# Front-Loading Recruitment Before Negative Earnings Surprises

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## Abstract

We study how firms adjust recruitment in anticipation of a negative earnings surprise. Using 13.9 million U.S. online job postings from 2011 to 2024, we document that firms with negative earnings surprises shift job postings from after to before the earnings announcement. We refer to this intertemporal reallocation as front-loading, and show that it reflects a shift in recruitment timing rather than an increase in labor demand. Front-loading firms exhibit average net hiring rates that are 0.562 percentage points higher—equivalent to about 37.4% of the sample mean—than those of bad-news firms that do not front-load, but do not experience more favorable capital market outcomes. We also find that the content of job postings differs for front-loaders. Overall, our results highlight that negative earnings surprises create labor-market frictions that affect recruitment.



**JEL Classification:** M41, J23, J63, G14

**Keywords:** Earnings surprises; Job postings; Real effects of disclosure; Recruitment; Labor market frictions

# 1 Introduction

Financial underperformance weakens firms' ability to retain and recruit skilled workers. High-ability employees are more likely to leave (Baghai et al. [2021]), and hiring becomes harder (Brown and Matsa [2016]) as current and prospective employees may infer firm stability and career prospects from earnings announcements and related news (Choi, Choi, and Malik [2023], deHaan, Li, and Zhou [2023]). In light of these negative labor effects of negative firm-specific news, we hypothesize and find evidence consistent with firms adjusting recruitment timing ahead of negative earnings surprises. Specifically, when firms face forthcoming unfavorable earnings news, they shift job postings from after to before the earnings announcement. We term this temporal reallocation 'front-loading' and study its labor market effects.

Using Lightcast data from 2011 to 2024 and a firm-quarter measure of abnormal job postings, we document an intertemporal reallocation of job postings around negative earnings surprises. In the three quarters before the earnings announcement ($Q_{-3}$ to $Q_{-1}$), abnormal job posting activity is approximately 9.0% to 13.4% higher for firms with negative earnings surprises, compared to non-bad-news firms. From $Q_0$ through $Q_{+2}$, this increase reverses: negative-surprise firms post less than non-negative-surprise firms. Résumé-based employee flow data indicate that front-loading is associated with realized hiring outcomes, rather than merely posting activity. However, the cumulative effect over the full event window is statistically indistinguishable from zero, consistent with intertemporal reallocation rather than aggregate expansion of labor demand.

Further, we find significantly higher net hiring rates for front-loaders, compared to negative earnings-surprise firms that do not front-load. This suggests that front-loading helps firms recruit before bad news complicates hiring. We also study whether job posting characteristics differ for

front-loading firms, and we find evidence consistent with differences across several dimensions, including skills, seniority, salary disclosure and duration. In addition, and given that job postings are used by investors as a source of firm-specific information (Gutiérrez et al. [2020], Chen and Li [2023], Sran [2025]), we also study whether front-loading firms suffer lower capital market penalties after the negative earnings surprise. We do not find evidence consistent with this, as short-window announcement-period returns are statistically similar across front-loading intensity groups.

We also find that front-loading is more pronounced and is associated with stronger labor market outcomes in more competitive labor markets, for R&D-intensive firms, which depend on specialized talent that is sensitive to adverse financial signals, and among heavily covered firms, where adverse information reaches prospective employees more rapidly after disclosure. Results are robust to alternative specifications, samples, and posting measures. We also show that the front-loading pattern is inconsistent with a growth-firm explanation, whereby firms with elevated hiring trajectories suffer an earnings setback and subsequently reduce posting activity.

Our main contribution comes from documenting a labor market response to negative earnings news: the intertemporal reallocation of recruitment. Prior work shows that financial distress can disrupt labor markets and impose employee-related costs: distressed firms attract fewer job applicants and experience greater talent loss (Brown and Matsa [2016], Baghai et al. [2021]), while poor financial reporting quality and bankruptcy risk are associated with compensating wage differentials and employee-related distress costs (Choi, Gipper, and Malik [2023], Graham, Kim, Li, and Qiu [2023]). Our evidence that firms shift recruitment to the period before negative earnings surprises fills this gap.

More generally, we also contribute to the literature on job postings as a source of firm-specific

information (Deming and Kahn [2018], Marinescu and Wolthoff [2020], Gutiérrez et al. [2020], Cao et al. [2023]; Choi, Pacelli et al. [2023]; deHaan et al. [2023], Aobdia et al. [2025], Sran [2025], Huang et al. [2026]). We extend this literature by showing that both the timing and characteristics of job postings vary with negative earnings news, and that front-loading is associated with labor market outcomes, but not with differential capital market reactions.

The remainder of the paper proceeds as follows. Section 2 develops the hypotheses. Section 3 describes the data sources, sample construction, variable measurement, and empirical design. Section 4 presents the main empirical evidence on abnormal job posting dynamics around earnings announcements and employee flow validation using résumé data, the labor and capital market outcomes of front-loading, and job posting characteristics analysis. Section 5 examines cross-sectional heterogeneity in front-loading across labor market competition, R&D intensity, and analyst coverage. Section 6 reports robustness tests. Section 7 concludes.

## 2 Hypothesis Development

Prior research shows that firm-specific negative news can materially impair firms' labor market position. Brown and Matsa [2016] show that financially distressed firms attract fewer job applicants, while Baghai et al. [2021] document that firms approaching bankruptcy lose skilled employees. These findings suggest that both prospective and current employees incorporate firm-specific financial information into employment decisions.

Consistent with these general arguments about firm-specific bad news, recent work provides evidence of current and prospective employees using earnings-related news. In particular, deHaan et al. [2023] show that earnings announcements trigger heightened job search activity by current

employees. This indicates that current employees update their beliefs about job security, compensation prospects, and career trajectories based on public financial information, and that they consider leaving when the information is negative. Similarly, Choi, Choi, and Malik [2023] document that prospective employees use earnings announcements to evaluate employers, with negative surprises reducing firm attractiveness in labor markets.

Given these findings, and because managers typically possess advance information about impending earnings performance through internal forecasting and reporting processes, firms facing forthcoming unfavorable earnings news have incentives to adjust recruitment timing. After negative news becomes public, firms face deteriorated recruitment conditions: weakened employer brand, smaller candidate pools, and diminished bargaining power. These anticipated frictions create incentives to shift recruitment from after to before the negative earnings surprise. By recruiting before negative information becomes public, managers secure talent while employer reputation remains intact, applicant pools are larger, and the competitive hiring position is stronger. Our main hypothesis is therefore as follows:

**Hypothesis 1:** *Firms facing forthcoming negative earnings surprises shift recruitment from the post-announcement period to the pre-announcement period.*

We further study the implications of this temporal shift (front-loading) for labor market outcomes, job posting characteristics, and capital market reactions. Given prior evidence that negative firm-specific news reduces employer attractiveness and applicant interest, we expect front-loading to be associated with stronger net hiring outcomes.

Postings are publicly observable to current employees, external candidates, labor market intermediaries, and other stakeholders. Their timing and content shape perceptions of organizational health and workforce investment. This creates incentives to adjust job posting content to improve la-

bor market outcomes (Cao et al. [2023]; Choi, Pacelli et al. [2023]; Sran [2025], Kim et al. [2025], Huang et al. [2026]). However, existing research has not examined whether firms adjust job posting content when anticipating information events that alter labor market conditions. If firms use postings to mitigate anticipated labor market frictions, we should observe differences in characteristics such as required skills, experience, compensation, and other employment terms.

Because job postings are informative to investors (Gutiérrez et al. [2020]), we also examine whether front-loading affects capital markets. It is unclear how investors see front-loading. While front-loading could be interpreted by investors as a signal of better future performance, therefore leading to a less negative stock market reaction after the negative earnings surprise, it is unclear whether this information is already impounded into prices, or if front-loading is interpreted as a signal of weakened future prospects.

Finally, the benefits of front-loading are unlikely to be uniform across firms. Front-loading should be more valuable when adverse earnings news creates larger labor-market frictions, such as in competitive labor markets, among firms dependent on specialized human capital, or when information about the earnings announcement disseminates rapidly. At the same time, accelerating recruitment requires financial flexibility because front-loading requires incurring labor costs ahead of schedule. Consequently, we expect front-loading to be concentrated among firms facing stronger labor-market frictions and with greater financial flexibility.

# 3 Data

## 3.1 Data Sources and Sample Construction

Our primary dataset comprises over 50 million online job postings from Lightcast spanning 2011 to 2024. Lightcast aggregates vacancy information from over 40,000 online sources and applies proprietary deduplication algorithms to produce unique records.[1] Lightcast also provides online résumé data from which we construct employee-level workforce flow measures, including join, turnover, and net employment changes.

We obtain firm financial data from Compustat Quarterly and stock return data from CRSP. We match job postings to U.S. publicly listed firms using the Compustat-CRSP Merged (CCM) database via fuzzy matching on employer names, manually validating a random subsample to confirm match accuracy. Earnings forecast data come from I/B/E/S, including analyst consensus forecasts, actual reported earnings, forecast revisions, and managerial guidance. We measure institutional ownership using LSEG 13F filings, which report quarterly equity holdings for institutional investment managers with at least $100 million in assets under management. We construct governance variables—board size, CEO duality, and CEO tenure—from BoardEx.

We apply four sample restrictions. We exclude internship postings and postings from staffing agencies to capture direct employer labor demand. We require firms to have at least ten unique job postings annually. To isolate responses to an initial negative earnings surprise rather than persistent underperformance, we require no negative earnings surprises in the prior three quarters $(Q_{-3}, Q_{-2}, Q_{-1})$; $Q_0$ is thus the first negative surprise following at least three consecutive quarters of meeting or beating expectations. We drop firms in the utilities (SIC 4900–4999) and financial

[1] Prior research confirms the reliability and validity of this dataset (Acemoglu et al. [2022], Gutiérrez et al. [2020]).

(SIC 6000–6999) sectors.

After applying these restrictions, the posting-level sample contains 13,904,281 unique job postings for 1,506 firms over 2011Q1–2024Q4.[2] We aggregate postings to the firm-quarter level and align those firm-quarters to 17,159 qualifying earnings announcement events. Expanding each event over the nine-quarter window from $Q_{-4}$ to $Q_{+4}$ yields 154,431 event-firm-quarter observations used in the main analyses. The unit of observation in the main tests is the event-firm-quarter unless otherwise noted. Panel A of Table 1 presents the sample construction process.

In the event-study data, the HHI, R&D, and analyst-coverage partition variables are attached to each event-firm-quarter observation. *LowHHI* uses the year-specific median of *MaxHHI* calculated across firms, whereas *HighRD* and *HighCover* use cutoffs calculated across firms within the same SIC-2 industry and event year.

## 3.2 Variable Measurement

Our primary dependent variable is abnormal job posting volume ($ABJP$), which measures deviations from a firm's normal recruitment patterns. Following Acemoglu et al. [2022], we apply the inverse hyperbolic sine (asinh) transformation to accommodate zero values and reduce right-skewness.[3] We define $ABJP$ as the difference between the asinh-transformed unique job postings ($JP$)[4] in quarter $q$ and the asinh-transformed three-year historical average for the corresponding

[2]The years 2011 and 2024 contain fewer observations because our benchmark regressions require a complete nine-quarter event window with no missing data.

[3]Following Acemoglu et al. [2022], Norton [2022], we apply the inverse hyperbolic sine transformation $\ln(x + \sqrt{x^2+1})$ to handle the skewed distribution of job postings, including zero values. For observations where the argument exceeds unity, the transformation approximates $\ln(2) + \ln(x)$, so that estimated coefficients can be interpreted as approximate percentage changes, analogous to a log-linear specification. We also run regressions for Hypothesis 1 without the inverse hyperbolic sine transformation on the dependent variable $ABJP_{i,q}$ and present the results in Table 11 column (3). The results are qualitatively and quantitatively consistent with those reported in Table 3, Panel A, Column (3), exhibiting both the same sign and a comparable magnitude.

[4]Unique postings count distinct positions, avoiding double-counting when firms post identical positions across multiple platforms.

fiscal quarter ($NormJP$)[5]:

$$NormJP_{i,q} = \frac{1}{3}\sum_{t=1}^{3} JP_{i,q-4t}$$

$$ABJP_{i,q} = \text{asinh}(JP_{i,q}) - \text{asinh}\left(NormJP_{i,q}\right)$$

We use the differenced measure ($ABJP$) rather than raw posting counts because firm and calendar-time fixed effects do not fully absorb the overlap between a firm's recurring recruitment calendar and the timing of earnings announcements.[6]

Our primary independent variable is *BADNEWS*, an indicator equal to one if the earnings surprise in the earnings announcement quarter ($Q_0$) is negative, and zero otherwise. Earnings surprise is defined as:

$$EarningsSurprise_{i,q} = \text{Actual EPS}_{i,q} - \text{Consensus Forecast}_{i,q}$$

where Actual EPS is the actual earnings per share of firm $i$ in quarter $q$ reported by I/B/E/S, and Consensus Forecast is the median analyst earnings forecast over the 90 days before the corresponding quarterly earnings announcement. We call the control group (i.e., *BADNEWS* is equal to zero) *GOODNEWS*. According to the sample restrictions in Section 3.1, both the *BADNEWS* and *GOODNEWS* groups have non-negative earnings surprises in the three consecutive quarters before the earnings announcement.

[5]We assign zero to firm-quarters with no postings. If a firm posts no positions over the preceding three years, we drop the observation because abnormal posting volume is undefined absent a historical benchmark.

[6]Raw posting counts confound structural differences in firms' habitual recruitment calendars with strategic timing responses. Subtracting the firm's own three-year same-quarter average removes this seasonal baseline, so a significant $ABJP$ reflects deviations from normal patterns rather than habitual timing.

Panel B of Table 1 shows that the final sample contains 17,159 firm-quarter observations. *BADNEWS* accounts for 18.16% (3,116 observations across 1,280 unique firms). The remaining 81.84% (14,043 observations across 1,299 unique firms) are *GOODNEWS* quarters.[7]

We construct several measures of job posting characteristics. *SKILLS* is the number of required skills per posting, *SPEC* is the number of specific skills, and *SOFT* is the number of soft skills, using Lightcast's skill taxonomy. *EDU* and *EXP* are required years of schooling and prior work experience, respectively. *SENIOR* is the average seniority level of posted positions (Junior=1, Intermediate=2, Senior=3), classified by Lightcast. *MGR* is the proportion of postings requiring managerial responsibilities, identified via proprietary parsing algorithms. *SALARY-FROM* and *SALARY-TO* are the lower and upper bounds of disclosed salary ranges. *SALARY-MID* is the midpoint of disclosed salary ranges. *SALARY-DISC* is the salary disclosure rate, the share of postings that include compensation information. *FULL* is the proportion of full-time positions among total postings. *WORD* is the total word count after removing HTML tags, a proxy for information disclosure following Sran [2025]. *DUR* is the average posting duration in days per quarter. *EFF* is posting effort, the ratio of total postings to unique positions. It captures cross-posting intensity across job boards identified via Lightcast.

Using Lightcast's online résumé database, we construct quarterly measures of workforce dynamics from individual employment histories. For the matched résumé subsample (16,564 firm-quarter observations), we observe employee inflows and outflows at each firm-quarter and compute raw quarterly rates—*Join*, *Turnover*, and *Net*—scaled by beginning-of-quarter headcount. We subtract

[7] *BADNEWS* observations account for less than 20% of the final sample because we require non-negative earnings surprises in the three consecutive quarters before the earnings announcement quarter for all firms to isolate responses to an initial negative earnings shock (see Section 3.1). We relax this restriction and report the related results in Table 11 column (2). The results are qualitatively and quantitatively consistent with those reported in Table 3, Panel A, Column (3), exhibiting both the same sign and a comparable magnitude.

each firm's previous three-year, same-calendar-quarter average from the corresponding raw rate to isolate abnormal flows, yielding *AbJoin*, *AbTurnover*, and *AbNet*. This seasonal adjustment removes firm-specific cyclical hiring patterns, so coefficients capture deviations from normal dynamics rather than predictable seasonal variation.

To capture capital market responses, we construct *CAR*, the cumulative abnormal return, computed as the sum of daily abnormal returns (firm return minus the CRSP value-weighted index return) over the $[-1, +1]$, $[-3, +3]$, and $[0, +30]$ trading-day windows around the earnings announcement date.

We include lagged firm-level controls for size, profitability, investment opportunities, R&D intensity, cash holdings, leverage, analyst following, labor intensity, institutional ownership, and governance characteristics (board size, CEO duality, and CEO tenure). Detailed definitions and data sources appear in Appendix.

All continuous variables are winsorized at the 1st and 99th percentiles. $ABJP$ is not winsorized because the inverse hyperbolic sine transformation already reduces the influence of extreme values while retaining observations with zero postings.

Table 2 reports descriptive statistics for the earnings announcement sample and for firm-level controls from 2011Q1 to 2024Q4. Mean *ABJP* is 0.30 at $Q_{-4}$, declining to $-0.17$ by $Q_{+4}$. The distribution has substantial cross-sectional dispersion, with the 99th percentile reaching 8.53 at $Q_{-4}$ and 6.97 at $Q_{-1}$. In the matched résumé subsample (16,564 firm-quarter observations), the median firm has 1,652 active employees (*HC-TOTAL*). Mean raw quarterly turnover, join, and net rates are 6.54%, 8.03%, and 1.50%, respectively. Seasonally adjusted abnormal flows show mean *AbJoin* declining from $-0.35$ pp to $-0.86$ pp, mean *AbTurnover* declining from 0.35 pp at $Q_{-4}$ to $-0.02$ pp at $Q_{+4}$, and mean *AbNet* declining from $-0.70$ pp to $-0.86$ pp. Workforce dynamics deteriorate

steadily over the post-announcement horizon. At $Q_0$, firms require 15.11 years of education (*EDU*) and 4.26 years of experience (*EXP*), with 23% of positions carrying managerial responsibilities (*MGR*). The mean salary midpoint is $71,906, the average posting duration is 55.92 days (*DUR*), and postings contain 555.17 words (*WORD*) and specify 19.16 skills (*SKILLS*). Posting effort averages 2.71 (*EFF*).

