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Rival Growth Prospects and Equity Prices: Evidence from Mass Layoff Announcements

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We investigate the impact of mass layoff announcements on the equity value of industry rivals. When a layoff announcement conveys good (bad) news for the announcer, rivals on average witness a 0.44 percent increase (0.60 percent decrease) in cumulative abnormal stock returns. This effect is concentrated on rivals with high growth opportunities. Consistent with this finding, we also show that our results are strongest in technology industries, where growth opportunities matter the most. Our results suggest that investors perceive layoff announcements as news about industry prospects rather than just the announcer.

Keywords: Mass Layoffs, Rivals, Firm characteristics.

JEL Codes: J63, G14.

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1. Introduction

Mass layoff announcements (henceforth layoff announcements) are important corporate events that have a significant impact on the announcing firm's stock value.[1] Moreover, there is substantial heterogeneity in market reactions because layoffs can be either good or bad news for the firm. For example, a company making the announcement of a large layoff may be either seeking to become more efficient or in financial trouble. While the firm-specific nature of the news can be observed in the movement of announcers' stock prices, it is harder to isolate industry effects. To understand the industry-specific components of layoff announcements, we investigate their effects on the announcing firm's rivals.

An unexpected layoff announcement may affect a firm's rivals in two ways. First, the layoff may indicate a systematic shock to the entire industry (e.g. technology shocks, market conditions, customer preferences). In these cases the announcement by one firm also reveals relevant information about its rivals. Second, the layoff may signal a strengthening (weakening) of the announcer's position in the industry. In these cases the announcement triggers a redistribution of wealth across firms in the industry. Following Lang and Stulz (1992), we measure industry (competitive) effects as a positive (negative) correlation of stock price reactions between the announcing firm and its rivals.

We assess the intra-industry information transfers through an event-study approach using a hand-collected sample of 676 layoffs. Consequently, our results elicit the market participants' perceptions about layoffs' information content. Moreover, our approach explicitly controls for the variation in market perceptions of the information content of a layoff proxied by the reaction of the announcer's stock price upon announcement. Failure to control for this variation may bias results downward.[2] To avoid such bias, we investigate the presence of industry and competitive effects in two different settings that are based on the announcer's stock reaction: good news and bad news announcements.[3]

We find that the industry effects dominate competitive effects irrespective of whether the layoff announcement is good news or bad news for the announcer. In particular, for a good news layoff announcement, rivals' average three-day cumulative abnormal return (CAR) centered on the announcement date is +0.44 percent. Similarly, for a bad news layoff announcement, rivals' average three-day CAR is -0.60 percent. While both parametric and

[1] See Worrell, Davidson, and Sharma (1991), Abowd, Milkovich, and Hannon (1990), Farber and Hallock (2009), among others.

[2] For example, if we are looking at the competitors' average stock reaction to an announcement and nearly 50 percent of the sample reacts in the opposite direction to the remaining sample, we will have a bias toward no results.

[3] A layoff announcement is classified as good news (bad news) for the announcer if the firm has a positive (negative) three-day CAR.

non-parametric tests indicate that the average impact on rivals is statistically significant, we also calculate the value gain/loss for rivals to show economic importance.[4] We find a mean (median) gain of \$31.74 million (\$0.39 million) in the "good news" case and a mean (median) loss of \$29.74 million (\$0.53 million) in the "bad news" case. However, while we do observe statistically significant average three-day CARs for rivals, we also observe quite a lot of within-industry heterogeneity in the reaction of rivals' stock price to the layoff announcement.

Having established that layoff announcements are seen by investors as changes in industry's medium and long-run prospects, our next goal is to analyze which rival characteristics are most associated with the observed stock price reaction. In particular, we expect that firms and industries whose value is concentrated in the present value of growth opportunities should face larger stock price reactions. Consequently, rivals with high growth opportunities should observe stronger stock price reactions when industry prospects change compared with rivals whose value comes primarily from assets in place. Subsequently, we expect results to be concentrated in technology industries, where growth options are a larger fraction of the firms' valuation.

Results corroborate our hypothesis. We find that net industry effects are strongest for rivals with the highest proxies for growth opportunities within the industry. For example, in the "good news" case, an increase of one standard deviation in the rival's Tobin's Q induces an increase in the rival's CAR of 0.451 percentage points. Similarly, rivals with positive R&D expenses see an additional 1.19 percentage points in their stock price reaction to a peer's layoff announcement. Similarly, in the "bad news" case, an increase of one standard deviation in the rival's Tobin's Q induces a more negative CAR by -0.233 percentage points. Similarly, an increase of one standard deviation in the rival's sales growth is associated with a decline in the rival's CAR by -0.21 percentage points. Finally, once we split our sample into technology vs. non-technology industries, we observe that rivals' abnormal stock price reactions are larger in technology industries.

Apart from rival characteristics, information transfers may also be affected by announcer and layoff characteristics. As a robustness test, we use a random effects regression model to allow us to measure the importance of announcer and announcement characteristics. However, this model demands stricter restrictions on the correlation between unobserved event characteristics and other controls. We compare the fixed effects and random effects methodologies using a Wald test and find that the random effects model is no worse than the fixed effects model. Nevertheless, our main results about rival characteristics are robust to

[4]We calculate the value gain/loss for each rival by multiplying their 3-day CAR with the market capitalization for the previous fiscal year.

the choice of regression model. In terms of announcer and layoff characteristics, we find that the announcer's CAR has a positive and significant coefficient, indicating the importance of industry effects. In contrast, no other announcer or layoff characteristics significantly affect rivals' stock reaction. Furthermore, the announcer's characteristics are unable to predict the sign of the announcer's stock price reaction. These results highlight the new information content released by the layoff announcement. While a firm's characteristics may help to predict the announcer's identity – announcers tend to be larger, older, less efficient (higher COGS and SG&A), and more diversified than their rivals, and have lower growth opportunities (low Tobin's Q) – they do not help to predict the market reaction to the announcement. Consequently, the layoff announcement itself is seen as an unexpected event, which makes market participants change their views about the industry's prospects.

