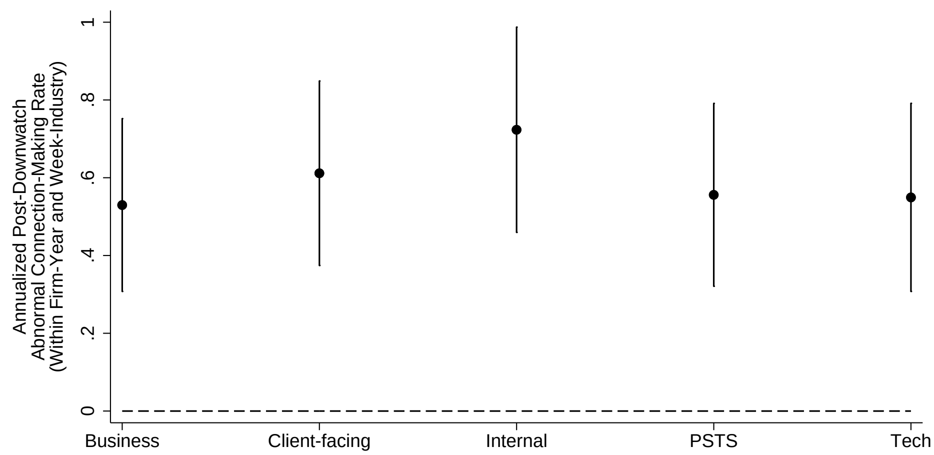
This figure shows profitability by year relative to a credit event in year y, for three samples of firms. The top panel is our full sample. The middle panel is for firms with BBB- credit ratings or better. The bottom panel is for firms with BB+ credit ratings or worse. Rating categories are ex ante, assigned at the start of the year. Credit events include both downwatches and downgrades, but we exclude firms that experienced prior credit events in years leading up to y. Abnormal is what is left over after removing firm-year and year-NAICS3 fixed effects. The bars represent 95% confidence interval using standard errors that are double-clustered by firm and year.

Figure D7: Connections Initiated After Downwatches, by Occupation

(a) Estimates by Occupation Group



(b) Estimates Excluding One Occupation Group at a Time



This figure shows estimates of new connections initiated in the 12 weeks following downwatch events, broken down by occupation group in the top panel, and excluding one occupation group at a time in the bottom panel. 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. The bars represent 95% confidence intervals using Driscoll-Kraay standard errors with a 5 week lag.