## 3.3 Empirical Design

In this section, we introduce the baseline econometric models used to test our theoretical predictions.

### 3.3.1 Abnormal Job Posting Dynamics

To estimate Hypothesis 1, we employ a cohort-based event-study design to examine job posting behavior around earnings announcements. Firms announcing earnings within the same calendar quarter constitute a cohort.[8] Specifically, we estimate the following equation:

$$\begin{aligned} \text{ABJP}_{i,q} = \beta_0 + \beta_1 \, BADNEWS_{i,Q0} + \sum_{k \in K} \lambda_k \, Q_k + \sum_{k \in K} \beta_k \, (BADNEWS_{i,Q0} \times Q_k) \\ + X'_{i,q-1}\Gamma + \delta_i + \gamma_{q \times y} + \theta_c + \varepsilon_{i,q} \end{aligned} \tag{1}$$

where $\text{ABJP}_{i,q}$ is the abnormal job postings for firm $i$ in quarter $q$, and $BADNEWS_{i,Q0}$ identifies whether firm $i$ has a negative earnings surprise in $Q_0$. Both variables are defined in Section 3.2. $Q_k$ represents event-time indicators from $Q_{-4}$ through $Q_{+4}$ relative to the announcement quarter $Q_0$

[8] For example, all firms announcing earnings during 2015Q2 form a single cohort. Firms with announcements across multiple periods contribute multiple cohorts.

(i.e., the baseline quarter).[9]

The omitted category is the control group (i.e., *GOODNEWS* firms) at $Q_0$. Accordingly, $\lambda_k$ captures the evolution of the *GOODNEWS* group over the eight-quarter event time (from $Q_{-4}$ through $Q_{+4}$) relative to $Q_0$. The coefficient $\beta_1$ measures the *BADNEWS–GOODNEWS* difference at the announcement quarter $Q_0$, while the *BADNEWS–GOODNEWS* differences at other event times $k \neq 0$ are given by the linear combination $\beta_1 + \beta_k$. Based on Hypothesis 1, we expect $\beta_1 + \beta_k$ to be positive for quarters before the earnings announcement. Firm fixed effects ($\delta_i$) absorb time-invariant firm characteristics, year-quarter fixed effects ($\gamma_{q\times y}$) absorb common time shocks, and cohort fixed effects ($\theta_c$) absorb common shocks specific to each announcement-event cohort. Standard errors are clustered at firm and year-quarter levels. Control vector $X_{i,q-1}$ includes lagged firm and governance characteristics discussed in Section 3.2.

### 3.3.2 Labor Market Outcomes: Employee Flow Dynamics and Job Posting Characteristics

To examine whether a negative earnings surprise affects real workforce flows in the labor market, we use résumé data from Lightcast and estimate the average difference in employee inflows and outflows between the *BADNEWS* and the *GOODNEWS* groups using Equation (2):

$$Y_{i,q} = \beta_0 + \beta_1 \, BADNEWS_{i,Q0} + \sum_{k\in K} \lambda_k \, Q_k + \sum_{k\in K} \beta_k \, (BADNEWS_{i,Q0} \times Q_k) + \mathbf{X}'_{i,q-1}\mathbf{\Gamma} + \delta_i + \gamma_{q\times y} + \theta_c + \varepsilon_{i,q} \tag{2}$$

where $Y_{i,q}$ represents abnormal employee flow rates ( AbJoin, AbTurnover, or AbNet) for firm $i$ in quarter $q$, defined in Section 3.2. We include firm, year-quarter, and cohort fixed effects and the

[9] We test our main hypotheses using parallel trend analyses (i.e., multiplying $BADNEWS_{i,Q0}$ with each quarter $Q_k$), instead of using a dummy variable capturing the pre- and post-announcement periods, to better identify the front-loading hiring activities over the nine-quarter period.

full set of controls, with standard errors two-way clustered by firm and year-quarter.

However, not all firms anticipating negative earnings surprises are able to front-load hiring activities. We further examine the implications of front-loading for employee flows, expecting front-loading *BADNEWS* firms to exhibit higher net hiring rates.

To test this prediction, we divide *BADNEWS* firms into two groups based on the cumulative $Q_{-3}$–$Q_{-1}$ job posting volume. Firms with positive cumulative abnormal postings that exceed the median among firms in the same SIC-2 industry, year, and quarter cohort are designated as *PreHigh*.[10] Other *BADNEWS* firms are referred to as *PreLow*. We modify the main independent variables of Equation (2) and estimate the following equation:

$$\begin{aligned} Y_{i,q} = \beta_0 &+ \beta_1 \cdot PreHigh_i + \beta_2 \cdot PreLow_i + \sum_{k \in K} \lambda_k \cdot Q_k \\ &+ \sum_{k \in K} \beta_k^{High} \cdot (Q_k \times PreHigh_i) + \sum_{k \in K} \beta_k^{Low} \cdot (Q_k \times PreLow_i) \\ &+ \mathbf{X}'_{i,q-1}\Gamma + \delta_i + \gamma_{q \times y} + \theta_c + \varepsilon_{i,q} \end{aligned} \tag{3}$$

where $Y_{i,q}$ represents abnormal employee flow rates ( AbJoin, AbTurnover, or AbNet) for firm $i$ in quarter $q$. *PreHigh* (*PreLow*) equals one for *PreHigh* (*PreLow*) *BADNEWS* firm-quarters and zero for the non-bad-news group (*GOODNEWS*). Equation (3) estimates different abnormal employee flows in join, turnover, and net rates for three comparable groups: *PreHigh BADNEWS* vs. *GOODNEWS* (captured by coefficients $\beta_1 + \beta_k^{High}$), *PreLow BADNEWS* vs. *GOODNEWS* (captured by coefficients $\beta_2 + \beta_k^{Low}$), and *PreHigh BADNEWS* relative to *GOODNEWS* vs. *PreLow BADNEWS* relative to *GOODNEWS* (captured by coefficients $(\beta_1 + \beta_k^{High}) - (\beta_2 + \beta_k^{Low})$).[11]

[10] We require positive cumulative abnormal postings to ensure that *PreHigh* designations reflect firms genuinely above their own historical posting benchmark, consistent with the front-loading hypothesis. Firms must carry positive cumulative abnormal postings and exceed the median for their SIC-2 industry, year, and quarter cohort to qualify as *PreHigh*; the remaining *BADNEWS* observations are *PreLow*.

[11] The *PreHigh–PreLow* differences are captured by tests $H_0: (\beta_1 + \beta_k^{High}) - (\beta_2 + \beta_k^{Low}) = 0$. Because *GOODNEWS*

We also expect that *BADNEWS* firms with high pre-announcement posting intensity (*PreHigh*) differ from other bad-news (*PreLow*) and non-bad-news firms (*GOODNEWS*) in the characteristics of posted positions. We test this prediction using Equation (3) by changing the dependent variable. Now $Y_{i,q}$ measures job posting characteristics discussed in Section 3.2, such as posting duration, effort, number of required skills per posting, seniority of posted positions, and salary disclosure.

### 3.3.3 Capital Market Outcomes

To examine whether front-loading affects capital markets, we estimate the short-term cumulative abnormal returns around the earnings announcement date for the two *BADNEWS* groups relative to *GOODNEWS*:

$$Y_{i,q} = \beta_1 PreHigh_{i,q} + \beta_2 PreLow_{i,q} + \mathbf{X}'_{i,q-1}\Gamma + \delta_i + \gamma_{q\times y} + \varepsilon_{i,q} \tag{4}$$

where $Y_{i,q}$ represents cumulative abnormal returns (CAR) over event windows $[-1,+1]$, $[-3,+3]$, and $[0,+30]$ days relative to earnings announcement. *PreHigh* and *PreLow* are defined in the same way as in Equation (3). We control for the full set of firm characteristics discussed in Section 3.2 and include firm and year-quarter fixed effects. Standard errors are clustered at the firm and the year-quarter level.

Equation (4) is estimated based on a sample at the event level (with 16,951 firm-quarter observations), rather than at the event-firm-quarter level (i.e., expanding each event over the nine-quarter window). This is because it estimates the difference in CAR among the two types of *BADNEWS* and *GOODNEWS* firms over short-term windows, [-1,+1], [-3,+3], and [0,+30] trading days, instead of several quarters around the earnings announcement date. The coefficient $\beta_1$ measures the difference

is the omitted baseline, this is algebraically identical to the direct *PreHigh–PreLow* comparison.

between the *PreHigh BADNEWS* group and the *GOODNEWS* group. Similarly, $\beta_2$ captures the difference between the *PreLow BADNEWS* group and the control group.

# 4 Baseline Results

In this section, we estimate empirical models described in Section 3.3 and show the baseline results.

## 4.1 Abnormal Job Posting Dynamics Around Negative Earnings Announcements

Table 3, Panel A reports the estimation results for Equation (1). Columns (1) to (3) sequentially include firm fixed effects, year-quarter fixed effects, control variables, and cohort fixed effects.

According to Equation (1), the evolution of abnormal job posting volume of the control group (*GOODNEWS*) over the nine-quarter period is captured by the coefficients of $Q_k$. Focusing on Column (3), the control group has a significantly lower abnormal posting volume in the pre-announcement period than in $Q_0$ (ranging from $-0.208$ at $Q_{-4}$ to $-0.068$ at $Q_{-1}$, statistically significant at 1%). After the non-negative earnings are announced, the *GOODNEWS* group has similar posting volume to that in $Q_0$.

The difference in abnormal posting volume between the *BADNEWS* and *GOODNEWS* groups is captured by the coefficient $\beta_1$ in the earnings announcement quarter, and by $\beta_1 + \beta_k$ in other quarters. The Wald tests of $H_0: \beta_1 + \beta_k = 0$ indicate that the *BADNEWS* group has higher abnormal posting volume than the *GOODNEWS* group before the earnings announcement. This difference is economically meaningful and statistically significant at the 5% or 10% level, ranging from 0.090

($t = 1.67$) to 0.134 ($t = 2.19$) between $Q_{-3}$ and $Q_{-1}$.[12] These results imply a greater posting volume for *BADNEWS* than for *GOODNEWS* during the three quarters preceding the earnings announcement quarter.[13]

At the announcement quarter ($Q_0$), *BADNEWS* firms exhibit an immediately lower abnormal posting volume than *GOODNEWS* following the negative earnings announcement ($\beta_1 = -0.157$, $t = -2.97$), which corresponds to approximately 15.7% fewer postings.

After the earnings release, the Wald tests indicate significantly lower posting volumes for *BADNEWS* than for *GOODNEWS* from $Q_{+2}$ to $Q_{+4}$. In $Q_{+2}$, for example, the coefficient of −0.181 ($t = -2.88$) corresponds to approximately 18.1% lower posting intensity (35 fewer positions per quarter). We interpret the evolution in abnormal job postings for the two groups as consistent with front-loading of job postings among *BADNEWS* firms. Therefore, the results of Table 3, Panel A support Hypothesis 1.

Table 3, Panel B shows that the above-mentioned front-loading of job postings among *BADNEWS* firms is an intertemporal reallocation of recruitment. Firms have cumulative abnormal posting volume that is 3.7% higher from $Q_{-4}$ to $Q_{-1}$ ($t = 2.56$) and 4.0% lower from $Q_0$ to $Q_{+3}$ ($t = -2.53$). The cumulative effect over the full eight-quarter window ($Q_{-4}$ to $Q_{+3}$) is insignificant (−0.005, $t = -0.39$). This pattern is consistent with intertemporal shifting of recruitment rather than a sustained increase in labor demand.

[12] As a back-of-the-envelope approximation, evaluated at the sample mean of normal postings, these differentials correspond to roughly 20 to 30 more postings per quarter for *BADNEWS* firms than for *GOODNEWS* firms. Raw position estimates are computed as mean postings $\times$ ($e^{\hat{\beta}} - 1$). In our sample, the average normal postings over a three-year period equal 207.86 per quarter.

[13] To ensure that our findings are not driven by defining abnormal job postings based on the focal firm's own history, we adopt an alternative *ABJP* measure. This is defined as the transformed firm-level job postings minus the transformed, leave-one-out mean of job postings within the same two-digit SIC industry and calendar quarter over the preceding three years (requiring a minimum of five firms). This adjustment accounts for historical industry-specific seasonal recruitment patterns. The estimated coefficients are 0.042 ($t = 2.18$) at $Q_{-2}$, 0.047 ($t = 2.24$) at $Q_{-1}$, and −0.039 ($t = -1.87$) at $Q_0$, displaying the same directional pattern as the baseline specification.

## 4.2 Labor Market Reactions to Front-loading of Job Postings

### 4.2.1 Employee Flow Dynamics around Negative Earnings Announcements

In this section, we examine whether front-loading among *BADNEWS* firms translates into actual hiring activity. Specifically, we study employee flow dynamics (i.e., abnormal join rate, abnormal turnover rate, and abnormal net hiring rate) between the *BADNEWS* and *GOODNEWS* groups. Table 4 reports the estimation results of Equation (2).

Column (1) shows results of the abnormal join rate. The coefficients of $Q_k$ are negative and all statistically significant at 1% from $Q_{-4}$ ($\lambda_{Q_{-4}}$= −0.260) to $Q_{-1}$ ($\lambda_{Q_{-1}}$= −0.045), meaning that *GOODNEWS* firms have significantly lower abnormal join rates in pre-announcement quarters than in $Q_0$. After non-negative earnings are released, the abnormal join rate recovers for the *GOODNEWS* group in one quarter after the earnings announcement ($\lambda_{Q_{+1}} = 0.038$, significant at the 1% level).

The Wald tests of $H_0: \beta_1 + \beta_k = 0$ indicate that *BADNEWS* firms have 0.155–0.232 pp higher join rates than the *GOODNEWS* group from $Q_{-4}$ through $Q_{-2}$ ($t$ = 1.98–3.15), with the $Q_{-2}$ coefficient representing 2.9% of the mean join rate. The high abnormal join rates of the *BADNEWS* group persist in the earnings announcement quarter. However, after the earnings release, the high abnormal join rates decrease significantly for the *BADNEWS* group. Join rates of the group are 0.165 pp lower at $Q_{+1}$ ($t = -2.39$), 0.254 pp lower at $Q_{+2}$ ($t = -3.10$), and 0.250 pp lower at $Q_{+4}$ ($t = -3.79$) than the *GOODNEWS* group, with the $Q_{+2}$ deficit representing 3.2% of the mean join rate. Post-announcement join rates are lower for *BADNEWS* firms.

Column (2) shows results of the abnormal turnover rate. Consistent with the join rate, *GOODNEWS* firms exhibit higher (although decreasing) abnormal turnover rates during the pre-earnings-announcement quarters than in $Q_0$ (from $\lambda_{Q-4} = 0.257$ to $\lambda_{Q-1} = 0.082$; all statistically significant

at 1%). After non-negative earnings are released, the turnover rate of the *GOODNEWS* group decreases one quarter after the earnings announcement ($\lambda_{Q+1} = -0.028$, significant at the 5% level). The Wald tests indicate that *BADNEWS* and *GOODNEWS* firms do not have significant differences in turnover rates from $Q_{-4}$ through $Q_{-2}$. However, *BADNEWS* firms have 0.106 pp lower turnover rates in $Q_{-1}$ (statistically significant at the 5% level) than *GOODNEWS* firms, representing 1.6% of the mean turnover rate. This employee attrition pattern does not persist after earnings announcements are released to the market. Turnover rates of *BADNEWS* firms exceed those of *GOODNEWS* firms by 0.123–0.226 pp across $Q_{+1}$–$Q_{+4}$ ($t = 2.10$–$5.01$). The $Q_{+2}$ abnormal-turnover difference of 0.226 percentage points represents approximately 3.5% of the mean turnover rate, while the $Q_{+4}$ difference of 0.126 percentage points represents approximately 1.9% of the mean.

Column (3) presents results of the abnormal net hiring rate, which captures the difference between the join and turnover rates. *GOODNEWS* firms have lower join rates and higher turnover rates in pre-announcement quarters than in $Q_0$. Accordingly, their abnormal net hiring rates are lower for the same period. After the non-negative earnings surprise announcement, the control group has higher net hiring rates for $Q_{+1}$ and $Q_{+2}$, due to higher join rates and lower turnover rates than those in $Q_0$. *BADNEWS* firms show higher abnormal net hiring rates than the *GOODNEWS* group before and during the earnings announcement quarter (0.147–0.255 pp from $Q_{-3}$ to $Q_0$; $t = 1.92$–2.55) because of the joint effect of higher join rates and lower abnormal turnover rates. During the post-announcement period, the *BADNEWS* group has lower net hiring rates than the control group, driven by both lower join rates and higher abnormal turnover. Specifically, *BADNEWS* firms experience a net workforce deterioration of 0.251–0.483 pp across $Q_{+1}$–$Q_{+4}$ (all significant at 1%, and the largest differential representing 32.2% of the mean net hiring rate). This result confirms that adverse earnings news creates recruitment frictions.

In summary, the results of Table 4 show that the front-loading pattern of abnormal job postings among *BADNEWS* firms translates into actual hiring activities. In addition, the results of abnormal net hiring rates are consistent with intertemporal reallocation rather than aggregate expansion of labor demand. Shifting job postings from the post-announcement period to the pre-period, *BADNEWS* firms manage to increase net hiring rates before the negative earnings surprise becomes public.