In summary, our results indicate that, on average, market participants perceive layoff announcements as revealing news about the industry's prospects. Consequently, rivals' stock price reactions are adjusted accordingly, showing a CAR that is positively correlated with the announcer's CAR. Moreover, the most affected rivals are the ones whose valuations are closely tied to industry's medium- and long-run prospects. These results allow researchers and policymakers to investigate the precision of investors' forecasts as well as potential behavioral biases. For example, an analysis of an industry's value- and equal-weighted portfolio in terms of its medium- and long-run operational and market performance would indicate whether realized performance consistently corroborate investors' expectations. Henceforth, a performance consistent with expectations would allow the use of stock market reaction at the time of a layoff announcement as a leading indicator of the industry expected long-run performance.

This paper contributes to the existing literature on information transfers by studying the industry effects of layoff announcements. Layoff announcements represent a powerful setting for examining information transfers for three important reasons. First, frictions in the labor market make it costly for firms to adjust the size of their labor force (see Hamermesh (1989) and Abowd and Kramarz (2003)). This implies that firms undertake a layoff only if they expect the reasons for adjustment to be long-lived; that is, layoffs are significant corporate events. Second, the quality of a firm's labor force is an important factor for firm pricing, such that changes in labor force composition should affect stock prices (see Bazdresch, Belo, and Lin (2014) and Merz and Yashiv (2007)). Third, layoffs are unique compared with other firm-specific news announcements commonly studied in that they can signal either good or bad news for the announcer. This makes for a compelling setting, since pooling observations and disaggregating into sub-samples based on the information content of the announcement provide vastly different results. Significant variation in announcers' reactions provides a unique opportunity to study information transfers. It is in this context that we identify and analyze the association between rivals' characteristics and intra-industry information transfers.

The literature on the impact of layoffs has up to now focused mainly on the impact of layoff announcements on the announcer's stock return. Earlier contributions (see Worrell, Davidson, and Sharma (1991); Abowd, Milkovich, and Hannon (1990), among others) have found a negative impact of layoff announcements on stock returns. However, more recent work by Brookman, Chang, and Rennie (2007) and Marshall, McColgan, and McLeish (2012) has found a positive average impact of layoff announcements on the announcing firm, in particular for the later periods. In fact, Farber and Hallock (2009) show that the impact of layoff announcements on the average stock returns of announcers has varied over time, being extremely negative during the 1970s but approaching zero in later periods. This pattern seems to have partially reverted from 2000 on. Hallock, Strain, and Webber (2012) extended the database used by Farber and Hallock (2009) to 2007. They show that stock price reactions to job loss announcements are less negative in the 1980s and 1990s compared with the 1970s, but the 2000s are not statistically different from the 1970s. In our data, we see a clear reversal of this attenuating pattern in the last decade, with announcer's stock market reaction becoming again, on average, negative and statistically significant.[5] Moreover, there is a wide dispersion in announcers' stock reactions, varying from -28.95 percent to $+26.81$ percent in our sample. The fraction of announcers with positive three-day CARs in a given year has usually been above 40 percent with an upward trend to nearly 45 percent by the end of our sample period, as shown in Figure 1.A. Consequently, the informational content of a given announcement can vary significantly from very negative to very positive. This differential informational content of the announcement shows the need to investigate the drivers of investor responses at industry rivals.

The literature that looks at the impact of layoffs on the announcing firm's rivals is quite small. A recent example is the study of the effect of large layoffs on the local economy by Gathmann, Helm, and Schönberg (2016). Using a sample of 62 layoff events obtained from the German Social Security Records, they find sizable and persistent negative spillover effects on the regional economy. Firms producing in the same broad industry as the layoff plant are the most affected. Employment decline at broad industry peers grows to 5 percent four years

[5] A possible explanation for this time series pattern is highlighted by Marshall, McColgan, and McLeish (2012). Studying a sample of U.K. layoff announcements in the periods before and during the global financial crisis, they show that layoffs are likely to be seen as negative by investors during economic downturns. In contrast, layoffs are usually seen in a positive light when announced during rising financial markets. While we observe a similar pattern in our sample, our results are robust to the introduction of time fixed effects and recession dummies.

after the layoff, compared with 2.4 percent in firms in other broad industries within the same local economy. Our study is complementary to theirs, since we account for quite different outcomes. On one side, we are unable to study the effect in the local economy – layoff announcements in our sample of U.S. firms are not specific about the geographical location of the layoffs. In contrast, our sample allows us to focus on variables of interest other than employment growth. In particular we focus on the industry-wide spillover effects of layoff announcements through investors expectations about rivals' future profitability proxied by stock price movements. Moreover, we are able to assess the impact of rivals' characteristics on these expectations beyond the basic industry classification.

2. Hypothesis Development and Methodology

2.1. Hypothesis Development

The key questions that this article addresses are:

1. How do industry rivals' stock prices react to layoff announcements?
2. How are these reactions affected by rivals' characteristics?

Our initial hypotheses test the effect of layoff announcements on rivals' cumulative abnormal return (CAR). As pointed out by Lang and Stulz (1992), an unexpected layoff announcement may affect an announcing firm's rivals in one of two ways. First, the layoff may indicate a systematic shock to the entire industry (for example, technology shocks, market conditions, or customer preferences). Consequently, the new information obtained through the layoff announcement affects the announcer and rivals in a similar manner. As a result, we expect the stock price reactions at both announcer and rival to go in the same direction. Second, the unexpected announcement may signal a firm-specific shock to the announcer's position in the industry that triggers a redistribution of wealth across firms in the industry. As a result, the new information obtained through the layoff announcement affects announcer and rivals in opposite ways; the weakening (strengthening) of the announcer is beneficial (detrimental) to rivals. The observed CAR indicates the net effect of these two opposing movements. We use the association between announcers' and rivals' CARs to estimate which effect dominates, on average. Hypotheses 1a and 1b summarize these two possibilities.

Hypothesis 1a: Announcer's and industry rivals' CARs are positively correlated.

Hypothesis 1b: Announcer's and industry rivals' CARs are negatively correlated.