However, not all *BADNEWS* firms front-load job postings. To further investigate the labor market response to front-loading, we differentiate *BADNEWS* firms with high abnormal job posting volume in the pre-announcement period (i.e., *PreHigh*) from those with low volume (i.e., *PreLow*), and estimate Equation (3). Table 5 reports the main results on abnormal employee flows. Figure 1 provides a graphical summary of the predicted abnormal join, turnover, and net hiring rates for *GOODNEWS*, *PreLow*, and *PreHigh* firms over the event window. According to the coefficients of $\lambda_k$, *GOODNEWS* firms show the same trends as those in Table 4 because the control group is not affected by high or low front-loading of job postings. Hence, we focus on the difference between *PreHigh* and *PreLow BADNEWS* firms.[14]

The estimation results of abnormal join rates are reported in Column (1). Firms with high front-loading of job postings (*PreHigh*) show significantly higher abnormal join rates than *GOODNEWS* firms across the entire pre-announcement window until the announcement quarter: 0.283 pp ($Q_{-4}$), 0.519 pp ($Q_{-3}$), 0.533 pp ($Q_{-2}$), 0.595 pp ($Q_{-1}$), and 0.413 pp ($Q_0$), all significant at 1%, with the average across $Q_{-4}$ through $Q_0$ representing approximately 5.8% of the mean join rate. After negative earnings are released to the market, the *PreHigh* group shows lower join rates than the

[14]We analyze the differences in abnormal employee flows among *PreHigh*, *PreLow*, and *GOODNEWS* firms based on Wald test results in Table 5.

*GOODNEWS* group in $Q_{+2}$ (−0.429 pp, $t = -4.32$; 5.3% of the mean join rate) and $Q_{+4}$ (−0.382 pp, $t = -3.89$). *PreLow* firms, in contrast, have lower abnormal join rates than the *GOODNEWS* group throughout the nine-quarter window, and coefficients are statistically significant in $Q_{-3}$ (−0.185 pp, $t = -1.95$), in $Q_{-1}$ (−0.282 pp, $t = -2.50$), and in $Q_{+1}$ (−0.276 pp, $t = -3.08$). Comparing the *PreHigh* and *PreLow* groups, we find that firms with high front-loading of postings have significantly higher abnormal join rates than the low front-loading group before the earnings surprise is announced. The difference in estimated abnormal join rates between the two groups ranges from 0.580 to 0.877 pp from $Q_{-3}$ to $Q_{-1}$ (all significant at 1%). The positive difference lasts until one quarter after the earnings announcement (0.230 pp, $t = 2.06$) but then reverses at $Q_{+2}$ (−0.336 pp, $t = -2.95$).

Column (2) reports estimation results of abnormal turnover rates. *PreHigh* firms show no significant differences from *GOODNEWS* firms throughout the pre-announcement window (from $Q_{-4}$ to $Q_0$). However, after the negative earnings surprise becomes public, this group of *BADNEWS* firms has significantly higher abnormal turnover rates than the control group across all four quarters in the post period (0.215–0.344 pp, $t = 3.18$–$5.07$, and the $Q_{+4}$ coefficient representing approximately 5.2% of the mean turnover rate). *PreLow* firms present a different pattern. The group of *BADNEWS* firms with low abnormal job posting intensity in the pre-announcement period has turnover rates similar to or even lower than those of *GOODNEWS* firms at $Q_{-1}$ (−0.215 pp, $t = -3.59$) before earnings become public, and shows only marginally higher turnover rates than the control group at $Q_{+2}$ (0.148 pp, $t = 1.91$). As a result, *BADNEWS* firms with high front-loading of job postings have significantly higher abnormal turnover rates than low front-loaders in almost all quarters, both before and after the earnings announcement.

Column (3) reports estimation results of the abnormal net hiring rate. Comparing *PreHigh*

and *GOODNEWS* firms, we find that *BADNEWS* firms with high front-loading of job postings have higher abnormal net hiring rates than the control group during the pre-announcement period: 0.358 pp at $Q_{-4}$, 0.476 pp at $Q_{-3}$, 0.484 pp at $Q_{-2}$, and 0.587 pp at $Q_{-1}$, all statistically significant at the 1% level. The $Q_{-1}$ coefficient represents 39.1% of the mean net hiring rate. After the earnings announcement, high front-loading *BADNEWS* firms have significantly lower net hiring rates than the control group due to both higher turnover rates and lower join rates during the period. Nevertheless, *PreLow* firms have similar net hiring rates to *GOODNEWS* firms during pre-announcement quarters, but have significantly lower net hiring rates in the two quarters after the announcement (−0.324 pp at $Q_{+1}$, $t = -2.96$, and −0.234 pp at $Q_{+2}$, $t = -1.92$). Therefore, *BADNEWS* firms with more front-loading of job postings have higher net hiring rates before the earnings announcements but lower rates afterwards than *PreLow* firms.

Overall, the results of Table 5 indicate that *PreHigh* firms maintain higher net hiring rates before the earnings announcement relative to both *PreLow* and *GOODNEWS* firms, while *BADNEWS* firms on average face elevated turnover and weaker join rates in the post-announcement period. These results imply that the high net hiring rates among *BADNEWS* firms relative to *GOODNEWS* firms before the earnings announcement reported in Table 4 are driven by *BADNEWS* firms with high front-loading of job postings (*PreHigh*). The results of the two tables indicate that front-loading of job postings by some firms expecting negative earnings surprise leads to real labor market reactions, reflected in the high join rates and net hiring rates of those firms.

### 4.2.2 Job Posting Characteristics around Negative Earnings Announcements

This section presents estimation results of Equation (3) with dependent variables capturing job posting characteristics, described in subsections 3.2 and 3.3.2. Specifically, we examine whether

*BADNEWS* firms with high front-loading (*PreHigh*) differ from *PreLow* and *GOODNEWS* firms in the characteristics of posted positions before and after the earnings announcement. Table 6 reports Wald test results for eight posting characteristics.[15]

*Skill Requirements.* *PreHigh* firms require more skills per posting, including both specific and soft skills, than *PreLow* and *GOODNEWS* firms, especially before the earnings announcement. These results imply that job postings by intensive front-loaders are more demanding in terms of required skills.

*Seniority.* *PreHigh* firms target higher seniority levels in their job postings than *PreLow* and *GOODNEWS* firms before the announcement, implying that job postings of *PreHigh* firms focus more on top managerial positions compared to the other two groups.

*Other Characteristics.* *PreHigh* firms are less likely to disclose salary information than *PreLow* and *GOODNEWS* firms before the announcement, while providing lengthier job descriptions. They also leave postings open for longer than *PreLow* firms in the pre-announcement period, and list vacancies across more job boards than *PreLow* and *GOODNEWS* firms throughout both the pre- and post-announcement windows.

These results indicate that front-loading coincides with changes in both posting volume and posting characteristics.

## 4.3 Capital Market Reactions to Front-loading of Job Postings

This section presents estimation results of Equation (4), examining capital market reactions. Table 7 reports cumulative abnormal returns (CAR) over three short event windows: $[-1, +1]$

[15] Variables that were predominantly insignificant across the event window (Full, MGR, EDU, EXP, SALARY-FROM, and SALARY-TO) have been omitted for brevity.

(Column (1)), $[-3, +3]$ (Column (2)), and $[0, +30]$ (Column (3)).

Both *PreHigh* and *PreLow BADNEWS* firms face significantly lower cumulative abnormal returns than *GOODNEWS* firms across all three event windows. In addition, Wald tests of $H_0: \beta_1 - \beta_2 = 0$ are statistically indistinguishable from zero across all event windows. These results indicate that the two *BADNEWS* groups, both with and without high front-loading of job postings, face comparable short-term returns after the announcement of the negative earnings surprise.

# 5 Cross-Sectional Tests: Expected Variation with labor market Characteristics

We next examine cross-sectional variation in front-loading and employee net flows. We expect front-loading to be more pronounced when recruiting is more difficult, and, therefore, where a negative earnings surprise can create more labor market frictions. In particular, we examine labor market competition, R&D intensity, and analyst coverage.

Regarding Labor Market Competition, we expect front-loading to be stronger if rival employers compete more aggressively for the same workers. Following Azar et al. [2022], we measure labor market competition using the Herfindahl-Hirschman Index (HHI) defined for five-digit Standard Occupational Classification (SOC5) occupation × metropolitan statistical area (MSA) markets. For each event-firm-quarter observation, *MaxHHI* is the maximum HHI across all markets in which the firm recruits.[16] We classify an observation as *LowHHI* when its *MaxHHI* is below the median among firms in the same event year; the complementary observations form the *HighHHI* group.

[16]Higher HHI values denote greater concentration and lower competition. Our sample exhibits a mean *MaxHHI* of 3,576 and a median of 2,959.

We show the results in the first two columns of Table 8. Within competitive labor markets (*LowHHI*), the Wald tests show that *BADNEWS* firms exhibit significantly higher front-loading relative to the non-negative-surprise benchmark within the subgroup (0.249, $t = 2.68$, and 0.254, $t = 2.93$, at $Q_{-2}$ and $Q_{-1}$, respectively). Within concentrated markets (*HighHHI*), the corresponding Wald test differentials are statistically indistinguishable from zero in the pre-announcement quarters. These posting differentials are accompanied by higher realized employee net hiring rates in competitive markets (as reported in the first two columns of Table 9), with significant differences at $Q_{-4}$ (0.266 pp, $t = 2.12$) and $Q_{-2}$ (0.343 pp, $t = 2.74$), while firms in concentrated labor markets show no significant pre-announcement differentials. After the earnings announcement, abnormal job posting intensity decreases for *BADNEWS* firms only in less competitive labor markets. However, employee net hiring rates decline in both markets. These results confirm that front-loading of recruitment (in both job posting volume and net employee flow rates) is more pronounced in highly competitive labor markets.

Regarding R&D Intensity, high-R&D firms typically operate in more competitive labor markets for specialized talent, making recruitment outcomes more sensitive to employer-specific news (Brown et al. [2009], Berk et al. [2010], Brown and Matsa [2016]). Front-loading should therefore be larger among high-R&D firms. We classify each event-firm-quarter observation as High R&D when R&D-to-assets exceeds the 75th percentile among firms in the same SIC-2 industry and event year, and classify the remaining observations as Low R&D.[17] Consistent with our expectations, the Wald tests in Columns (3) and (4) of Table 8 show that *BADNEWS* firms have higher abnormal job posting intensity than *GOODNEWS* firms in the sample with high R&D intensity in one quarter before the earnings announcement (0.262, $t = 2.20$). The corresponding Low R&D sample

[17] We use the 75th percentile to split samples because the sample median of R&D intensity is zero.

estimates are statistically indistinguishable from zero in most pre-announcement quarters. Columns (3) and (4) of Table 9 show that net flow rate estimates follow a similar pattern during the pre-announcement period. Highly innovative *BADNEWS* firms exhibit significantly higher net hiring rates than *GOODNEWS* firms (0.507 pp at $Q_{-2}$, $t = 2.33$, and 0.449 pp at $Q_{-1}$, $t = 2.24$), while the Low R&D estimates are statistically indistinguishable from zero in most pre-announcement quarters. After the earnings announcement, High R&D *BADNEWS* firms show similar job posting volume to the control group, and lower net rates than *GOODNEWS* firms in $Q_{+4}$ ($-0.350$, $t = -2.03$), whereas *BADNEWS* firms in the Low R&D sample show both lower job posting volume and net rates than the control group.

With respect to Analyst Coverage, we expect front-loading to be stronger among firms with heavy analyst coverage because analyst coverage accelerates the dissemination of negative earnings news (Hong et al. [2000]): when more analysts track a firm, bad news reaches a wider audience more rapidly after the announcement. This narrows the window during which pre-announcement recruitment is relatively advantageous and raises the payoff to accelerating hiring before disclosure. We measure event-quarter analyst coverage as the number of analysts issuing EPS forecasts in I/B/E/S. An event-firm-quarter observation belongs to the high-coverage group when analyst coverage exceeds the median among firms in the same SIC-2 industry and event year; the remaining observations form the low-coverage group. In columns (5) and (6) of Table 8, Wald tests show that *BADNEWS* firms have significantly higher abnormal job posting intensity than *GOODNEWS* firms before the earnings announcement in the sample with high analyst coverage (0.178 at $Q_{-2}$, $t = 2.19$, and 0.155 at $Q_{-1}$, $t = 2.25$), while the corresponding estimated job posting differences for the sample with low analyst coverage are statistically indistinguishable from zero during the same period. Columns (5) and (6) of Table 9 present a very similar pattern for net employee flow

rates. In the high-analyst-coverage sample, *BADNEWS* firms have significantly higher net rates than *GOODNEWS* firms in the pre-announcement quarters (0.272 pp at $Q_{-3}$, $t = 2.54$, and 0.322 pp at $Q_{-2}$, $t = 4.11$). We do not observe any significant differences between the two groups in net rates before the earnings announcement in the sample with low analyst coverage. After earnings are announced, the high-analyst-coverage sample exhibits lower job posting intensity for *BADNEWS* firms than for *GOODNEWS* ones. However, *BADNEWS* firms have both lower job postings and net flow rates than *GOODNEWS* firms in the low-analyst-coverage sample. These results confirm that front-loading of recruitment is more pronounced for firms with high analyst coverage.

Overall, in this section we study distinct dimensions of the environment in which front-loading is most valuable — competitive labor markets, dependence on specialized human capital, and rapid post-announcement information diffusion. Across all three, the evidence points consistently toward front-loading being more pronounced where negative earnings news poses more pronounced recruitment challenges.[18]

# 6 Robustness Tests

## 6.1 Alternative Explanation

An alternative explanation to our results is that the firms that we identify as front-loaders are growth firms that hire more until they suffer the negative earnings surprise, when they stop hiring.

[18] As discussed in Section 2, financial flexibility facilitates firms' ability to front-load recruitment, as shifting recruitment forward requires firms to incur recruitment and labor costs earlier. Consistent with this prediction, *BADNEWS* firms with above-median liquidity exhibit higher abnormal job posting volume than *GOODNEWS* firms at $Q_{-2}$ (0.230, $t = 2.38$). They also exhibit significantly higher abnormal net hiring rates from $Q_{-3}$ through $Q_0$. In contrast, among firms with below-median liquidity, we find no evidence of front-loading, as *BADNEWS* firms do not exhibit either higher abnormal job posting volume prior to the earnings announcement or a significant pre-announcement increase in abnormal net hiring rates relative to *GOODNEWS* firms.

While plausible, our empirical work does not support this alternative explanation. Front-loaders do not exhibit weaker subsequent operating performance than comparable firms, which is difficult to reconcile with the view that they simply represent firms whose growth becomes unsustainable.[19]

Still, to further address this concern, we examine whether front-loaders are associated with analyst forecast revisions. One mechanism through which a growth-based explanation could generate our results is if unusually strong hiring leads analysts to revise earnings expectations upward, thereby increasing the likelihood of a subsequent negative earnings surprise. To examine this possibility, we regress analyst consensus forecast revisions and forecast errors over current- and next-quarter forecast horizons on alternative metrics of job posting intensity: postings since the prior earnings date (JP-REV), 6-month (JP-6M) and 12-month (JP-12M) trailing postings, and a top-quartile posting indicator (High-REV). Table 10 reports the results. Across all specifications, the estimated coefficients on recruiting intensity are close to zero and statistically insignificant (e.g., JP-REV: $-0.000$, $t = -0.62$; HIGH-REV: $-0.000$, $t = -0.12$). Therefore, front-loading is not associated with upward analyst forecast revisions, which does not support the alternative explanation that growth is driving our results.

[19]To further examine whether front-loaders are simply growth firms whose expansion subsequently becomes unsustainable, we compare the future operating performance of front-loaders and non-front-loaders. Specifically, we estimate the following equation:

$$Y_{i,q} = \beta_0 + \beta_1 PreHigh_{i,q} + \beta_2 PreLow_{i,q} + X'_{i,q-1}\Gamma + \delta_i + \gamma_{q\times y} + \varepsilon_{i,q}$$

where $Y_{i,q}$ represents firm's future performance (i.e., one- and two-year-ahead ROA and sales growth). With this specification, we test whether front-loading *BADNEWS* firms exhibit different future operating performance than *BADNEWS* firms that do not front-load, using *GOODNEWS* firms as the baseline group. The Wald test results indicate that front-loaders and non-front-loaders have very similar predicted future operating performance: $\beta_1 - \beta_2 = -0.0001$, $t = -0.08$, for ROA at $t + 1$; $\beta_1 - \beta_2 = -0.0006$, $t = -0.60$, for ROA at $t + 2$; $\beta_1 - \beta_2 = 0.014$, $t = 1.53$, for sales growth at $t + 1$; and $\beta_1 - \beta_2 = -0.0065$, $t = -0.88$, for sales growth at $t + 2$.

## 6.2 Alternative Samples and Specifications

We test the baseline model, Equation (1), across alternative sample restrictions and measurement choices to assess robustness. Table 11 shows the results.

*Excluding the COVID-19 Pandemic.* To ensure that our findings are not an artifact of the severe labor market disruptions during the pandemic, we exclude years 2020 and 2021 from the sample period, and Column (1) reports the results. The front-loading dynamic persists when excluding the pandemic period ($Q_{-2}$: 0.129, $t = 1.91$; $Q_{-1}$: 0.114, $t = 1.86$).

*Relaxing the Isolated-Event Restriction.* Our baseline sample restricts attention to firm-quarters in which $Q_0$ is the first negative earnings surprise in the event window, excluding observations with negative earnings surprises in $Q_{-1}$, $Q_{-2}$, or $Q_{-3}$, to reduce contamination of event-time posting patterns by overlapping negative earnings surprises. Column (2) relaxes this restriction, retaining firm-quarters with consecutive negative earnings surprises, thereby substantially expanding the sample. The front-loading pattern persists. Under this relaxed specification, the differential at $Q_{-4}$ becomes statistically significant (0.121, $t = 3.09$), consistent with the broader sample extending the estimated posting differential to $Q_{-4}$.

*Alternative Functional Form.* Column (3) replaces our inverse hyperbolic sine transformation with a simple arithmetic difference between raw posting counts and the historical benchmark ($JP - NormJP$). The results show the front-loading of job postings remains statistically significant and has a large economic effect (39.20 additional postings at $Q_{-2}$, $t = 2.98$; 35.21 at $Q_{-1}$, $t = 1.82$).

*Propensity-Score Matching.* To avoid observable pre-event differences between the *BAD-NEWS* and *GOODNEWS* groups, we use a propensity-score matching (PSM) design and report results in Column (4). PSM matches each negative-surprise firm-quarter to three nearest-neighbor

nonnegative-surprise firm-quarters (1:3 matching) based on $Q_{-4}$ firm characteristics (size, profitability, investment opportunities, R&D intensity, cash holdings, and leverage). The PSM results confirm the front-loading pattern.

# 7 Conclusion

We document that firms anticipating negative earnings surprises front-load recruitment by increasing job posting volumes during the three quarters preceding the earnings announcement. This front-loading translates into actual employee inflows before announcements, followed by offsetting declines afterwards, indicating temporal reallocation rather than net workforce expansion.

Our results are consistent with firms front-loading to secure talent before negative news worsens the firm's labor market attractiveness. We find that negative earnings surprises substantially reduce join rates and increase turnover, consistent with adverse earnings news creating recruitment frictions. Front-loading firms achieve higher net hiring rates than bad-news firms that do not front-load and they also change the content of their postings, demanding more specialized skills, disclosing less salary information, and emphasizing senior positions. We do not find differential capital markets effects for front-loaders. Finally, cross-sectional evidence shows that front-loading is more pronounced in competitive labor markets.

These findings speak to two streams of research. For the literature on the labor market consequences of firm-specific bad news, we provide the first evidence that firms adjust recruitment timing around earnings announcements, extending prior work that documents the labor market frictions created by bad news but not firm-level recruitment responses to them. For the literature on job postings as a source of firm-specific information, we show that both the timing and content of job

postings vary systematically around earnings announcements, and that these variations are associated with realized employee inflows and stronger recruitment outcomes. Future research could examine the relative roles of recruitment timing and job posting content in explaining the labor market benefits associated with front-loading.

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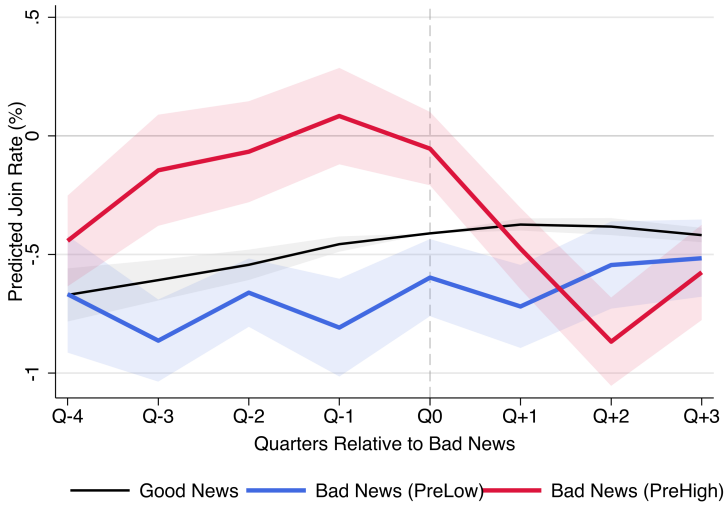
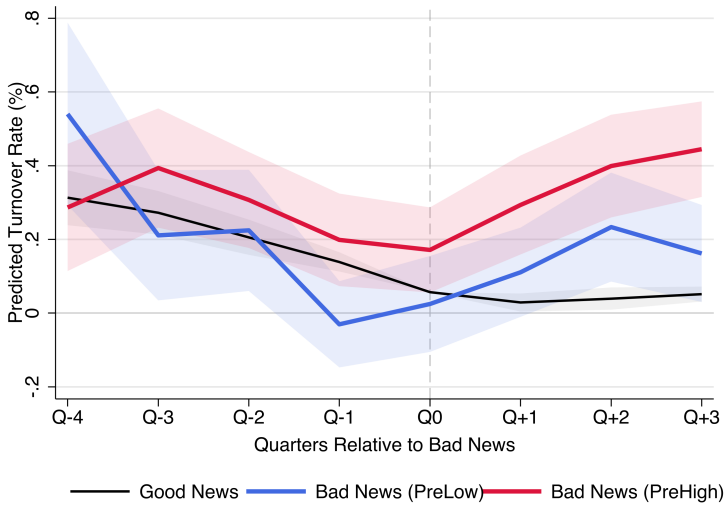
**Figure 1**
**(Color Online) Predicted Abnormal Employee Flows Around Negative Earnings Announcements**

**Panel A. Predicted Abnormal Join Rate Levels**

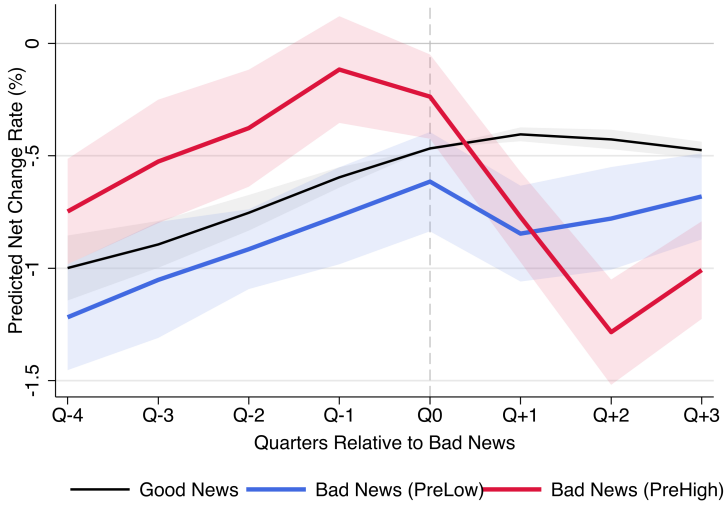



**Panel B. Predicted Abnormal Turnover Rate Levels**



## Figure 1 (Continued)

## Panel C. Predicted Abnormal Net Rate Levels




*Note:* This figure presents abnormal employee flow dynamics around negative earnings announcements, separately for negative-surprise quarters with above-median pre-announcement recruitment intensity (*PreHigh*) and those with below-median intensity (*PreLow*). Good News events serve as the control group. Results are based on estimating:

$$Y_{i,q} = \alpha + \sum_{k \in K} \lambda_k \cdot Q_k + \sum_{k \in K} \beta_k^{Low} \cdot (Q_k \times PreLow_i) + \sum_{k \in K} \beta_k^{High} \cdot (Q_k \times PreHigh_i) + \mathbf{X}'_{i,q-1}\Gamma + \delta_i + \gamma_{q \times y} + \theta_c + \varepsilon_{i,q} \tag{5}$$

where $Y_{i,q}$ denotes the abnormal employee flow rate for firm $i$ in quarter $q$. **Panel A** examines *AbJoin*, the abnormal employee inflow rate adjusted by the firm's three-year historical seasonal average. **Panel B** examines *AbTurnover*, the abnormal employee outflow rate using the same adjustment. **Panel C** examines *AbNet*, defined as abnormal join rate minus abnormal turnover rate. $Q_k$ indexes the displayed event quarters $k \in \{-4, -3, -2, -1, 0, +1, +2, +3\}$ relative to the earnings announcement, with $k = 0$ as the regression reference period. Each panel plots predicted employee flow levels (fitted values from the regression, holding controls at sample means) for all three groups, where the **Black Line** shows Good News firms (control), the **Blue Line** shows PreLow bad news firms, and the **Red Line** shows PreHigh bad news firms. All specifications include firm fixed effects ($\delta_i$), year–quarter fixed effects ($\gamma_{q \times y}$), event-quarter cohort fixed effects ($\theta_c$), and firm-level controls (SIZE, ROA, Q, CAPX, R&D, LIQ, LEV, ANALYST, LABOR, IO, BSIZE, DUAL, TENURE). The sample comprises U.S. public firms from 2011Q1 to 2024Q4. Standard errors are two-way clustered by firm and year–quarter. Shaded areas represent 95% confidence intervals.

## Table 1
## Sample Construction and News Type Distribution

*Note:* This table summarizes our sample construction procedure. We begin with online job postings from 2011Q1 to 2024Q4 that can be matched to the necessary financial data. Consistent with prior literature, we exclude firms in utilities (SIC 4900–4999) and financial services (SIC 6000–6999), whose hiring behavior, regulatory constraints, and earnings processes differ structurally from those of non-regulated operating firms, making them unsuitable for analyzing discretionary labor-demand adjustments. Panel A outlines the sequential removal of observations with missing data across multiple sources (I/B/E/S, CRSP, 13-F, BoardEx, and resume data) to ensure full variable coverage for all regressions. *Repeated bad news events:* We exclude earnings announcements in quarter $t$ if the firm also experienced a negative earnings surprise in any of the prior three quarters ($Q_{-1}$, $Q_{-2}$, or $Q_{-3}$). This restriction ensures our bad-news sample captures firms' responses to the *first* negative earnings surprise rather than persistent underperformance. *Incomplete cohort data:* We remove firm-quarter observations lacking complete data for the entire event window ($Q_{-4}$ through $Q_{+4}$ relative to the announcement), allowing us to estimate balanced event-study dynamics. This process yields a final sample of 13,904,281 unique job postings, 17,159 earnings announcement (EA) events, and 1,506 unique firms. Panel B reports the distribution of these final earnings announcement observations into non-bad-news ($BADNEWS = 0$) and bad-news ($BADNEWS = 1$) groups, where *BADNEWS* is defined as a negative earnings forecast error (Actual $\text{EPS}_{i,Q0}$ − Consensus $\text{Forecast}_{i,Q0} < 0$).

### Panel A: Sample Construction

| **Period: 2011Q1–2024Q4** | **Unique Postings** | **EA Events** | **Unique Firms** |
|---|---|---|---|
| Online job postings with necessary financial data | 52,348,225 | 139,517 | 4,302 |
| (Less) Missing I/B/E/S data | (8,698,833) | (70,767) | (1,603) |
| (Less) Missing CRSP data | (306,518) | (446) | (6) |
| (Less) Missing 13-F data | (0) | (0) | (0) |
| (Less) Missing BoardEx data | (2,721,235) | (6,778) | (273) |
| (Less) Missing resume data | (0) | (0) | (0) |
| (Less) Incomplete cohort data | (3,326,233) | (5,524) | (114) |
| (Less) Bad news events before $Q_0$ | (23,391,125) | (38,843) | (800) |
| **Final Sample** | **13,904,281** | **17,159** | **1,506** |

### Panel B: Distribution of BADNEWS Observations

| News Type | **Observations** | **Percent** |
|---|---|---|
| Good News ($BADNEWS = 0$) | 14,043 | 81.84% |
| Bad News ($BADNEWS = 1$) | 3,116 | 18.16% |
| **Total** | **17,159** | **100.00%** |

**Table 2**
**Descriptive Statistics**

*Note:* Table 2 reports descriptive statistics for the main variables used in the analysis. The sample comprises 17,159 earnings announcement observations from 2011Q1 to 2024Q4. *ABJP* is the abnormal job posting volume for event quarters $Q_{-4}$ through $Q_{+4}$ relative to the announcement quarter ($Q_0$). *CAR* is cumulative abnormal return over the indicated event window in trading days. Workforce size and raw employee flow rates are reported for the matched résumé subsample ($N$ = 16,564); raw rates express quarterly flows as percentages of beginning-of-quarter headcount (*HC-START*), providing the base rates against which abnormal flow coefficients can be gauged. All continuous variables except *ABJP* are winsorized at the 1st and 99th percentiles; *ABJP* is not winsorized because the inverse hyperbolic sine transformation already mitigates the influence of extreme values. Variable definitions are provided in the Appendix.

| | N | Mean | SD | 1st | 25th | Median | 75th | 99th |
|---|---|---|---|---|---|---|---|---|
| ***Job Posting Volume*** | | | | | | | | |
| JP | 17,159 | 232.90 | 562.93 | 0.00 | 11.00 | 45.00 | 152.00 | 3,470.00 |
| NormJP | 17,159 | 207.86 | 518.48 | 0.50 | 10.67 | 38.00 | 130.67 | 3,294.33 |
| ***Abnormal Job Posting Volume*** | | | | | | | | |
| $ABJP_{Q-4}$ | 17,159 | 0.30 | 2.98 | -8.25 | -1.14 | 0.40 | 1.84 | 8.53 |
| $ABJP_{Q-3}$ | 17,159 | 0.23 | 2.86 | -8.21 | -1.15 | 0.36 | 1.75 | 7.87 |
| $ABJP_{Q-2}$ | 17,159 | 0.20 | 2.79 | -8.33 | -1.13 | 0.38 | 1.74 | 7.30 |
| $ABJP_{Q-1}$ | 17,159 | 0.21 | 2.75 | -8.16 | -1.07 | 0.42 | 1.73 | 6.97 |
| $ABJP_{Q0}$ | 17,159 | 0.16 | 2.77 | -8.50 | -1.14 | 0.37 | 1.71 | 6.89 |
| $ABJP_{Q+1}$ | 17,159 | 0.06 | 2.75 | -8.42 | -1.22 | 0.27 | 1.61 | 6.68 |
| $ABJP_{Q+2}$ | 17,159 | -0.06 | 2.78 | -8.67 | -1.36 | 0.17 | 1.52 | 6.69 |
| $ABJP_{Q+3}$ | 17,159 | -0.11 | 2.75 | -8.82 | -1.37 | 0.12 | 1.44 | 6.51 |
| $ABJP_{Q+4}$ | 17,159 | -0.17 | 2.79 | -8.95 | -1.42 | 0.09 | 1.42 | 6.41 |
| ***Abnormal Employee Flow Rate*** | | | | | | | | |
| *AbNet* | | | | | | | | |
| $AbNet_{Q-4}$ | 16,502 | -0.70 | 4.07 | -16.53 | -2.13 | -0.27 | 1.26 | 10.07 |
| $AbNet_{Q-3}$ | 16,514 | -0.68 | 4.02 | -16.06 | -2.12 | -0.26 | 1.27 | 9.90 |
| $AbNet_{Q-2}$ | 16,522 | -0.59 | 3.92 | -15.89 | -2.00 | -0.18 | 1.32 | 9.54 |
| $AbNet_{Q-1}$ | 16,530 | -0.49 | 3.83 | -14.84 | -1.92 | -0.13 | 1.36 | 9.62 |
| $AbNet_{Q0}$ | 16,538 | -0.45 | 3.82 | -15.10 | -1.86 | -0.11 | 1.38 | 9.64 |
| $AbNet_{Q+1}$ | 16,544 | -0.53 | 3.81 | -14.94 | -1.94 | -0.17 | 1.30 | 9.48 |
| $AbNet_{Q+2}$ | 16,548 | -0.67 | 3.84 | -15.27 | -2.04 | -0.30 | 1.19 | 9.23 |
| $AbNet_{Q+3}$ | 16,552 | -0.78 | 3.85 | -15.17 | -2.12 | -0.39 | 1.08 | 8.99 |
| $AbNet_{Q+4}$ | 16,550 | -0.86 | 3.84 | -15.40 | -2.20 | -0.44 | 1.00 | 8.78 |
| *AbJoin* | | | | | | | | |
| $AbJoin_{Q-4}$ | 16,502 | -0.35 | 3.48 | -12.54 | -1.74 | -0.13 | 1.30 | 9.38 |
| $AbJoin_{Q-3}$ | 16,514 | -0.38 | 3.47 | -12.44 | -1.79 | -0.17 | 1.25 | 10.01 |
| $AbJoin_{Q-2}$ | 16,522 | -0.36 | 3.41 | -12.44 | -1.72 | -0.12 | 1.26 | 9.10 |
| $AbJoin_{Q-1}$ | 16,530 | -0.33 | 3.34 | -11.77 | -1.67 | -0.10 | 1.25 | 9.10 |
| $AbJoin_{Q0}$ | 16,538 | -0.35 | 3.31 | -11.65 | -1.71 | -0.13 | 1.22 | 8.97 |
| $AbJoin_{Q+1}$ | 16,544 | -0.44 | 3.30 | -11.49 | -1.82 | -0.22 | 1.17 | 8.87 |
| $AbJoin_{Q+2}$ | 16,548 | -0.57 | 3.28 | -11.43 | -2.04 | -0.35 | 1.08 | 8.42 |
| $AbJoin_{Q+3}$ | 16,552 | -0.71 | 3.28 | -11.45 | -2.17 | -0.47 | 0.95 | 8.58 |
| $AbJoin_{Q+4}$ | 16,550 | -0.86 | 3.27 | -11.72 | -2.32 | -0.61 | 0.84 | 8.36 |
| *AbTurnover* | | | | | | | | |
| $AbTurnover_{Q-4}$ | 16,502 | 0.35 | 2.35 | -6.04 | -0.85 | 0.25 | 1.39 | 8.62 |
| $AbTurnover_{Q-3}$ | 16,514 | 0.30 | 2.33 | -5.98 | -0.91 | 0.21 | 1.35 | 8.08 |
| $AbTurnover_{Q-2}$ | 16,522 | 0.24 | 2.34 | -6.13 | -0.95 | 0.17 | 1.32 | 7.92 |