In cases in which an unexpected layoff announcement signals a firm-specific shock to the announcer's position in the industry, we would expect the effect to be strongest in highly concentrated industries. As pointed out by Lang and Stulz (1992), in perfectly competitive industries, shareholders of existing firms cannot earn rents from an increase in demand. Hypothesis 1c summarizes this statement.

> **Hypothesis 1c:** If announcer's and industry rivals' CARs are negatively correlated, rivals in concentrated industries show larger absolute CARs.

In order to test hypothesis 1c, we partition our sample with respect to industry concentration, calculated based on a version of the modified Herfindahl-Hirschman Index (MHHI) first introduced by O'Brien and Salop (2000) and described in Azar, Schmalz, and Tecu (2017). As shown by Azar et al. (2017) and Azar, Raina, and Schmalz (2016), controlling for cross-ownership is relevant in order to fully grasp the actual competitive pressures within the industry. Using more traditional concentration measures, such as the Herfindahl-Hirschman index (HHI), may overstate these pressures.[6] Following Azar et al. (2017), we use 13-F filings with the Securities and Exchange Commission, as provided by Thomson Reuters, to identify institutional ownership in order to calculate our measure for three-digit SIC industries, according to the expression presented in equation (1):

$$SMHHI = \sum_j \sum_k s_j s_k \frac{\sum_i \beta_{ij}\beta_{ik}}{\sum_i \beta_{ij}^2}; \tag{1}$$

where s_j is the product market share of firm j, β_{ij} represents ownership share of firm j accruing to shareholder i, and k indexes firm j's rivals. The difference between our measure and the one presented by O'Brien and Salop (2000) is that we do not control for the voting shares. We call our measure of industry concentration a simplified modified Herfindahl-Hirschman index (SMHHI). By using a simplified version of their measure, we are able to look at longer periods of time (starting in 1979), while the MHHI can only be calculated starting in 2006, the year when the 13-F filings start reporting information on voting vs. non-voting shares. However, for the available data, the correlation between the measures of institutional shareholders' ownership as a fraction of the total shares calculated with all shares and voting shares is above 90 percent. Consequently, the calculated measures for SMHHI and MHHI are quite similar for the period 2006 onward.[7]

[6] Nevertheless, our results are qualitatively the same if we focus on the traditional Herfindahl-Hirschman index (HHI).

[7] In fact, the difference between the measures of institutional shareholders' ownership as a fraction of the total shares calculated with all shares and voting shares is less than 1 percent for more than 90 percent of the observations in our database.

Our next hypotheses address research question 2, which relates rivals' stock price reactions to their financial characteristics. As we observe in Figures 1B and 2, there is a lot of within-industry variability in rivals' stock price reaction to a given layoff announcement. We investigate how these reactions are related to rivals' observed characteristics, once we control for event fixed effects. In the case in which layoffs indicate a systematic shock to the industry, we expect that the new information released signals changes in the industry's medium- and long-run prospects. Consequently, rivals whose value comes primarily through the present value of growth opportunities would be the most affected ones.

> **Hypothesis 2a:** If announcer's and industry rivals' CARs are positively correlated, firms with high growth opportunities show larger absolute CARs.

We use three proxies for growth opportunities: a dummy for investment in R&D, Tobin's Q, and sales growth. As shown in the literature (see Martin (2002), Chapter 14, for a summary), investment in R&D is associated with high growth opportunities. Similarly, the literature in corporate finance usually uses Tobin's Q as a proxy for growth (see Hubbard (1998)). However, Biddle, Hilary, and Verdi (2009) defend the use of sales growth as a proxy for growth opportunities because Tobin's Q can arguably be affected by the quality of financial reporting and because marginal Q is notoriously hard to measure. Moreover, Pinnuck and Lillis (2007) and Jung, Lee, and Weber (2014) show that sales growth is highly correlated with firms' hiring decisions.

Further, we expect that in technology industries, a larger fraction of the firms' value comes from growth opportunities (for example, Demers and Lev (2001)). Consequently, we predict that rivals' stock price reactions would be significantly larger and more concentrated in technology industries, in particular among rivals with the largest proxies for growth opportunities.[8]

> **Hypothesis 2b:** If announcer's and industry rivals' CARs are positively correlated, rivals with high growth opportunities in technology industries show the largest absolute CARs.

We divide the sample into technology and non-technology industries, where the technology sectors are defined based on the classification by Loughran and Ritter (1997).[9]

[8] Moreover, according to the previous literature (see Chemmanur, Cheng, and Zhang (2013) and Anderson, Banker, and Ravindran (2000)), workers in non-technology firms are more likely to face human capital losses due to displacement. Consequently, workers in non-technology industries are likely to demand higher wages for the same displacement risk, affecting firms' layoff and capital structure decisions.

[9] Because we cluster in three-digit SIC industries, we adjusted Loughran and Ritter (1997), accordingly. In particular, we consider the following three-digit SIC industries as tech industries: 357, 366, 367, 382, 384, 481, 489, and 737. Similar results are obtained if we use a different definition of technology industries, such as the one presented in Anderson, Banker, and Ravindran (2000).

2.2. Methodology

In order to study the market's response to the announcement of a layoff, we employ an event study methodology. This approach is consistent with much of the prior literature on the information content of layoff announcements (for example, Farber and Hallock (2009)) and intra-industry information transfers (Madura, Akhigbe, and Bartunek (1995) and Goins and Gruca (2008)). We specifically focus on three-day CARs for non-announcing firms around the layoff announcement date, as reported by the Wall Street Journal. Farber and Hallock (2009) also use Wall Street Journal announcements as the "event date" and acknowledge the possibility of information leakage prior to the WSJ release; if anything, leakage should bias against finding statistically significant results.

We start our analysis testing hypotheses 1a, 1b, and 1c. We perform univariate tests for the average effects of layoff announcements on industry rivals. Specifically, we create a value-weighted portfolio of industry rivals for each announcement in order to reflect the industry's shifting composition. Our estimates for the abnormal returns follow the method proposed by Scholes and Williams (1977). To test hypothesis 1c, we consider the subsamples with high- and low-SMHHI, which split the industries at the sample's median SMHHI.[10] As robustness checks, we also consider the case of equally-weighted portfolios, one-tail tests, and regular OLS estimates for the abnormal returns. Since all of our results are qualitatively the same across these specifications, we omit the robustness tables. We consider both parametric tests – which assume that errors are normally distributed – and non-parametric tests, which rely on other properties of the data, such as the ranking of variables, instead of normality. Moreover, we also present results for the adjusted standardized cross-sectional test (see Boehmer, Masumeci, and Poulsen (1991) and Kolari and Pynnönen (2010)) that controls for cross-sectional correlation. This test can be seen as a robustness check in our analysis, since the use of a portfolio of rivals already addresses the issues of event-time clustering and cross-sectional correlation.