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**Table 2 (Continued)**

| | N | Mean | SD | 1st | 25th | Median | 75th | 99th |
|---|---|---|---|---|---|---|---|---|
| $AbTurnover_{Q-1}$ | 16,530 | 0.16 | 2.29 | -6.37 | -1.01 | 0.13 | 1.24 | 7.53 |
| $AbTurnover_{Q0}$ | 16,538 | 0.10 | 2.28 | -6.34 | -1.06 | 0.09 | 1.19 | 7.44 |
| $AbTurnover_{Q+1}$ | 16,544 | 0.09 | 2.31 | -6.23 | -1.10 | 0.07 | 1.16 | 7.65 |
| $AbTurnover_{Q+2}$ | 16,548 | 0.09 | 2.39 | -6.34 | -1.12 | 0.05 | 1.14 | 8.40 |
| $AbTurnover_{Q+3}$ | 16,552 | 0.05 | 2.44 | -6.47 | -1.17 | 0.01 | 1.10 | 8.38 |
| $AbTurnover_{Q+4}$ | 16,550 | -0.02 | 2.46 | -6.35 | -1.25 | -0.05 | 1.05 | 8.24 |
| ***Workforce Size and Employee Flow Rates*** | | | | | | | | |
| *HC-TOTAL* | 16,564 | 5,944 | 12,766 | 46 | 568 | 1,652 | 4,368 | 74,184 |
| *JoinCount* | 16,564 | 414 | 881 | 2 | 37 | 111 | 328 | 5,218 |
| *LeaveCount* | 16,564 | 362 | 783 | 2 | 31 | 93 | 281 | 4,657 |
| *NetCount* | 16,564 | 55 | 338 | -588 | -4 | 11 | 57 | 1,317 |
| *Turnover* | 16,564 | 6.54 | 2.95 | 1.40 | 4.52 | 6.01 | 7.96 | 16.49 |
| *Join* | 16,564 | 8.03 | 4.27 | 1.36 | 5.09 | 7.14 | 9.95 | 23.03 |
| *Net* | 16,564 | 1.50 | 3.59 | -7.94 | -0.49 | 1.12 | 3.14 | 12.93 |
| ***Capital Market Reactions*** | | | | | | | | |
| $CAR[-1,+1]$ | 17,159 | 0.00 | 0.09 | -0.26 | -0.04 | 0.00 | 0.05 | 0.26 |
| $CAR[-3,+3]$ | 17,156 | 0.00 | 0.10 | -0.28 | -0.05 | 0.00 | 0.06 | 0.30 |
| $CAR[0,+30]$ | 17,154 | 0.00 | 0.11 | -0.32 | -0.05 | 0.00 | 0.06 | 0.32 |
| ***Job Postings Variables*** | | | | | | | | |
| $EFF_{Q0}$ | 17,055 | 2.71 | 1.43 | 1.00 | 1.72 | 2.37 | 3.25 | 8.78 |
| $EDU_{Q0}$ | 16,850 | 15.11 | 1.25 | 12.04 | 14.30 | 15.45 | 16.00 | 17.80 |
| $EXP_{Q0}$ | 16,852 | 4.26 | 1.50 | 1.00 | 3.24 | 4.25 | 5.22 | 8.34 |
| $SENIOR_{Q0}$ | 17,055 | 2.11 | 0.17 | 1.64 | 2.00 | 2.09 | 2.21 | 2.60 |
| $MGR_{Q0}$ | 17,055 | 0.23 | 0.15 | 0.00 | 0.13 | 0.21 | 0.31 | 0.78 |
| $SALARY\text{-}MID_{Q0}$ | 11,094 | 71,906 | 49,156 | 20,000 | 39,347 | 56,195 | 90,000 | 293,953 |
| *SALARY-FROM* | 11,094 | 63,476 | 42,997 | 18,720 | 35,954 | 50,000 | 76,959 | 268,179 |
| *SALARY-TO* | 11,094 | 80,751 | 60,092 | 20,440 | 41,600 | 61,555 | 100,208 | 400,000 |
| $DUR_{Q0}$ | 17,055 | 55.92 | 16.81 | 3.27 | 49.05 | 59.50 | 66.66 | 85.00 |
| $FULL_{Q0}$ | 17,051 | 0.96 | 0.10 | 0.42 | 0.98 | 1.00 | 1.00 | 1.00 |
| $SKILLS_{Q0}$ | 17,055 | 19.16 | 6.44 | 3.30 | 15.18 | 19.58 | 23.55 | 34.25 |
| $WORD_{Q0}$ | 17,055 | 555.17 | 185.00 | 163.59 | 429.93 | 540.91 | 661.02 | 1,094.99 |
| *SPEC* | 17,055 | 12.24 | 5.07 | 1.44 | 8.54 | 12.51 | 15.80 | 24.71 |
| *SOFT* | 17,055 | 2.20 | 1.68 | 0.00 | 0.97 | 1.78 | 3.15 | 7.50 |
| *SAL-DISC* | 17,055 | 0.10 | 0.20 | 0.00 | 0.00 | 0.01 | 0.08 | 0.96 |
| ***Firm Characteristics*** | | | | | | | | |
| *SIZE* | 17,159 | 7.92 | 1.69 | 4.41 | 6.72 | 7.88 | 9.02 | 12.09 |
| *ROA* | 17,159 | 0.01 | 0.04 | -0.14 | 0.00 | 0.01 | 0.03 | 0.09 |
| *Q* | 17,159 | 2.85 | 2.13 | 0.83 | 1.47 | 2.09 | 3.38 | 11.16 |
| *CAPX* | 17,159 | 0.02 | 0.03 | 0.00 | 0.01 | 0.01 | 0.03 | 0.14 |
| *R&D* | 17,159 | 0.02 | 0.02 | 0.00 | 0.00 | 0.00 | 0.02 | 0.11 |
| *LIQ* | 17,159 | 0.15 | 0.14 | 0.00 | 0.05 | 0.11 | 0.20 | 0.63 |
| *LEV* | 17,159 | 0.55 | 0.24 | 0.10 | 0.39 | 0.54 | 0.69 | 1.25 |
| *ANALYST* | 17,159 | 10.67 | 7.00 | 1.00 | 5.00 | 9.00 | 15.00 | 31.00 |
| *LABOR* | 17,159 | 0.52 | 0.50 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |
| *IO* | 17,159 | 0.81 | 0.19 | 0.16 | 0.73 | 0.86 | 0.94 | 1.00 |
| *BSIZE* | 17,159 | 7.71 | 2.17 | 3.00 | 6.00 | 8.00 | 9.00 | 13.00 |
| *DUAL* | 17,159 | 0.42 | 0.49 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| *TENURE* | 17,159 | 8.87 | 20.36 | 0.08 | 1.91 | 3.87 | 7.60 | 119.91 |

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**Table 2 (Continued)**

| | N | Mean | SD | 1st | 25th | Median | 75th | 99th |
|---|---|---|---|---|---|---|---|---|
| *MaxHHI* | 17,159 | 3,576.72 | 2,421.68 | 220.16 | 1,600.00 | 3,272.46 | 5,029.59 | 10,000.00 |
| ***Cross-sectional Indicators*** | | | | | | | | |
| *PreHigh* | 17,159 | 0.09 | 0.28 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| *PreLow* | 17,159 | 0.09 | 0.29 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| *LowHHI* | 17,159 | 0.43 | 0.50 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| *HighCover* | 17,159 | 0.53 | 0.50 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |

**Table 3 Panel A**

**Abnormal Job Postings Around Negative Earnings Announcements: Front-Loading Evidence**

*Note:* This table reports results from estimating:

$$\text{ABJP}_{i,q} = \beta_0 + \beta_1\, BADNEWS_{i,Q0} + \sum_{k\in K} \lambda_k\, Q_k + \sum_{k\in K} \beta_k\, (BADNEWS_{i,Q0} \times Q_k) + X'_{i,q-1}\Gamma + \delta_i + \gamma_{q\times y} + \theta_c + \varepsilon_{i,q}$$

where $\text{ABJP}_{i,q}$ is abnormal job posting volume, measured as $\text{asinh}(JP_{i,q}) - \text{asinh}(NormJP_{i,q})$, $BADNEWS_{i,Q0}$ equals one if the earnings forecast error (Actual $\text{EPS}_{i,Q0}$ − $\text{Consensus Forecast}_{i,Q0}$) is negative at announcement quarter Q0, and $Q_k$ denotes event-quarter indicators for $k \in \{-4, -3, -2, -1, +1, +2, +3, +4\}$ relative to the earnings announcement, with Q0 omitted as reference. $X'_{i,q-1}$ includes firm-level controls (SIZE, ROA, Q, CAPX, R&D, LIQ, LEV, ANALYST, LABOR, IO) and governance controls (BSIZE, DUAL, TENURE). $\delta_i$ denotes firm fixed effects, $\gamma_{q\times y}$ denotes year-quarter fixed effects, and $\theta_c$ denotes event-quarter cohort fixed effects (grouping firms whose earnings announcements fall in the same calendar quarter). Wald tests assess whether bad news firms differ from good news firms at each quarter: $H_0 : \beta_1 + \beta_k = 0$. t-statistics in parentheses are based on standard errors clustered two-way at the firm and year-quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | Abnormal Job Postings (*ABJP*) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| ***Baseline:*** | | | |
| $BADNEWS_{Q0}$ | −0.198*** | −0.180*** | −0.157*** |
| | (−3.298) | (−3.081) | (−2.974) |
| ***Dynamics (Interactions):*** | | | |
| $BADNEWS_{Q0}\times Q_{-4}$ | 0.328*** | 0.328*** | 0.252*** |
| | (3.438) | (3.529) | (3.365) |
| $BADNEWS_{Q0}\times Q_{-3}$ | 0.311*** | 0.311*** | 0.247*** |
| | (4.134) | (4.281) | (3.948) |
| $BADNEWS_{Q0}\times Q_{-2}$ | 0.360*** | 0.360*** | 0.291*** |
| | (4.608) | (4.773) | (5.099) |
| $BADNEWS_{Q0}\times Q_{-1}$ | 0.327*** | 0.327*** | 0.275*** |
| | (6.795) | (6.908) | (7.182) |
| $BADNEWS_{Q0}\times Q_{+1}$ | 0.070 | 0.070 | 0.072 |
| | (1.084) | (1.139) | (1.266) |
| $BADNEWS_{Q0}\times Q_{+2}$ | −0.034 | −0.034 | −0.023 |
| | (−0.453) | (−0.473) | (−0.404) |
| $BADNEWS_{Q0}\times Q_{+3}$ | 0.008 | 0.008 | 0.034 |
| | (0.082) | (0.083) | (0.407) |
| $BADNEWS_{Q0}\times Q_{+4}$ | 0.032 | 0.032 | 0.048 |
| | (0.534) | (0.522) | (0.806) |
| ***Time-Period Effects:*** | | | |
| $Q_{-4}$ | 0.087 | 0.087 | −0.208*** |
| | (0.980) | (0.978) | (−4.196) |
| $Q_{-3}$ | 0.011 | 0.011 | −0.185*** |
| | (0.197) | (0.196) | (−4.924) |
| $Q_{-2}$ | −0.027 | −0.027 | −0.147*** |
| | (−0.611) | (−0.610) | (−5.339) |
| $Q_{-1}$ | −0.008 | −0.008 | −0.068*** |
| | (−0.310) | (−0.306) | (−3.454) |
| $Q_{+1}$ | −0.107*** | −0.107*** | −0.014 |

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**Table 3, Panel A (Continued)**

| | Abnormal Job Postings (*ABJP*) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | (−4.177) | (−4.158) | (−1.016) |
| $Q_{+2}$ | −0.208*** | −0.208*** | −0.024* |
| | (−4.773) | (−4.765) | (−1.708) |
| $Q_{+3}$ | −0.271*** | −0.271*** | −0.015 |
| | (−4.702) | (−4.686) | (−0.955) |
| $Q_{+4}$ | −0.329*** | −0.329*** | – |
| | (−4.798) | (−4.777) | |
| ***Controls:*** | | | |
| *SIZE* | | 0.190 | 0.190 |
| | | (1.358) | (1.354) |
| *ROA* | | 0.747 | 0.747 |
| | | (1.015) | (1.009) |
| *Q* | | 0.147*** | 0.147*** |
| | | (5.057) | (5.039) |
| *CAPX* | | −0.263 | −0.263 |
| | | (−0.218) | (−0.217) |
| *R&D* | | −4.529 | −4.529 |
| | | (−1.483) | (−1.477) |
| *LIQ* | | 0.193 | 0.193 |
| | | (0.523) | (0.522) |
| *LEV* | | −0.559* | −0.559* |
| | | (−1.680) | (−1.675) |
| *ANALYST* | | −0.017 | −0.017 |
| | | (−1.180) | (−1.176) |
| *LABOR* | | 0.107 | 0.107 |
| | | (0.787) | (0.786) |
| *IO* | | −0.154 | −0.154 |
| | | (−0.497) | (−0.496) |
| *BSIZE* | | 0.019 | 0.019 |
| | | (0.541) | (0.539) |
| *DUAL* | | 0.065 | 0.065 |
| | | (0.698) | (0.694) |
| *TENURE* | | −0.009 | −0.009 |
| | | (−1.259) | (−1.255) |
| *CONSTANT* | 0.193*** | −1.242 | −1.263 |
| | (3.449) | (−0.933) | (−0.953) |
| **Wald Tests:** $H_0 : \beta_1 + \beta_k = 0$ | | | |
| $k = -4$ $(Q_{-4})$ | 0.130* | 0.148** | 0.094 |
| | (1.800) | (2.055) | (1.437) |
| $k = -3$ $(Q_{-3})$ | 0.112* | 0.130** | 0.090* |
| | (1.889) | (2.178) | (1.674) |
| $k = -2$ $(Q_{-2})$ | 0.162** | 0.180*** | 0.134** |
| | (2.501) | (2.734) | (2.191) |

*Continued on next page*

**Table 3, Panel A (Continued)**

| | Abnormal Job Postings (*ABJP*) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $k = -1$ ($Q_{-1}$) | $0.128^{**}$ | $0.146^{***}$ | $0.117^{**}$ |
| | (2.469) | (2.771) | (2.288) |
| $k = 0$ ($Q_0$) | $-0.198^{***}$ | $-0.180^{***}$ | $-0.157^{***}$ |
| | (−3.298) | (−3.081) | (−2.974) |
| $k = +1$ ($Q_{+1}$) | $-0.129^{*}$ | −0.111 | −0.086 |
| | (−1.874) | (−1.622) | (−1.365) |
| $k = +2$ ($Q_{+2}$) | $-0.232^{***}$ | $-0.214^{***}$ | $-0.181^{***}$ |
| | (−3.492) | (−3.252) | (−2.884) |
| $k = +3$ ($Q_{+3}$) | $-0.191^{***}$ | $-0.173^{**}$ | $-0.123^{*}$ |
| | (−2.592) | (−2.350) | (−1.733) |
| $k = +4$ ($Q_{+4}$) | $-0.166^{***}$ | $-0.148^{**}$ | $-0.109^{**}$ |
| | (−2.756) | (−2.421) | (−1.964) |
| Observations | 154,431 | 154,431 | 154,431 |
| R-squared | 0.196 | 0.200 | 0.235 |
| Controls | Y | Y | Y |
| Fixed Effects: | | | |
| Firm | Y | Y | Y |
| Year-Quarter | Y | Y | Y |
| Cohort | N | N | Y |
| Cluster SE | Firm + Year-Quarter | | |

**Table 3 Panel B**
**Cumulative Effects Tests: Reallocation vs. Expansion**

*Note:* This panel reports cumulative effects tests based on the specification in Table 3 Panel A, Column (3). It uses the same abnormal-job-posting concept and historical normal-posting benchmark as Panel A, but measures cumulative posting activity over three earnings-announcement windows: the pre-announcement window ($Q_{-4}$ to $Q_{-1}$), the announcement and post-announcement window ($Q_0$ to $Q_{+3}$), and the full event window ($Q_{-4}$ to $Q_{+3}$). The measure compares the inverse hyperbolic sine of a firm's actual unique job postings with the inverse hyperbolic sine of its average posting volume in the same calendar quarter during the previous three years. Standard errors are clustered two-way by firm and announcement cohort. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| **Test Specification** | **Coefficient** | **Std. Error** | ***t*-stat** |
|---|---|---|---|
| **Test 1: Pre-Announcement** ($Q_{-4}$ to $Q_{-1}$) | $0.036^{**}$ | 0.014 | 2.56 |
| **Test 2: Post-Announcement** ($Q_0$ to $Q_{+3}$) | $-0.041^{**}$ | 0.016 | −2.53 |
| **Test 3: Full Window** ($Q_{-4}$ to $Q_{+3}$) | −0.005 | 0.012 | −0.39 |

## Table 4
## Employee Flow Dynamics around Negative Earnings Announcements

*Note:* This table reports results from estimating:

$$Y_{i,q} = \beta_0 + \beta_1 \, BADNEWS_{i,Q0} + \sum_{k \in K} \lambda_k \, Q_k + \sum_{k \in K} \beta_k \, (BADNEWS_{i,Q0} \times Q_k) + \mathbf{X}'_{i,q-1}\mathbf{\Gamma} + \delta_i + \gamma_{q \times y} + \varepsilon_{i,q}$$

where $Y_{i,q}$ represents abnormal employee flows for firm $i$ in quarter $q$, measured as deviations from the firm's three-year, same-quarter average. Column (1) examines AbJoin (employees joining in quarter $q$ / employees at quarter start) - three-year average. Column (2) examines AbTurnover (employees leaving in quarter $q$ / employees at quarter start) - three-year average. Column (3) examines AbNet = AbJoin - AbTurnover. $BADNEWS_{i,Q0}$ equals one if the earnings forecast error (Actual $\text{EPS}_{i,Q0}$ − $\text{Consensus Forecast}_{i,Q0}$) is negative. $Q_k$ denotes event quarters $k \in \{-4, -3, -2, -1, 0, +1, +2, +3, +4\}$ relative to the earnings announcement, with $k = 0$ omitted as reference. All specifications include firm fixed effects ($\delta_i$), year-quarter fixed effects ($\gamma_{q \times y}$), cohort fixed effects, and firm-level controls ($\Theta_{i,q}$). Wald tests assess whether bad news firms differ from good news firms at each quarter: $H_0 : \beta_1 + \beta_k = 0$. t-statistics in parentheses are based on standard errors clustered two-way at the firm and year-quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | *AbJoin* | *AbTurnover* | *AbNet* |
| ***Baseline:*** | | | |
| $BADNEWS_{Q0}$ | 0.139** | −0.009 | 0.147** |
| | (2.590) | (−0.189) | (2.028) |
| ***Dynamics (Interactions):*** | | | |
| $BADNEWS_{Q0} \times Q_{-4}$ | 0.036 | 0.066 | −0.027 |
| | (0.476) | (0.671) | (−0.215) |
| $BADNEWS_{Q0} \times Q_{-3}$ | 0.016 | −0.012 | 0.061 |
| | (0.171) | (−0.172) | (0.471) |
| $BADNEWS_{Q0} \times Q_{-2}$ | 0.093 | 0.020 | 0.063 |
| | (1.268) | (0.351) | (0.673) |
| $BADNEWS_{Q0} \times Q_{-1}$ | 0.002 | −0.098* | 0.108 |
| | (0.020) | (−1.997) | (0.959) |
| $BADNEWS_{Q0} \times Q_{+1}$ | −0.303*** | 0.131*** | −0.441*** |
| | (−4.465) | (2.964) | (−5.253) |
| $BADNEWS_{Q0} \times Q_{+2}$ | −0.393*** | 0.235*** | −0.629*** |
| | (−4.911) | (3.394) | (−6.012) |
| $BADNEWS_{Q0} \times Q_{+3}$ | −0.202*** | 0.207*** | −0.398*** |
| | (−2.679) | (3.672) | (−4.302) |
| $BADNEWS_{Q0} \times Q_{+4}$ | −0.389*** | 0.135* | −0.534*** |
| | (−4.596) | (1.830) | (−5.084) |
| ***Time-Period Effects:*** | | | |
| $Q_{-4}$ | −0.260*** | 0.257*** | −0.533*** |
| | (−4.504) | (6.710) | (−7.131) |
| $Q_{-3}$ | −0.198*** | 0.216*** | −0.427*** |
| | (−4.499) | (7.115) | (−7.980) |

Continued on next page

**Table 4 (Continued)**

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | *AbJoin* | *AbTurnover* | *AbNet* |
| $Q_{-2}$ | −0.133*** | 0.149*** | −0.287*** |
| | (−4.012) | (6.072) | (−6.961) |
| $Q_{-1}$ | −0.045*** | 0.082*** | −0.129*** |
| | (−2.814) | (6.077) | (−5.566) |
| $Q_{+1}$ | 0.038*** | −0.028** | 0.063*** |
| | (2.863) | (−2.319) | (3.999) |
| $Q_{+2}$ | 0.029 | −0.017 | 0.040* |
| | (1.593) | (−1.126) | (1.814) |
| $Q_{+3}$ | −0.007 | −0.005 | −0.008 |
| | (−0.456) | (−0.511) | (−0.403) |
| $Q_{+4}$ | – | – | – |
| **Wald Tests:** $H_0 : \beta_1 + \beta_k = 0$ | | | |
| $k = -4$ ($Q_{-4}$) | 0.175** | 0.058 | 0.120 |
| | (2.413) | (0.699) | (1.364) |
| $k = -3$ ($Q_{-3}$) | 0.155** | −0.021 | 0.208* |
| | (1.978) | (−0.347) | (1.918) |
| $k = -2$ ($Q_{-2}$) | 0.232*** | 0.011 | 0.210** |
| | (3.150) | (0.191) | (2.394) |
| $k = -1$ ($Q_{-1}$) | 0.141 | −0.106** | 0.255** |
| | (1.575) | (−2.472) | (2.546) |
| $k = 0$ ($Q_0$) | 0.139** | −0.009 | 0.147** |
| | (2.590) | (−0.189) | (2.028) |
| $k = +1$ ($Q_{+1}$) | −0.165** | 0.123** | −0.294*** |
| | (−2.390) | (2.548) | (−3.544) |
| $k = +2$ ($Q_{+2}$) | −0.254*** | 0.226*** | −0.483*** |
| | (−3.095) | (3.921) | (−5.198) |
| $k = +3$ ($Q_{+3}$) | −0.063 | 0.199*** | −0.251*** |
| | (−0.898) | (5.008) | (−3.268) |
| $k = +4$ ($Q_{+4}$) | −0.250*** | 0.126** | −0.387*** |
| | (−3.788) | (2.098) | (−4.822) |
| Observations | 148,800 | 148,800 | 148,800 |
| R-squared | 0.276 | 0.186 | 0.216 |
| Controls | Y | Y | Y |
| Fixed Effects: | | | |
| Firm | Y | Y | Y |
| YearQuarter | Y | Y | Y |
| Cohort | Y | Y | Y |
| Cluster SE | | Firm + YearQuarter | |

## Table 5
## Labor Market Benefits of Front-Loading Around Negative Earnings Announcements

*Note:* This table reports results from estimating:

$$Y_{i,q} = \beta_0 + \beta_1 \cdot PreHigh_i + \beta_2 \cdot PreLow_i + \sum_{k \in K} \lambda_k \cdot Q_k + \sum_{k \in K} \beta_k^{High} \cdot (Q_k \times PreHigh_i) + \sum_{k \in K} \beta_k^{Low} \cdot (Q_k \times PreLow_i) + \mathbf{X}'_{i,q-1}\Gamma + \delta_i + \gamma_{q \times y} + \theta_c + \varepsilon_{i,q}$$

where $Y_{i,q}$ represents abnormal employee flows for firm $i$ in quarter $q$. Column (1) examines AbJoin. Column (2) examines AbTurnover. Column (3) examines AbNet = AbJoin - AbTurnover. $PreHigh_i$ equals one if cumulative abnormal job postings over $Q_{-3}$ to $Q_{-1}$ are positive and exceed the median among firms in the same SIC-2 industry, year, and quarter cohort; $PreLow_i$ equals one for the remaining $BADNEWS$ observations. $Q_k$ denotes event quarters $k \in \{-4, -3, -2, -1, 0, +1, +2, +3, +4\}$ relative to the earnings announcement, with $k = 0$ omitted as the reference period. The table reports coefficient estimates for main effects of pre-hiring intensity ($\beta_1$, $\beta_2$), baseline time pattern ($\lambda_k$), and interaction terms capturing differential dynamics ($\beta_k^{High}$, $\beta_k^{Low}$). Wald tests assess pairwise group differences at each quarter: $H_0^{High-Low} : (\beta_1 + \beta_k^{High}) - (\beta_2 + \beta_k^{Low}) = 0$; $H_0^{Low-Good} : (\beta_2 + \beta_k^{Low}) = 0$; $H_0^{High-Good} : (\beta_1 + \beta_k^{High}) = 0$. $\mathbf{X}'_{i,q-1}$ includes firm-level controls. t-statistics in parentheses are based on standard errors clustered two-way at the firm and year-quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | *AbJoin* | *AbTurnover* | *AbNet* |
| ***Main Effects*** ($\beta_1, \beta_2$)***:*** | | | |
| $PreLow$ | −0.116 | −0.078 | −0.030 |
| | (−1.402) | (−1.200) | (−0.274) |
| $PreHigh$ | 0.413*** | 0.065 | 0.338*** |
| | (5.269) | (1.117) | (3.552) |
| ***Dynamics (Interactions,*** $Q_k \times PreHigh$***):*** | | | |
| $Q_{-4} \times PreHigh$ | −0.130 | −0.141 | 0.021 |
| | (−1.027) | (−1.377) | (0.138) |
| $Q_{-3} \times PreHigh$ | 0.106 | 0.007 | 0.139 |
| | (0.802) | (0.079) | (0.846) |
| $Q_{-2} \times PreHigh$ | 0.119 | −0.014 | 0.146 |
| | (1.090) | (−0.205) | (1.165) |
| $Q_{-1} \times PreHigh$ | 0.182** | −0.055 | 0.249** |
| | (2.296) | (−0.770) | (2.185) |
| $Q_{+1} \times PreHigh$ | −0.459*** | 0.150*** | −0.599*** |
| | (−4.709) | (2.687) | (−5.433) |
| $Q_{+2} \times PreHigh$ | −0.842*** | 0.245*** | −1.088*** |
| | (−7.668) | (2.855) | (−7.991) |
| $Q_{+3} \times PreHigh$ | −0.515*** | 0.278*** | −0.764*** |
| | (−4.146) | (3.060) | (−5.656) |
| $Q_{+4} \times PreHigh$ | −0.796*** | 0.271*** | −1.058*** |

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**Table 5 (Continued)**

| VARIABLES | (1) *AbJoin* | (2) *AbTurnover* | (3) *AbNet* |
|---|---|---|---|
| | (−7.053) | (2.824) | (−7.753) |
| ***Dynamics (Interactions, $Q_k \times PreLow$):*** | | | |
| $Q_{-4} \times PreLow$ | 0.190** | 0.259* | −0.071 |
| | (2.362) | (1.737) | (−0.434) |
| $Q_{-3} \times PreLow$ | −0.068 | −0.029 | −0.010 |
| | (−0.529) | (−0.273) | (−0.058) |
| $Q_{-2} \times PreLow$ | 0.069 | 0.050 | −0.014 |
| | (0.755) | (0.573) | (−0.100) |
| $Q_{-1} \times PreLow$ | −0.166 | −0.138 | −0.023 |
| | (−1.107) | (−1.613) | (−0.126) |
| $Q_{+1} \times PreLow$ | −0.159* | 0.114* | −0.294** |
| | (−1.723) | (1.706) | (−2.462) |
| $Q_{+2} \times PreLow$ | 0.024 | 0.226** | −0.204 |
| | (0.218) | (2.430) | (−1.294) |
| $Q_{+3} \times PreLow$ | 0.089 | 0.142* | −0.058 |
| | (0.794) | (1.860) | (−0.601) |
| $Q_{+4} \times PreLow$ | −0.013 | 0.009 | −0.049 |
| | (−0.090) | (0.087) | (−0.272) |
| ***Baseline Time Pattern ($\lambda_k$):*** | | | |
| $Q_{-4}$ | −0.260*** | 0.256*** | −0.532*** |
| | (−4.499) | (6.693) | (−7.125) |
| $Q_{-3}$ | −0.197*** | 0.216*** | −0.427*** |
| | (−4.494) | (7.102) | (−7.972) |
| $Q_{-2}$ | −0.133*** | 0.149*** | −0.287*** |
| | (−4.004) | (6.049) | (−6.948) |
| $Q_{-1}$ | −0.045*** | 0.082*** | −0.129*** |
| | (−2.719) | (6.027) | (−5.527) |
| $Q_{+1}$ | 0.037*** | −0.028** | 0.063*** |
| | (2.757) | (−2.244) | (3.901) |
| $Q_{+2}$ | 0.028 | −0.017 | 0.040* |
| | (1.567) | (−1.123) | (1.795) |
| $Q_{+3}$ | −0.007 | −0.005 | −0.008 |
| | (−0.456) | (−0.467) | (−0.410) |
| $Q_{+4}$ | – | – | – |
| **Wald Tests:** | | | |
| *High vs Good ($H_0$: $\beta_1 + \beta_k^{High} = 0$)* | | | |
| $k = -4$ | 0.283*** | −0.076 | 0.358*** |

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**Table 5 (Continued)**

| VARIABLES | (1) *AbJoin* | (2) *AbTurnover* | (3) *AbNet* |
|---|---|---|---|
| | (2.578) | (−1.002) | (2.911) |
| $k = -3$ | 0.519*** | 0.072 | 0.476*** |
| | (4.525) | (0.934) | (3.412) |
| $k = -2$ | 0.533*** | 0.052 | 0.484*** |
| | (4.994) | (0.745) | (3.711) |
| $k = -1$ | 0.595*** | 0.011 | 0.587*** |
| | (5.472) | (0.166) | (4.596) |
| $k = 0$ | 0.413*** | 0.065 | 0.338*** |
| | (5.269) | (1.117) | (3.552) |
| $k = +1$ | −0.046 | 0.215*** | −0.261** |
| | (−0.514) | (3.176) | (−2.573) |
| $k = +2$ | −0.429*** | 0.310*** | −0.751*** |
| | (−4.324) | (4.237) | (−6.138) |
| $k = +3$ | −0.102 | 0.344*** | −0.427*** |
| | (−0.973) | (5.074) | (−3.766) |
| $k = +4$ | −0.382*** | 0.337*** | −0.721*** |
| | (−3.890) | (3.984) | (−6.008) |
| *Low vs Good ($H_0$: $\beta_2 + \beta_k^{Low} = 0$)* | | | |
| $k = -4$ | 0.073 | 0.181 | −0.101 |
| | (0.693) | (1.422) | (−0.965) |
| $k = -3$ | −0.185* | −0.107 | −0.041 |
| | (−1.953) | (−1.269) | (−0.324) |
| $k = -2$ | −0.047 | −0.027 | −0.044 |
| | (−0.585) | (−0.337) | (−0.451) |
| $k = -1$ | −0.282** | −0.215*** | −0.053 |
| | (−2.496) | (−3.586) | (−0.438) |
| $k = 0$ | −0.116 | −0.078 | −0.030 |
| | (−1.402) | (−1.200) | (−0.274) |
| $k = +1$ | −0.276*** | 0.036 | −0.324*** |
| | (−3.078) | (0.592) | (−2.956) |
| $k = +2$ | −0.093 | 0.148* | −0.234* |
| | (−0.917) | (1.911) | (−1.917) |
| $k = +3$ | −0.028 | 0.064 | −0.089 |
| | (−0.321) | (0.986) | (−0.935) |
| $k = +4$ | −0.129 | −0.069 | −0.079 |
| | (−1.429) | (−0.894) | (−0.695) |
| *High vs Low ($H_0$: $(\beta_1 + \beta_k^{High}) - (\beta_2 + \beta_k^{Low}) = 0$)* | | | |
| $k = -4$ | 0.210 | −0.257* | 0.460*** |
| | (1.332) | (−1.951) | (3.149) |

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**Table 5 (Continued)**

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | *AbJoin* | *AbTurnover* | *AbNet* |
| $k = -3$ | 0.704*** | 0.179* | 0.517*** |
| | (5.058) | (1.676) | (3.432) |
| $k = -2$ | 0.580*** | 0.079 | 0.528*** |
| | (5.108) | (0.815) | (3.661) |
| $k = -1$ | 0.877*** | 0.226*** | 0.640*** |
| | (6.644) | (2.584) | (4.320) |
| $k = 0$ | 0.530*** | 0.143* | 0.368** |
| | (4.398) | (1.702) | (2.495) |
| $k = +1$ | 0.230** | 0.179** | 0.063 |
| | (2.056) | (2.090) | (0.481) |
| $k = +2$ | −0.336*** | 0.162* | −0.516*** |
| | (−2.945) | (1.672) | (−3.223) |
| $k = +3$ | −0.074 | 0.279*** | −0.338** |
| | (−0.566) | (2.655) | (−2.410) |
| $k = +4$ | −0.253* | 0.406*** | −0.641*** |
| | (−1.889) | (3.749) | (−3.771) |
| Observations | 148, 800 | 148, 800 | 148, 800 |
| R-squared | 0.277 | 0.186 | 0.217 |
| Controls | Y | Y | Y |
| Fixed Effects: | | | |
| Firm | Y | Y | Y |
| YearQuarter | Y | Y | Y |
| Cohort | Y | Y | Y |
| Cluster SE | | Firm + YearQuarter | |