While these tests allow us to evaluate the net impact of a layoff announcement on the average stock price reaction of a value-weighted portfolio of rivals, they have a few drawbacks. First, pooling all observations does not allow researchers to evaluate the impact of the announcement across firms within the same industry. As we observe in Figures 1B and 2, not only is there a wide dispersion in the reactions of rivals to a particular announcement, but also this dispersion increased throughout the period that we analyze. Consequently, this approach is unsuited to test hypothesis 2, since it conceals the distinctions among within-

[10] We also consider other splits (for example, around mean concentration) and other samples (for example, eliminating the deciles around the median). The results were qualitatively similar, so we decided to omit them, but they are available upon request.

industry rivals' characteristics and reactions. Second, this approach does not take into account the potential for event-specific unobserved effects. This potentially introduces an omitted variables bias in the results, particularly when studying events with heterogeneous outcomes like layoff announcements.

In order to test hypothesis 2, we take advantage of the panel-like structure of the data, in which we usually observe several layoffs per three-digit SIC industry classification across time. This panel-like structure also allows us to control for unobserved heterogeneity at the industry and time period levels. In particular, we run the following model:

$$CAR_{it} = \alpha + \beta * \mathbf{x_{it}} + \gamma * \mathbf{z}_{event} + c_{event} + u_{it}, \tag{2}$$

where CAR_{it} is the cumulative abnormal return for rival i given a layoff announcement at time t by a firm in the industry. $\mathbf{z}_{event}$ are event-specific variables such as the characteristics of the announcer and the industry in which the layoff announcement occurs, while c_{event} are characteristics of the event that are unobserved by the econometricians. The control variables that are specific to the rival and will be included in $x_{i,t}$ are described in Table 1. Usually, the literature considers two potential cases for the relationship between c_{event} and the observable variables $\Omega = [\mathbf{x}, \mathbf{z}]$, namely $Cov(c_{event}, \Omega) \neq 0$ and the more strict assumption $Cov(c_{event}, \Omega) = 0$. First, we assume that $Cov(c_{event}, \Omega) \neq 0$. In order to avoid an omitted variables bias, we run fixed effects regressions clustered at the event level, thereby controlling for both unobserved industry and time characteristics. As usual in a fixed effects regression, while we obtain consistent estimates for β, we are unable to obtain estimates for γ since they are absorbed.

In order to test hypothesis 2b, we run fixed effects specifications in subsamples that are broken down based on the level of technological intensity in the industries. In particular, we split the sample based on the classification by Loughran and Ritter (1997), as described in Section 2.1.

It is important to highlight that the characteristics of the layoff announcement are also absorbed by event fixed effects. Nonetheless, layoff characteristics – in particular announcers' stock price reactions – are critical to identify the nature of the revealed information and its potential interaction with the variables of interest. In order to recover this information, we interact the direction of the announcer's stock price reaction to its own announcement with our proxies for growth opportunities. In order to facilitate the presentation, we present specifications with two interaction terms based on both good and bad announcer news while omitting a main effect. This specification allows us to directly look at the results presented in the tables without further calculations. Notwithstanding, results are the same as those obtained using specifications with main effects (level variable) and interaction terms (one interaction term with good announcer news, for example).

We also consider the case in which $Cov(c_{event}, \Omega) = 0$. In this case, we may consider c_{event} together with the idiosyncratic error $u_{i,t}$ without generating an omitted variables bias. In this case, both pooled OLS and FGLS estimators are consistent. However, the random effects GLS estimator is more efficient for cases in which St. Dev.$(c_{event}) \neq 0$. We run a random effects model and we test the null hypothesis H_0 : St. Dev.$(c_{event}) = 0$ through a Breusch and Pagan (1980) test.[11] Since we rejected the hypothesis, we omitted the OLS results. The benefit of a random effects model is that it allows us to obtain estimates for γ, the coefficient for the event-specific variables.[12]

Finally, in order to verify if either the fixed effects or the random effects model is the most suited for our case, we test the hypothesis $H_0 : Cov(\Omega, c_{event}) = 0$. We follow Wooldridge (2010) and run the following auxiliary regression:[13]

$$CAR_{i,t} = \theta * w_{i,t} + \eta * \bar{v}_{i,t} + \epsilon_{i,t} \tag{3}$$

where $\bar{v}_{i,t}$ are the time averages of all time-varying regressors, while $w_{i,t}$ includes all remaining time-varying and time-constant regressors, as well as the constant. We use a joint Wald test on $H_0 : \eta = 0$ to test if $Cov(\Omega, c_{event}) = 0$. We also include cluster-robust standard errors to allow for heteroscedasticity and serial correlation. Our results do not reject that a random effects model is best suited for our problem.[14] However, the assumption $Cov(\Omega, c_{event}) = 0$ is quite strong. Consequently, we still focus our presentation on the more robust fixed effects model, and we present the random effects results in the extended analysis.

3. Data and Sample Selection

3.1. Sample Construction

Our initial sample consists of layoff announcements between 1979 and 2010 for all firms listed in the S&P 500 at any point in that time period and their rivals from the same three-digit SIC code-year.[15]

[11] Details about the test are presented in the online appendix.

[12] In all our specifications, we report cluster robust Huber-White standard errors.

[13] Usually, a Hausman test is used to test random vs. fixed effects models. However, a Hausman test is only valid under homoscedasticity and cannot include time fixed effects, conditions that are unlikely satisfied in our case.

[14] We obtained an F-statistic $F(15, 657) = 1.14$, with a p-value of 0.3144.