## Table 6
## Job Posting Characteristics Around Earnings Announcements

*Note:* This table reports Wald test estimates from the three-group event study regression:

$$Y_{i,q} = \beta_0 + \beta_1 PreHigh_i + \beta_2 PreLow_i + \sum_k \lambda_k Q_k + \sum_k \beta_k^{High}(Q_k \times PreHigh_i) + \sum_k \beta_k^{Low}(Q_k \times PreLow_i) + \mathbf{X}'_{i,q-1}\Gamma + \delta_i + \gamma_{q\times y} + \theta_c + \varepsilon_{i,q}.$$

where $Y_{i,q}$ is a posting characteristic for firm $i$ in event quarter $q$. $PreHigh_i$ equals one if cumulative abnormal job postings over $Q_{-3}$ to $Q_{-1}$ are positive and exceed the median among firms in the same SIC-2 industry, year, and quarter cohort; $PreLow_i$ equals one for the remaining $BADNEWS$ observations. Columns report: *EFF* = Posting Effort; *DUR* = Duration (Days); *SKILLS* = Num Skills; *SPEC* = Num Spec Skills; *SOFT* = Num Soft Skills; *SENIOR* = Seniority Score; *SAL-DISC* = Pct Sal Disclosed; *WORD* = Word Count. The table is organized into three panels: *High − Low*, testing $H_0 : (\beta_1 + \beta_k^{High}) - (\beta_2 + \beta_k^{Low}) = 0$; *High vs Good*, testing $H_0 : \beta_1 + \beta_k^{High} = 0$; and *Low vs Good*, testing $H_0 : \beta_2 + \beta_k^{Low} = 0$. All specifications include firm, year×quarter, and cohort fixed effects and firm-level controls. t-statistics in parentheses are based on standard errors clustered by firm and calendar quarter. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Event Qtr | SKILLS | SPEC | SOFT | SENIOR | SAL-DISC | WORD | EFF | DUR |
| **High vs Low** | | | | | | | | |
| $k = -4$ | 0.145 | 0.151 | 0.014 | −0.004 | −0.006 | 0.745 | 0.104 | 0.909* |
| | (0.83) | (1.22) | (0.48) | (−0.77) | (−1.12) | (0.14) | (1.63) | (1.95) |
| $k = -3$ | 0.404*** | 0.244*** | 0.025 | 0.000 | −0.014*** | 4.259 | 0.101* | 0.880* |
| | (3.17) | (2.82) | (0.74) | (0.01) | (−3.05) | (0.83) | (1.83) | (1.92) |
| $k = -2$ | 0.498*** | 0.266*** | 0.033 | −0.005 | −0.012** | 9.983* | 0.186*** | 0.625 |
| | (3.53) | (2.84) | (1.09) | (−1.02) | (−2.00) | (1.89) | (3.04) | (1.48) |
| $k = -1$ | 0.308* | 0.226* | 0.086** | 0.010** | −0.005 | 3.634 | 0.211*** | 0.122 |
| | (1.87) | (1.94) | (2.52) | (2.15) | (−1.07) | (0.70) | (3.55) | (0.26) |
| $k = 0$ | 0.297* | 0.148 | 0.044 | 0.013*** | −0.005 | 11.670** | 0.179*** | 0.052 |
| | (1.75) | (1.26) | (1.48) | (2.69) | (−1.07) | (2.27) | (3.65) | (0.12) |
| $k = +1$ | 0.077 | −0.039 | −0.012 | −0.001 | −0.009* | 6.751 | 0.088 | 0.569 |
| | (0.47) | (−0.31) | (−0.28) | (−0.26) | (−1.87) | (1.39) | (1.22) | (1.30) |
| $k = +2$ | 0.139 | 0.068 | 0.031 | 0.000 | −0.003 | 12.331** | 0.173** | 0.214 |
| | (0.79) | (0.60) | (0.84) | (0.03) | (−0.58) | (2.42) | (2.31) | (0.47) |
| $k = +3$ | 0.087 | 0.082 | 0.061* | 0.005 | −0.008 | 8.143 | 0.135** | 0.334 |
| | (0.49) | (0.72) | (1.75) | (0.92) | (−1.14) | (1.41) | (2.05) | (0.73) |
| $k = +4$ | 0.061 | 0.074 | −0.003 | −0.003 | −0.006 | 7.685 | 0.130* | 0.348 |
| | (0.37) | (0.69) | (−0.09) | (−0.69) | (−1.02) | (1.35) | (1.76) | (0.72) |
| **High vs Good** | | | | | | | | |
| $k = -4$ | −0.006 | 0.032 | −0.016 | −0.002 | −0.004 | 0.062 | 0.037 | 0.290 |
| | (−0.05) | (0.37) | (−0.68) | (−0.55) | (−0.95) | (0.02) | (0.70) | (0.98) |
| $k = -3$ | 0.312*** | 0.190*** | 0.036* | 0.005 | −0.009*** | 3.850 | 0.016 | 0.212 |
| | (2.93) | (2.72) | (1.69) | (1.40) | (−2.96) | (0.94) | (0.36) | (0.86) |
| $k = -2$ | 0.378*** | 0.219*** | 0.064*** | 0.000 | −0.009** | 6.126 | 0.082** | 0.293 |
| | (3.60) | (3.01) | (2.88) | (0.02) | (−2.42) | (1.59) | (2.03) | (0.98) |
| $k = -1$ | 0.231* | 0.152* | 0.054** | 0.008*** | −0.010** | 1.142 | 0.044 | −0.287 |
| | (1.91) | (1.76) | (2.28) | (3.42) | (−2.34) | (0.30) | (1.00) | (−0.89) |
| $k = 0$ | 0.192 | 0.103 | 0.040* | 0.008** | −0.007* | 2.944 | 0.035 | −0.036 |
| | (1.60) | (1.30) | (1.69) | (2.50) | (−1.87) | (0.77) | (0.94) | (−0.14) |
| $k = +1$ | 0.021 | −0.051 | −0.022 | 0.001 | −0.010** | 5.106 | 0.073* | 0.320 |
| | (0.20) | (−0.68) | (−0.83) | (0.15) | (−2.27) | (1.32) | (1.93) | (1.11) |
| $k = +2$ | 0.098 | 0.078 | 0.051** | 0.000 | −0.008 | 6.933* | 0.143** | 0.340 |
| | (0.85) | (0.94) | (2.03) | (0.01) | (−1.59) | (1.79) | (2.64) | (1.16) |
| $k = +3$ | 0.082 | 0.056 | 0.035 | 0.002 | −0.009 | 7.884** | 0.095* | 0.417 |
| | (0.73) | (0.71) | (1.30) | (0.69) | (−1.55) | (2.18) | (1.80) | (1.32) |
| $k = +4$ | 0.052 | 0.060 | 0.023 | −0.003 | −0.008 | 7.251* | 0.104 | 0.341 |
| | (0.44) | (0.71) | (0.99) | (−0.79) | (−1.36) | (1.70) | (1.66) | (1.07) |

*Continued on next page*

**Table 6 (Continued)**

| Event Qtr | (1) SKILLS | (2) SPEC | (3) SOFT | (4) SENIOR | (5) SAL-DISC | (6) WORD | (7) EFF | (8) DUR |
|---|---|---|---|---|---|---|---|---|
| **Low vs Good** | | | | | | | | |
| $k = -4$ | −0.152 | −0.119 | −0.030 | 0.002 | 0.003 | −0.683 | −0.067 | −0.618 |
| | (−1.47) | (−1.52) | (−1.41) | (0.60) | (0.67) | (−0.21) | (−1.32) | (−1.55) |
| $k = -3$ | −0.092 | −0.054 | 0.011 | 0.005 | 0.005 | −0.409 | −0.085* | −0.668* |
| | (−0.85) | (−0.66) | (0.32) | (1.13) | (1.34) | (−0.12) | (−1.80) | (−1.86) |
| $k = -2$ | −0.120 | −0.047 | 0.031 | 0.005 | 0.002 | −3.857 | −0.104** | −0.332 |
| | (−0.98) | (−0.59) | (1.05) | (1.15) | (0.50) | (−1.03) | (−2.36) | (−1.14) |
| $k = -1$ | −0.077 | −0.074 | −0.032 | −0.002 | −0.005 | −2.492 | −0.167*** | −0.409 |
| | (−0.65) | (−0.89) | (−1.08) | (−0.60) | (−0.99) | (−0.62) | (−4.05) | (−1.31) |
| $k = 0$ | −0.105 | −0.045 | −0.004 | −0.005 | −0.002 | −8.726** | −0.143*** | −0.088 |
| | (−0.80) | (−0.48) | (−0.14) | (−1.12) | (−0.56) | (−2.39) | (−3.64) | (−0.28) |
| $k = +1$ | −0.057 | −0.012 | −0.010 | 0.002 | −0.000 | −1.645 | −0.015 | −0.249 |
| | (−0.44) | (−0.13) | (−0.36) | (0.50) | (−0.09) | (−0.44) | (−0.25) | (−0.75) |
| $k = +2$ | −0.041 | 0.010 | 0.020 | −0.000 | −0.004 | −5.398 | −0.030 | 0.126 |
| | (−0.31) | (0.11) | (0.67) | (−0.02) | (−0.90) | (−1.57) | (−0.58) | (0.40) |
| $k = +3$ | −0.004 | −0.026 | −0.026 | −0.002 | −0.001 | −0.259 | −0.040 | 0.083 |
| | (−0.04) | (−0.35) | (−1.03) | (−0.63) | (−0.23) | (−0.06) | (−0.86) | (0.25) |
| $k = +4$ | −0.009 | −0.015 | 0.026 | 0.000 | −0.002 | −0.433 | −0.026 | −0.007 |
| | (−0.09) | (−0.21) | (1.02) | (0.14) | (−0.30) | (−0.09) | (−0.61) | (−0.02) |
| Observations | 153,452 | 153,452 | 153,452 | 153,452 | 153,452 | 153,452 | 153,452 | 153,452 |
| Controls | Y | Y | Y | Y | Y | Y | Y | Y |
| Firm fixed effects | Y | Y | Y | Y | Y | Y | Y | Y |
| YearQuarter fixed effects | Y | Y | Y | Y | Y | Y | Y | Y |
| Cohort fixed effects | Y | Y | Y | Y | Y | Y | Y | Y |
| Cluster SE | Firm + YearQuarter | | | | | | | |

## Table 7
## Capital Market Benefits of Front-Loading: Short-Window Abnormal Returns

*Note:* This table reports results from estimating:

$$Y_{i,q} = \beta_0 + \beta_1 PreHigh_{i,q} + \beta_2 PreLow_{i,q} + X'_{i,q-1}\Gamma + \delta_i + \gamma_{q\times y} + \varepsilon_{i,q}$$

where $Y_{i,q}$ represents cumulative abnormal returns (CAR) for firm $i$ around quarter $q$. Columns (1)–(3) examine CAR over short event windows of $[-1,+1]$, $[-3,+3]$, and $[0,+30]$ days relative to the earnings announcement date. The sample includes both bad news and good news announcements; good news observations serve as the omitted reference group. $PreHigh$ equals one if cumulative abnormal job postings during $Q_{-3}$ to $Q_{-1}$ are positive and exceed the median among firms in the same SIC-2 industry, year, and quarter cohort; $PreLow$ comprises the remaining bad news observations. Wald tests assess whether the high and low pre-hiring groups differ: $H_0 : \beta_{\text{High}} - \beta_{\text{Low}} = 0$. $X'_{i,q-1}$ includes firm-level controls. $\delta_i$ denotes firm fixed effects and $\gamma_{q\times y}$ denotes year-quarter fixed effects. Standard errors in parentheses for coefficient rows; t-statistics in parentheses for Wald test rows. Standard errors are clustered two-way at the firm and year-quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | (1) | (2) | (3) |
|---|---|---|---|
| | CAR | CAR | CAR |
| Event Window | $[-1,+1]$ | $[-3,+3]$ | $[0,+30]$ |
| | | | |
| $PreHigh$ | $-0.057^{***}$ | $-0.059^{***}$ | $-0.062^{***}$ |
| | (0.003) | (0.004) | (0.004) |
| $PreLow$ | $-0.056^{***}$ | $-0.059^{***}$ | $-0.060^{***}$ |
| | (0.003) | (0.004) | (0.004) |
| **Wald Tests:** $H_0 : \beta_1 - \beta_2 = 0$ | | | |
| | −0.001 | −0.001 | −0.002 |
| | (−0.15) | (−0.15) | (−0.39) |
| | | | |
| Observations | 16,951 | 16,949 | 16,947 |
| R-squared | 0.164 | 0.168 | 0.176 |
| Controls | Y | Y | Y |
| Fixed Effects: | | | |
| Firm | Y | Y | Y |
| YearQuarter | Y | Y | Y |
| Cluster SE | | Firm + YearQuarter | |

**Table 8**
**Cross-Sectional Heterogeneity in Abnormal Job Postings**

*Note:* This table reports split-sample estimates of the event study specification for abnormal job postings (ABJP). The partition variables are attached to each event-firm-quarter observation. Columns (1) and (2) partition by labor market concentration (HHI), measured for five-digit SOC occupation × MSA markets: *MaxHHI* is the maximum HHI across the markets in which the firm recruits, and Low HHI comprises firms below the median of *MaxHHI* among firms in the same event year. Columns (3) and (4) partition by R&D intensity: *HighRD* comprises observations where R&D-to-assets exceeds the 75th percentile among firms in the same SIC-2 industry and event year. Columns (5) and (6) partition by analyst coverage: *HighCover* comprises observations where analyst coverage exceeds the median among firms in the same SIC-2 industry and event year. Controls, firm, year-quarter, and cohort fixed effects are included. t-statistics based on standard errors clustered at the firm and year-quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | HHI | | R&D | | Analyst Coverage | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| VARIABLES | Low | High | High | Low | High | Low |
| **Wald Tests:** $H_0$: $\hat{\beta} + \hat{\gamma}_k = 0$ | | | | | | |
| $k = -4$ | 0.042 | 0.141* | 0.011 | 0.101 | 0.063 | 0.114 |
| | (0.461) | (1.725) | (0.089) | (1.256) | (0.721) | (1.212) |
| $k = -3$ | 0.075 | 0.117 | 0.082 | 0.078 | 0.095 | 0.102 |
| | (0.760) | (1.610) | (0.610) | (1.228) | (1.262) | (1.201) |
| $k = -2$ | 0.249*** | 0.064 | 0.168 | 0.108* | 0.178** | 0.109 |
| | (2.678) | (0.821) | (1.158) | (1.674) | (2.187) | (1.181) |
| $k = -1$ | 0.254*** | 0.033 | 0.262** | 0.067 | 0.155** | 0.100 |
| | (2.928) | (0.511) | (2.198) | (1.236) | (2.253) | (1.204) |
| $k = +1$ | −0.019 | −0.110 | −0.156 | −0.084 | −0.103 | −0.054 |
| | (−0.185) | (−1.577) | (−1.448) | (−1.145) | (−1.116) | (−0.666) |
| $k = +2$ | −0.059 | −0.246*** | −0.168 | −0.197*** | −0.145 | −0.197*** |
| | (−0.555) | (−3.014) | (−1.244) | (−2.802) | (−1.438) | (−2.739) |
| $k = +3$ | −0.038 | −0.158* | −0.176 | −0.125 | 0.020 | −0.238** |
| | (−0.336) | (−1.809) | (−1.125) | (−1.483) | (0.201) | (−2.443) |
| $k = +4$ | −0.086 | −0.099 | −0.229 | −0.096 | 0.014 | −0.196*** |
| | (−1.047) | (−1.158) | (−1.529) | (−1.501) | (0.161) | (−2.691) |
| Observations | 66,762 | 87,669 | 29,762 | 124,668 | 82,116 | 72,315 |
| R-squared | 0.259 | 0.266 | 0.270 | 0.242 | 0.257 | 0.262 |
| Controls | Y | Y | Y | Y | Y | Y |
| Fixed Effects: | | | | | | |
| Firm | Y | Y | Y | Y | Y | Y |
| YearQuarter | Y | Y | Y | Y | Y | Y |
| Cohort | Y | Y | Y | Y | Y | Y |
| Cluster SE | Firm + YearQuarter | | | | | |

**Table 9**
**Cross-Sectional Heterogeneity in Abnormal Net Employee Flow Rate Around Bad News**

*Note:* This table reports split-sample estimates of the event study specification for the abnormal net employee flow rate (*AbNet*, defined as AbJoin − AbTurnover, i.e., the net change in workforce expressed as a percentage of beginning-of-quarter headcount relative to the firm's three-year same-quarter average). The partition variables are attached to each event-firm-quarter observation. Columns (1) and (2) partition by labor market concentration (HHI), measured for five-digit SOC occupation × MSA markets: *MaxHHI* is the maximum HHI across the markets in which the firm recruits, and Low HHI comprises firms below the median of *MaxHHI* among firms in the same event year. Columns (3) and (4) partition by R&D intensity: *HighRD* comprises observations where R&D-to-assets exceeds the 75th percentile among firms in the same SIC-2 industry and event year. Columns (5) and (6) partition by analyst coverage: *HighCover* comprises observations where analyst coverage exceeds the median among firms in the same SIC-2 industry and event year. Controls, firm, year-quarter, and cohort fixed effects are included. t-statistics based on standard errors clustered at the firm and year-quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | HHI | | R&D | | Analyst Coverage | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| VARIABLES | Low | High | High | Low | High | Low |
| **Wald Tests:** $H_0$: $\hat{\beta}_1 + \hat{\gamma}_k = 0$ | | | | | | |
| $k = -4$ | 0.266** | 0.069 | 0.156 | 0.151* | 0.193* | 0.073 |
| | (2.116) | (0.732) | (0.759) | (1.885) | (1.895) | (0.618) |
| $k = -3$ | 0.130 | 0.135* | 0.278 | 0.097 | 0.272** | −0.015 |
| | (1.060) | (1.676) | (1.238) | (1.079) | (2.539) | (−0.154) |
| $k = -2$ | 0.343*** | 0.125 | 0.507** | 0.138 | 0.322*** | 0.104 |
| | (2.737) | (1.593) | (2.334) | (1.629) | (4.105) | (0.818) |
| $k = -1$ | 0.241 | 0.039 | 0.449** | 0.040 | 0.079 | 0.151 |
| | (1.345) | (0.638) | (2.236) | (0.489) | (0.588) | (1.289) |
| $k = +1$ | −0.054 | −0.267*** | 0.094 | −0.257*** | −0.142 | −0.225** |
| | (−0.456) | (−2.988) | (0.534) | (−3.361) | (−1.489) | (−2.095) |
| $k = +2$ | −0.307** | −0.240*** | −0.188 | −0.301*** | −0.304*** | −0.237** |
| | (−2.212) | (−2.914) | (−1.067) | (−3.535) | (−3.081) | (−2.115) |
| $k = +3$ | −0.157 | −0.016 | 0.065 | −0.128* | −0.149 | −0.006 |
| | (−1.189) | (−0.208) | (0.281) | (−1.791) | (−1.597) | (−0.058) |
| $k = +4$ | −0.311*** | −0.226*** | −0.350** | −0.257*** | −0.259*** | −0.263** |
| | (−2.609) | (−2.773) | (−2.031) | (−3.385) | (−2.998) | (−2.527) |
| Observations | 63,979 | 84,820 | 28,701 | 120,098 | 79,786 | 69,014 |
| R-squared | 0.287 | 0.293 | 0.337 | 0.265 | 0.316 | 0.267 |
| Controls | Y | Y | Y | Y | Y | Y |
| Fixed Effects: | | | | | | |
| Firm | Y | Y | Y | Y | Y | Y |
| YearQuarter | Y | Y | Y | Y | Y | Y |
| Cohort | Y | Y | Y | Y | Y | Y |
| Cluster SE | Firm + Year-Quarter | | | | | |