[15] 15Even though there are concerns about using SIC codes to identify industries and some alternatives are suggested in the literature (see Hoberg and Phillips (2010) and Bhojraj, Lee, and Oler (2003)), we decided

During the sample period, 1,269 unique firms were at some point listed in the S&P 500 index. For each of these firms, we use Factiva to search for layoff announcements published in the Wall Street Journal. Following Farber and Hallock (2009), we focus only on Wall Street Journal announcements, since we believe that any significant news related to S&P 500 firms will be reported in that publication. Additionally, since we are primarily concerned with the effect of layoff announcements on rivals, we are not interested in unannounced layoffs. We search Factiva for the following keywords: "layoff," "layoffs," "lay-off," "laid off," "restructure," "restructured," "restructuring," "downsize," "downsizing," "downsized," "plant closure," and "plant closing." We collect 2,364 layoff announcements by 502 distinct firms. For each layoff announcement, we document the date of the layoff announcement, the size of the layoff, and the reason given for the layoff.[16]

We obtain firm-specific financial data for announcers and rivals from Compustat. Our sample is restricted to only U.S. firms. Further, we exclude financial firms (SIC 6000-6799) and utility firms (SIC 4610-4991) because of their highly regulated nature, as well as firms without industry classification (SIC 9999). For each firm announcing a layoff, we determine a group of rivals based on their classification in the same three-digit SIC code. We then restrict our sample to isolate the information content of the layoff announcements. First, we eliminate any layoff announcements in which the layoff firm had made earnings, stock splits, or dividend announcements within a $[-5, +5]$ window around the layoff announcement date, since these concurrent announcements may affect short-run returns. We also eliminate any rival that made one of these announcements within the same event window. Second, in order to focus on layoff announcements that contain new information, we eliminate any announcement that explicitly refers to a previous announcement, as well as any layoff that occurs within 100 days of a previous layoff by the same firm. Third, we restrict our sample to firms listed in one of the three main exchanges (AMEX, NYSE, and NASDAQ). Moreover, there is a clear distinction between how much attention firms that are currently in the S&P 500 receive from the media and investors relative to firms that were previously members of the index as well as candidates for inclusion. Hence, we focus on announcers that are actively in the S&P 500 index on the date of announcement. Fourth, we eliminate firms that delist within 180 days from the announcement. Since exchanges are required to communicate delisting decisions 180 days prior to the event, we exclude these cases to avoid any contamination of the layoff

to use the three-digit SICs not only because we wanted to be able to compare our results with those in the previous literature, but also because we wanted a classification that would be likely be used by investors to identify potential rivals.

[16]In previous versions of this paper, we included analysis that controlled for the reason given for the layoff. Given that results were qualitatively the same and the reasons' dummies had no statistical significance, we omit those results in the current version.

announcement effect. Finally, we eliminate any observation for which variables relevant to our analysis are missing. The baseline sample for our main analysis consists of 658 layoff announcements by 251 unique announcers and a sample of 3,127 unique rivals, representing 25,819 firm-event observations for rivals during our sample period, 1979-2010.

We use lagged independent variables so that we can control for the financial position and performance prior to the layoff announcement for both announcer and rivals. These variables include leverage, firm size (measured in terms of the log of total assets), firm age, Tobin's Q, sales growth, cash holdings, number of employees, R&D expense, return on assets (ROA), cost of goods sold (COGS), selling, general and administrative expense (SG&A), as well as measures of distress (for example, Altman's Z-score) and measures of financial constraint (for example, Whited and Wu (2006)'s index). Details on the construction of the variables are presented in Table 1. All of our variables are adjusted for inflation (constant 2000 dollars). We also winsorize control variables at the 1 percent level to reduce the effect of extreme outliers. Our results are robust to changes in the winsorization level.

Unfortunately, Compustat's labor compensation data are quite incomplete: Compustat's variable on staff expense - total (xlr) is available for just 4.37 percent of our sample observations, while the variable on staff expense - wages and salaries (xstfws) is missing for our the entire sample. Hence, we are unable to control directly for labor costs. However, we have indirect controls for labor costs, for both production workers – through COGS – and non-production workers, by SG&A. Similarly, owing to the wage-size premium – large firms on average pay higher wages than smaller ones – firm size is also a proxy for the wage bill (see Brown and Medoff (1989)). Finally, the previous literature has shown (see Chemmanur, Cheng, and Zhang (2013) and Berk, Stanton, and Zechner (2010)) that leverage is associated with a higher wage bill. Therefore, while we are unable to directly control for labor costs, we include several proxies for higher overall labor expenses.

For our event study, we collect daily returns data from the Center for Research in Security Prices (CRSP). We use the market-adjusted returns model with Scholes and Williams (1977)'s beta and value-weighted market index to calculate CARs. Our pre-event estimation window is up to 200 days long (minimum three days) and it ends 101 days before the layoff announcement. We calculate CARs for short-run event windows of 3, 5, and 11 days, centered on the day of the layoff announcement. Since results are qualitatively similar across the event windows, we present results using the three-day event window in our analysis. This window choice allows us to compare our results with previous results in the literature.

Table 2 shows how layoff announcements are distributed across industries. As expected, the majority of the layoffs occurred in manufacturing (84 percent) followed by services (8 percent), and retail (5 percent). As we show in the appendix Table A2, our results are qualitatively the same if we restrict our sample to only manufacturing firms. We also see a significant variation in the average number of rivals per event across industries, with numbers varying from 178 in services to two in Transportation.[17] Once we restrict our sample to rivals that are currently members of the S&P 500 index, the numbers drop significantly, but there is still significant variability across industries. In terms of industry average layoff sizes as fractions of the pre-layoff labor force, we see that layoffs vary from 0.99 percent of the firm's labor force (in wholesale trade) to 9.16 percent in mining. Finally, in terms of the distribution of layoffs over time, we see in online appendix Table IA.3 that layoffs are spread out across the sample period. Based on initial clustering analysis, we do not find that layoffs occur in clear time clusters in our sample.

3.2. Summary Statistics

We report the summary statistics for announcers and rivals in Table 3. We divide the results across announcements into positive versus negative stock price reactions of the announcer's firm, and we label the reactions "good news" and "bad news" cases, respectively. This analysis is important because we observe substantial variation in the announcer's market reaction to its own layoff announcement (CAR), with the fraction of announcers with positive CAR in any given year in our sample being usually above 40 percent as shown in Figure 1.A.

Table 3 shows that, compared with rivals, announcers are bigger, more leveraged, less financially constrained (based on the Whited-Wu index), and older, regardless of the announcer's stock price reaction.[18] The differences between announcers and rivals are statistically significant.[19] This is not surprising, since all of the announcers are listed in the S&P 500 index at the time of the announcement, while only 11.66 percent of the rivals are S&P 500 members. However, we obtain qualitatively similar results if we restrict our sample to only those rivals from the S&P 500. In the online appendix Table IA.2, we present the descriptives only for rivals that are currently members of the S&P 500 index. In terms of profitability, we see that, although announcers have a lower ROA than their S&P 500 rivals, they outperform the average/median of the full rival group. This result corroborates what has been found in the literature (Chen, Mehrotra, Sivakumar, and Wayne (2001)). Moreover, in terms of growth options, our proxies for growth (Tobin's Q, sales growth, and R&D) indicate that announcers are likely to have lower growth opportunities – in particular, Tobin's

[17] Rivals in these cases are Genesee & Wyoming Inc., Railtex Inc., Wisconsin Central Transportation, and Florida East Coast Industries.

[18] Announcers are bigger in terms of total assets as well as number of employees.

[19] While the results presented in Table 3 are not clustered at the event level, results are qualitatively the same when we calculate cluster-adjusted t-values.

Q and sales growth. This is true even after restricting the sample to rivals with S&P 500 membership. Finally, in terms of the distinctions between announcers with good and bad market reactions, we do not observe a clear distinction across their average characteristics. This is important, since it reveals that a layoff announcement adds information that could not be easily discerned by observing financial characteristics.

In terms of the layoff characteristics, we observe a wide variation in both the number of employees displaced and the fraction of the announcer's labor force affected. In terms of the layoff size, we see a range in the sample from 50 to 24,600, with a median layoff size of 675. We also see that layoffs that the market perceives positively for the announcer are slightly larger in number than those perceived negatively. However, there is no clear distinction in the fraction of the labor force displaced between good and bad news announcements. In both cases, we can see that, on average, the layoff announcement affects 5 percent of the firm's labor force, while the median announcement affects 3 percent.

In terms of stock price reaction, we see that rivals' stock price reactions move, on average, in the same direction as the announcer's reaction. This is a first indication that industry effect dominates the competitive effect. Moreover, the fraction of rivals with positive CARs at any given announcement increases over time, as we can see in Figure 1.B, following a pattern similar to the one observed for announcers in Figure 1.A. Finally, the standard deviation of rivals' reactions has also increased over time – as we can observe in Figure 2 – suggesting that industry peers became more heterogeneous with time, while demonstrating that layoff announcements became more "newsworthy," as pointed out by Hallock and Mashayekhi (2003).

3.3. Likelihood of Becoming an Announcer

In order to take into account the joint effect of the variables discussed, we estimate a probit model of the likelihood of a given firm announcing a layoff while controlling for year and industry effects.[20] As we see in Table 4, the stylized facts presented above are confirmed by the probit. Announcers tend to be larger, older, less efficient (higher COGS and SG&A), more leveraged, and more diversified, and have lower growth opportunities (low Tobin's Q) than their rivals.[21] For example, based on the specification including both firm and

[20] In order to keep comparability in size, we restrict the non-announcing rivals to the S&P 500 group. Standard errors are clustered by layoff event.

[21] Since we collected layoff announcements for all firms that were in the S&P 500 at any given point within the 1979-2010 period, we have in the overall database announcements not only by firms that are currently in the S&P 500, but also by firms that were dropped from the index and firms that would eventually be added to the index in the future. We restrict our main analysis to the sample of announcements by firms currently in the index. In a previous version of this table, we not only included all firms that are in the index at any

industry fixed effects, increasing Tobin's Q by one standard deviation on average decreases the likelihood that a firm announces a layoff by 2.5 percentage points. Differently, increasing firm size (log total assets) by one standard deviation on average increases the likelihood that a firm will announce a layoff by 3.9 percentage points.

Table 5 shows the association between an announcer's characteristics and the likelihood that the market perceives the layoff announcement as positive news. No explanatory variable shows a statistically significant correlation with the likelihood of a positive announcer's stock price reaction, particularly once we introduce year and industry fixed effects. This result reinforces the fact that a layoff announcement adds information that could not be easily discerned by observing the announcer's financial characteristics.

4. Results

4.1. Average Effects Models

To test hypotheses 1a and 1b, we test for an average industry-wide effect of the layoff announcement. We aim to determine how the information content of the layoff announcement itself – in particular the announcer's own stock price reaction – can be important in determining the net effect on rivals. The panels in Table 6 show the results for our sample. Our tests are constructed using value-weighted portfolios of rivals with stock returns available from CRSP. Table 6 and online appendix Table IA.4 include several parametric and non-parametric tests of the average effects. Since their results mostly agree with each other, we do not go into details about each test's unique strengths and weaknesses.[22]

We separate the results across the announcer's own stock price reaction, by looking at overall, good news, and bad news cases one at a time. Panel A shows that there is no clear net effect in the overall sample. However, this test is aggregating two subsamples with opposite information content, generating a bias toward no results. Once we break down the sample with respect to the direction of the announcer's stock reaction, we see a clear pattern. Panels B and C show that the industry effect dominates the competitive effect, since the net effect on the portfolio of rivals is clearly positively correlated with the announcer's reaction. Therefore, our results corroborate hypothesis 1a and reject hypothesis 1b. In particular, in the "good news" case, rivals' average three-day CAR centered on the announcement date is +0.44 percent. Moreover, both parametric and non-parametric tests indicate that the

given point, but also controlled for current membership using a dummy variable. The dummy of current S&P 500 status was positive and significant, justifying our concerns that current members may have more exposure to the media and are more likely to have their layoffs announced in the Wall Street Journal.