## Table 10
## Job Postings Intensity and Analyst Forecast Revisions

| | *REVISION* | | *Forecast Error* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *JP-REV* | −0.000 | | | |
| | (−0.615) | | | |
| *High-REV* | | −0.000 | | |
| | | (−0.124) | | |
| *JP-6M* | | | −0.005 | |
| | | | (−0.323) | |
| *JP-12M* | | | | −0.000 |
| | | | | (−0.032) |
| Observations | 631,918 | 631,918 | 3,293,090 | 3,293,090 |
| R-squared | 0.124 | 0.124 | 0.718 | 0.718 |
| Controls | Y | Y | Y | Y |
| Fixed Effects: | | | | |
| Firm | Y | Y | Y | Y |
| Year × Quarter | Y | Y | Y | Y |
| Analyst | Y | Y | Y | Y |
| Horizon | Y | Y | Y | Y |
| Cluster SE | Firm + Analyst | | | |

*Note:* This table examines whether job posting activity predicts analyst expectations. The dependent variables are analyst forecast revisions (REVISION, columns 1–2) and Forecast Error (columns 3–4). Job posting measures include *JP-REV* (postings between previous earnings announcement and forecast date), *HIGH-REV* (indicator for top quartile *JP-REV*), *JP-6M* (postings over six months), and *JP-12M* (postings over twelve months). For readability, *JP-REV* variables are scaled by 1,000. All specifications include firm-level controls and governance controls, with firm, year-quarter, analyst, and forecast horizon fixed effects. t-statistics in parentheses are based on standard errors clustered at the firm and analyst levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

**Table 11**
**Robustness Tests: Alternative Samples and Specifications**

*Note:* This table reports results from estimating:

$$\text{ABJP}_{i,q} = \beta_0 + \beta_1 BADNEWS_{i,q} + \sum_{k \in K} \gamma_k (BADNEWS \times Q_k)_{i,q} + \sum_{k \in K} \lambda_k Q_k + X'_{i,q-1}\Gamma + \delta_i + \gamma_{q \times y} + \theta_c + \varepsilon_{i,q}$$

where $\text{ABJP}_{i,q}$ is $\text{asinh}(JP_{i,q}) - \text{asinh}(NormJP_{i,q})$, where $NormJP_{i,q}$ is the firm's historical average (mean job postings over the same fiscal quarter in the prior three years). Each term applies the inverse hyperbolic sine to raw posting counts; the benchmark is the simple average of the same calendar quarter across the firm's prior three years, purging firm-level posting trends and seasonal patterns. $BADNEWS$ equals one if the earnings forecast error (Actual $\text{EPS}_{i,Q0}$ − Consensus $\text{Forecast}_{i,Q0}$) is negative. $Q_k$ denotes event quarters $k \in \{-4, -3, -2, -1, +1, +2, +3, +4\}$ relative to the earnings announcement, with $k = 0$ omitted. Column (1) excludes 2020–2021 (COVID-19 period). Column (2) uses the relaxed sample allowing pre-event bad news. Column (3) employs an alternative ABJP measure based on raw posting count differences. Column (4) utilizes Propensity Score Matching (1:3 matching on firm characteristics at $Q_{-4}$). Wald tests assess whether bad news firms differ from good news firms at each quarter: $H_0 : \beta_1 + \gamma_k = 0$. Firm-level and governance controls are included but not displayed for brevity. $\delta_i$ denotes firm fixed effects, $\gamma_{q \times y}$ denotes year-quarter fixed effects, and $\theta_c$ denotes cohort fixed effects. t-statistics in parentheses are based on standard errors clustered two-way at the firm and year-quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

| | Excl. COVID-19 | Relaxed Sample | Alternative ABJP | PSM (1:3) |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VARIABLES | | | *ABJP* | |
| **Wald Tests:** $H_0$: $\hat{\beta}_1 + \hat{\gamma}_k = 0$ | | | | |
| $k = -4$ | 0.081 | 0.121*** | 9.718 | 0.057 |
| | (1.114) | (3.087) | (0.662) | (0.690) |
| $k = -3$ | 0.074 | 0.171*** | 23.86 | 0.002 |
| | (1.219) | (4.430) | (1.507) | (0.021) |
| $k = -2$ | 0.129* | 0.189*** | 39.20*** | 0.105 |
| | (1.910) | (4.842) | (2.977) | (1.327) |
| $k = -1$ | 0.114* | 0.094*** | 35.21* | 0.132** |
| | (1.863) | (2.701) | (1.820) | (2.024) |
| $k = +1$ | −0.096 | −0.090** | 8.791 | −0.092 |
| | (−1.384) | (−2.459) | (0.508) | (−1.233) |
| $k = +2$ | −0.159** | −0.142*** | 0.073 | −0.180** |
| | (−2.208) | (−3.592) | (0.004) | (−2.532) |
| $k = +3$ | −0.122 | −0.133*** | 18.45 | −0.130 |
| | (−1.456) | (−3.112) | (0.859) | (−1.605) |
| $k = +4$ | −0.109 | −0.114*** | 8.529 | −0.143** |
| | (−1.566) | (−2.879) | (0.441) | (−2.084) |
| Observations | 123,399 | 351,648 | 154,431 | 81,603 |
| R-squared | 0.242 | 0.191 | 0.150 | 0.237 |
| Fixed Effects: | | | | |
| Firm | Y | Y | Y | Y |
| Year × Quarter | Y | Y | Y | Y |
| Cohort | Y | Y | Y | Y |
| Cluster SE | | | Firm + Year-Quarter | |

# Appendix: Variable Definitions

| Variable | Definition | Source |
|---|---|---|
| **Panel A: Job Posting Variables** | | |
| *JP* | The number of unique job positions released by a firm in quarter $q$. | Lightcast |
| *NormJP* | The normal level of job postings, measured as the average number of unique job positions released by a firm over the same fiscal quarter in the preceding three years. | Lightcast |
| *ABJP* | Abnormal job posting volume, measured as the inverse hyperbolic sine of *JP* minus the inverse hyperbolic sine of *NormJP*. | Lightcast |
| *PreHigh* | Indicator variable equal to 1 if cumulative abnormal job postings (sum of ABJP) over quarters $Q_{-3}$, $Q_{-2}$, and $Q_{-1}$ are positive and exceed the median ABJP level of firms in the same SIC-2 industry, year, and quarter cohort; 0 otherwise. | Lightcast |
| *PreLow* | Indicator variable equal to 1 for bad news firms with cumulative abnormal job postings over $Q_{-3}$ to $Q_{-1}$ that are not classified as PreHigh; 0 otherwise. | Lightcast |
| *JP-REV* | Total volume of unique job postings during the analyst forecast revision period (between previous earnings announcement and forecast date), measured in thousands. | Lightcast |
| *High-REV* | Indicator variable equal to 1 if JP-REV is above the 75th percentile of the sample distribution; 0 otherwise. | Lightcast |
| *JP-6M* | Total volume of unique job postings in the six-month window prior to the analyst's forecast date, measured in thousands. | Lightcast |
| *JP-12M* | Total volume of unique job postings in the twelve-month window prior to the analyst's forecast date, measured in thousands. | Lightcast |
| **Panel B: Job Posting Characteristics Variables** | | |
| *EFF* | Average job posting effort, calculated as the ratio of total (duplicated) postings to unique positions for a given firm-quarter. Duplicate postings occur when a single unique job is cross-posted to multiple job board websites, as identified by Lightcast. Higher values indicate greater posting effort. | Lightcast |
| *DUR* | Average number of days job postings remain active and accepting applicants for a given firm-quarter. Represents median posting duration in the selected region, occupation, and company. | Lightcast |
| *EDU* | Average educational level required across all job postings for a given firm-quarter, measured in years of education. Extracted from detailed educational credential requirements in posting text. | Lightcast |

*Continued on next page*

*Appendix (continued)*

| Variable | Definition | Source |
|---|---|---|
| *EXP* | Average number of years of work experience required across all job postings for a given firm-quarter. Extracted from job posting text using machine learning algorithms. | Lightcast |
| *MGR* | Average proportion of job postings requiring managerial responsibilities for a given firm-quarter. Identified through parsing and extraction of job posting text using Lightcast's proprietary algorithms. Ranges from 0 to 1. | Lightcast |
| *SKILLS* | Average total number of skills required per job posting for a given firm-quarter. Identified using Lightcast's comprehensive taxonomy of over 33,000 skills extracted from job posting text. | Lightcast |
| *SENIOR* | Firm-quarter average seniority level of job postings, where Junior=1, Intermediate=2, and Senior=3. Captures the average hierarchical seniority of posted positions, as classified by Lightcast based on textual indicators in job titles and descriptions. | Lightcast |
| *SALARY-FROM* | Lower bound of the disclosed salary range in job postings for a given firm-quarter. | Lightcast |
| *SALARY-TO* | Upper bound of the disclosed salary range in job postings for a given firm-quarter. | Lightcast |
| *SALARY-MID* | Average midpoint value of salary ranges disclosed in job postings for a given firm-quarter. Calculated as the mean of the midpoint between minimum and maximum salary bounds across all postings that disclose salary information. | Lightcast |
| *SAL-DISC* | Proportion of job postings that disclose salary information within a given firm-quarter. Calculated as the number of postings with non-missing salary data divided by total postings. Ranges from 0 to 1. | Lightcast |
| *FULL* | Proportion of full-time positions among all job postings for a given firm-quarter. Full-time positions coded as 1, part-time as 0. Ranges from 0 to 1. | Lightcast |
| *WORD* | Average word count of job posting descriptions for a given firm-quarter. Calculated as the mean number of words across all job postings after removing HTML tags. Higher values indicate more detailed or comprehensive job descriptions. | Lightcast |
| *SPEC* | Average number of specialized (technical or hard) skills per job posting for a given firm-quarter. Specialized skills are primarily required within a subset of occupations or equip one to perform specific tasks (e.g., "NumPy" or "Hotel Management"). | Lightcast |

*Continued on next page*

*Appendix (continued)*

| Variable | Definition | Source |
|---|---|---|
| *SOFT* | Average number of soft (baseline or cross-cutting) skills per job posting for a given firm-quarter. Soft skills are broadly applicable across many different occupations and relate to interpersonal, communication, or cognitive abilities (e.g., "Communication" or "Problem Solving"). | Lightcast |
| **Panel C: Resume Data and Employee Flow Variables** | | |
| *HC-START* | Number of employees present at the beginning of the quarter, defined as profiles that started before the quarter and did not end before quarter start. | Lightcast |
| *HC-TOTAL* | Total number of unique employee profiles that were active at any point during the quarter. | Lightcast |
| *JoinCount* | Number of employees whose profiles indicate a job start during the quarter. | Lightcast |
| *LeaveCount* | Number of employees whose profiles indicate a job end during the quarter. | Lightcast |
| *NetCount* | Net change in headcount during the quarter, measured as JoinCount minus LeaveCount. | Lightcast |
| *Turnover* | Raw employee turnover rate in quarter $q$, measured as LeaveCount divided by HC-START, expressed in percentage terms. | Lightcast |
| *Join* | Raw employee hiring rate in quarter $q$, measured as JoinCount divided by HC-START, expressed in percentage terms. | Lightcast |
| *Net* | Raw net headcount growth rate in quarter $q$, measured as (JoinCount − LeaveCount) divided by HC-START, expressed in percentage terms. | Lightcast |
| *AbTurnover* | Abnormal employee turnover rate in quarter $k$, measured as Turnover minus the firm's three-year, same-quarter average turnover rate. | Lightcast |
| *AbJoin* | Abnormal hiring rate in quarter $k$, measured as Join minus the firm's three-year, same-quarter average hiring rate. | Lightcast |
| *AbNet* | Abnormal net headcount growth rate in quarter $k$, measured as Net minus the firm's three-year, same-quarter average net growth rate. | Lightcast |
| **Panel D: Analyst Forecasting Variables** | | |
| *Forecast Error* | Earnings forecast error, calculated as actual EPS minus the I/B/E/S consensus forecast. A higher (lower) value indicates earnings above (below) analyst expectations. | I/B/E/S, Compustat |

*Continued on next page*

*Appendix (continued)*

| Variable | Definition | Source |
|---|---|---|
| *BADNEWS* | Indicator variable equal to 1 if the firm's earnings forecast error (actual EPS minus the I/B/E/S consensus forecast) is negative; 0 otherwise. | I/B/E/S, Compustat |
| *REVISION* | Analyst forecast revision, calculated as (Revised forecast − Initial forecast) / —Initial forecast—. | I/B/E/S |
| *ANALYST* | Number of analysts providing earnings forecasts for the firm in a given year-quarter. | I/B/E/S |
| **Panel E: Firm Characteristics Variables** | | |
| *HHI* | Following Azar et al. [2022], we measure labor market concentration using the Herfindahl-Hirschman Index (HHI), defined at the intersection of five-digit SOC occupations and metropolitan statistical areas (MSAs). Higher HHI values indicate greater concentration and lower competition. For each event-firm-quarter observation, *HHI* is the maximum HHI across the markets in which the firm recruits. Missing values of *HHI* are replaced with the mean of the three nearest observed values for the same firm. *LowHHI* is an indicator equal to 1 when *HHI* is below the median among firms in the same event year and 0 otherwise. | Lightcast |
| *HighRD* | For each event-firm-quarter observation, an indicator equal to 1 if the firm's R&D intensity (R&D expenditures divided by total assets) exceeds the 75th percentile among firms in the same two-digit SIC industry and event year, following the convention in Section 5; 0 otherwise. | Compustat |
| *HighCover* | For each event-firm-quarter observation, an indicator equal to 1 if the number of analysts issuing earnings forecasts for the firm exceeds the median among firms in the same SIC-2 industry and event year; 0 otherwise. *LowCover* equals 1 for firms at or below the same median threshold; 0 otherwise. | I/B/E/S |
| *SIZE* | Natural logarithm of total assets at the end of the quarter. | Compustat |
| *ROA* | Return on assets, calculated as the sum of the last four quarters of operating income after depreciation (OIADPQ) divided by total assets five quarters ago (ATQ), following Choi, Choi, and Malik (2023). | Compustat |
| *Q* | Tobin's Q, calculated as the ratio of market value of assets to book value of assets: (ATQ − CEQQ + PRCCQ × CSHOQ) / ATQ. | Compustat |
| *CAPX* | Capital expenditures scaled by total assets, calculated as CAPXY / ATQ. | Compustat |

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*Appendix (continued)*

| Variable | Definition | Source |
|---|---|---|
| *R&D* | Research and development expenses scaled by total assets, calculated as XRDQ / ATQ. Set to zero when missing. | Compustat |
| *LIQ* | Cash and short-term investments scaled by total assets, calculated as CHEQ / ATQ. | Compustat |
| *LEV* | Total debt scaled by total assets, calculated as (DLTTQ + DLCQ) / ATQ. | Compustat |
| *IO* | Institutional ownership, calculated as total shares held by institutional investors filing SEC Form 13F divided by shares outstanding at quarter-end. Institutional holdings aggregated by CUSIP8 and calendar quarter. Shares outstanding from CRSP (SHROUT × 1,000) or Compustat (CSHOQ × 1,000,000) when CRSP unavailable. Winsorized to [0, 1]. | Thomson Reuters 13F, CRSP, Compustat |
| *LABOR* | Labor intensity indicator, equal to 1 if the ratio of employees to total assets (EMP / ATQ) is above the sample median; 0 otherwise. Captures the degree to which a firm relies on human capital relative to physical and financial capital. | Compustat |
| **Panel F: Governance Controls** | | |
| *BSIZE* | Number of active directors on the board at the annual report date, measured as the count of unique directors with active roles. | BoardEx |
| *DUAL* | Indicator variable equal to 1 if the CEO also serves as Chairman of the board at the annual report date; 0 otherwise. | BoardEx |
| *TENURE* | Number of years the CEO has been in office, calculated as the time elapsed from the CEO's start date to the annual report date, measured in years. | BoardEx |
| **Panel G: Capital Market Variables** | | |
| *CAR* | Cumulative abnormal return over the indicated event window, computed from daily stock returns relative to the market model around the earnings announcement. | CRSP |
| **Panel H: Time Indicators** | | |
| $Q_k$ | Indicator variable equal to 1 for quarters occurring $k$ periods relative to the earnings announcement quarter; 0 otherwise, where $k \in \{-4, -3, -2, -1, 0, +1, +2, +3, +4\}$. Negative values denote pre-announcement quarters, $k = 0$ represents the earnings announcement quarter, and positive values denote post-announcement quarters. | |