[22]Dutta (2014) discusses the different tests in details.

average impact on rivals is statistically different from zero. Similarly, in the "bad news" case, rivals' average centered three-day CAR is -0.60 percent and statistically different from zero. Based on these results, we calculate the value change for each rival by multiplying the rival's CAR in the event window by its market capitalization at the end of the previous fiscal year. We find a mean (median) gain of \$31.74 million (\$0.39 million) in the "good news" case and a mean (median) loss of \$29.74 million (\$0.53 million) in the "bad news" case.

Moreover, we observe that the effect is concentrated in the $(-1, +1)$ event window, in particular for the bad news case. In this sense, we see that the layoff announcement is unanticipated by the market. These results corroborate the initial findings obtained in Table 3, panel A based on the summary statistics. Finally, in the online appendix Table IA.4, we break down the abnormal returns within the event window, by looking at the magnitude of the abnormal return on different days within the event window. Results show little to no information leakage, while corroborating the results presented in table 6. Our results are also robust to focusing only on announcements that have a reaction for the announcer that is statistically significant – that is, statistically significantly different from zero – as well as to focusing on the manufacturing subsample. For brevity, we omit these tables.

Once the results in Table 6 reject hypothesis 1b, testing hypothesis 1c becomes a robustness exercise. Toward this goal, we consider the subsamples with high- and low-SMHHI. As suggested by Lang and Stulz (1992), the competitive effect should be strongest in concentrated industries, that is, high-SMHHI industries. Finding no evidence of net competitive effects in high-SMHHI industries would further corroborate the results in Table 6 that industry effects dominate investors' perception of layoff announcements' information content. Table 7 presents our results. Panels A and B show the results for concentrated industries (high SMHHI). In the "good news" case (panel A), we observe no significant net effect of the layoff announcement on industry rivals. While the average CARs have a sign that indicate a competitive effect, not only are they not statistically significant, but also their economic magnitude is quite small. In contrast, in the "bad news" case, we see a clear net industry effect. In particular, rivals' average three-day CAR centered on the announcement date is -0.99 percent and statistically different from zero. Consequently, even in concentrated industries we find no evidence of a net competitive effect. In the best case scenario ("good news" case in high-SMHHI industries), competitive effects are strong enough to at best counteract industry effects. However, the lack of significant industry effects in this case may be due to the small sample size rather than to a somewhat stronger competitive effect. For completeness, panels C and D of Table 7 present the results for low-SMHHI industries. As expected, industry effects dominate the rivals' average stock price reaction. In particular, in the "good news" case, rivals' average three-day CAR centered on the announcement date is +0.73 percent and statistically different from zero. Similarly, in the "bad news" case, rivals' average centered three-day CAR is -0.40 percent and statistically different from zero. In summary, results in Table 7 show no evidence of competitive effects even within concentrated industries, rejecting hypothesis 1c and corroborating the findings presented in Table 6.

4.2. Fixed Effects Model

The results in Section 4.1 corroborate hypothesis 1a, showing that industry effects dominate competitive effects. Consequently, the natural follow-up tests should be focused on hypotheses 2a and 2b. In order to test hypothesis 2a, we estimate a fixed effects model. We present the results for our benchmark specifications in Table 8. These specifications include all of the control variables presented in the rivals' column in Table 3 panel A, as well as event fixed effects. We also cluster standard errors by industry. For brevity, we omit reporting the coefficient estimates for the controls in Table 8. In the online appendix Table IA.1, we present the results for all regressors' coefficients. Here, we focus on the results for our proxies for growth opportunities in model 4, which includes all interactions.

Our results in Table 8 show the importance of controlling for the direction of the announcer's stock price reaction in interpreting the results. In the "good news" case, rivals with high growth opportunity proxies observe a more positive reaction in their own stock price relative to that of low growth rivals. In particular, an increase of one standard deviation in the rival's Tobin's Q induces an increase in the rival's CAR of 0.451 percentage points. Similarly, rivals with positive R&D expenses see an additional 1.19 percentage points in their stock price reaction to a peer's layoff announcement. Finally, while the rival's sales growth coefficient is not statistically significant in the full specification presented in model 4, the coefficient has the correct positive sign. On the other hand, when the layoff is "bad news" for the announcers, we observe that the market response for rivals with high growth opportunity proxies is relatively worse than for other rivals. In particular, an increase of one standard deviation in the rival's Tobin's Q induces a more negative CAR by -0.233 percentage points. Similarly, an increase of one standard deviation in the rival's sales growth is associated with a decline in the rival's CAR by -0.21 percentage points. Finally, while the coefficient for R&D is not statistically significant, it has the correct negative sign. Overall, our fixed effects specification findings corroborate hypothesis 2a, showing that rivals whose value predominantly reflects growth opportunities are the ones most likely to experience the strongest industry effects.

To test hypothesis 2b, we split our sample between technology and non-technology industry groups. We present results for the tech-industries subsample in Table 9. As expected, results are in line with what we observed for the overall sample in Table 8. In the good news case, rivals with high growth opportunity proxies observe a more positive reaction in their own stock price. In particular, an increase of one standard deviation in the rival's Tobin's Q induces an increase in the rival's CAR of 0.591 percentage points. Similarly, rivals with positive R&D expenses see an additional 1.63 percentage points in their stock price reaction to a layoff announcement in the industry. Finally, while the rival's sales growth coefficient is not statistically significant in the full specification presented in model 4, the coefficient has the correct positive sign. In the bad news case, rivals with high growth opportunity proxies fare worse than other rivals, although results are weaker than in the good news case in terms of both statistical significance and economic magnitude. In particular, an increase of one standard deviation in the rival's sales growth is associated with a decline in the rival's CAR by -0.287 percentage points. Coefficients for Tobin's Q and R&D are not statistically significant in the full model presented in column 4, but have the correct negative sign.

Table 10 presents results for non-tech industries. As expected, results are weaker than in the tech-industries, not only because growth opportunities are a smaller fraction of the firm's value in non-tech industries, but also because our sample size drops significantly (down to 7,354 firm-event observations from the original sample size of 25,802 in Table 8). Results for the good news case are insignificant across all growth proxies. In the bad news case, we observe that rivals with a high Tobin's Q suffer more negative stock price reactions. the results are not statistically significant for either R&D or sales growth. In summary, the results in Tables 9 and 10 corroborate hypothesis 2b.

Finally, even though our tests in tables 6 and 7 indicate that industry effects dominate competitive effects, as a robustness exercise we split our sample across industries with different degrees of concentration. In particular, we split the sample across the median of the calculated SMHHI. The results for the subsample of low-SMHHI industries are presented in Table 11. We focus on the results for the full model presented in column 4. The results for the low-concentration industries corroborate the ones presented for the full sample in Table 8. In the good news case, rivals with high growth opportunity proxies observe a more positive reaction in their own stock price. In particular, an increase of one standard deviation in the rival's Tobin's Q induces an increase in the rival's CAR of 0.543 percentage points. Similarly, rivals with positive R&D expenses see an additional 1.43 percentage points in their stock price reaction to a peer's layoff announcement. Finally, while the rival's sales growth coefficient is not statistically significant in the full specification presented in model 4, the coefficient has the correct positive sign. In the bad news case, rivals with high growth opportunity proxies fare relatively worse than other rivals. In particular, an increase of one standard deviation in the rival's sales growth is associated with a decline in the rival's CAR by -0.176 percentage points. A similar result obtains for Tobin's Q, although the coefficient is not statistically significant in model 4. Finally, while the coefficient for R&D is not statistically significant, it has the correct negative sign.

Results for the high-SMHHI industries are presented in Table 12. The results from Table 7, panel A, show no net effect of layoff announcements on rivals' mean CAR. Consequently, it is unsurprising that we find no significant coefficients for the "good news" case. In the "bad news" case, we observe that both Tobin's Q and sales growth have coefficients that are negative and statistically different from zero. Focusing on the results for the full model presented in column 4, we see that an increase of one standard deviation in the rival's Tobin's Q induces a decline in the rival's CAR of -0.522 percentage points. Similarly, an increase of one standard deviation in the rival's sales growth is associated with a decline in the rival's CAR by -0.447 percentage points. The results are not statistically significant for our R&D indicator.

In summary, our results indicate not only that industry effects dominate the information spillovers generated by layoff announcements, but also that rivals with high growth opportunities are the most affected by the news. Moreover, the effect is strongest in technology industries, where growth opportunities are presumably most valuable.

4.3. Random Effects Model

Table 13 presents our results for the random effects model. As we discussed in Section 2, following the test proposed by Wooldridge (2010), we are unable to reject the hypothesis that $Cov(\Omega, c_{event}) = 0$. Consequently, the random effects model is, in principle, preferable to the fixed effects model for two reasons. First, the random effects model allows us to directly estimate the coefficient of variables that are constant at the event level, such as announcer and layoff characteristics. Second, even though both the random and fixed effects models can be consistently estimated, the random effects model provides more efficient estimators.

The results presented in Table 13 are in line with the ones obtained in Tables 8–12 using the fixed effect model. Industry effects dominate the competition effects, with rivals whose values are more associated with growth opportunities experiencing a stronger positive correlation between their stock price reaction and the announcer's. Moreover, the importance of growth opportunities is significantly higher in technology industries, as we would expect.

In terms of specific results, Table 13 presents the following. In the case of announcer good news, column **All** shows that rivals that have positive R&D investments observe a 0.7 percentage point higher CAR following the layoff announcement than no-R&D rivals.

Similarly, the CARs for rivals with positive R&D investments in the "good news" case are 0.86 percentage points and 1.61 percentage points higher than their no-R&D counterparts in the low SMHHI and technology industry subsamples, respectively. On the other hand, other proxies for growth opportunities – Tobin's Q and sales growth – are not statistically significant in the "good news" case for most subsamples. In the "bad news" case, rivals with sales growth that is one standard deviation above the average observe a CAR that is -0.29 percentage points lower than the average in the full sample specification. Similarly, these rivals observe a CAR that is -0.25 percentage points and -0.35 percentage points lower than the average in the low SMHHI and technology industry subsamples, respectively. On the other hand, other proxies for growth opportunities – Tobin's Q and R&D investment – are not statistically significant in the "bad news" case for most subsamples.

Finally, the magnitude of the average rival's reaction is positively correlated with the announcer's reaction across all subsamples. In particular, in the full sample case, an announcement with a CAR one standard deviation above the mean (announcer's CAR = +4.77 percent) is associated with an average rival's CAR of +0.632 percent. In contrast, an announcer's CAR that is one standard deviation below the mean (announcer's CAR = -5.40 percent) is associated with an average rival's CAR of -0.439 percent. In either case, the average rival's CAR is statistically different from zero. Consequently, the results from the random effects model corroborate the findings of the aggregated tests presented in Section 4.1. Consequently, these results reinforce the need to take into account the magnitude and direction of the announcer's CAR in order to properly factor in the information released during a layoff announcement. Moreover, the fact that announcers' and rivals' stock price reactions are, on average, in the same direction again corroborates the claim that industry effects dominate competition effects.

4.4. Robustness Checks

In the appendix tables, we present several robustness checks. In Table A1 we restrict our sample to rivals that are currently in the S&P 500. In Table A2, we restrict our sample to manufacturing industries – as seen in Table 2, the majority of our sample layoff announcements are in manufacturing. Tables A3 and A4 consider event windows $[-5, +5]$ and $[-11, 11]$, respectively. Finally, in Table A5, we restrict our sample to announcements where the announcing firm's stock price reaction was statistically different from zero. Overall, our results are qualitatively the same across all of these different robustness tests. The statistical significance of some coefficients becomes weaker, which is expected given the decline in sample size.

5. Conclusion

In this paper, we examine the impact of layoff announcements on the announcer's industry rivals. We show that on average industry effect dominates competition effect. Consequently, rivals' stock market reaction moves in the same direction as the announcer's reaction. Moreover, rivals whose value is driven by growth prospects – proxied by sales growth, R&D investment, and Tobin's Q – on average face larger stock price reactions than other industry rivals. Furthermore, results are stronger in technology industries, where growth options are a larger fraction of the firms' valuation. Taken together, these results point toward layoffs being perceived by investors as conveying news about the medium to long-term prospects of the industry.

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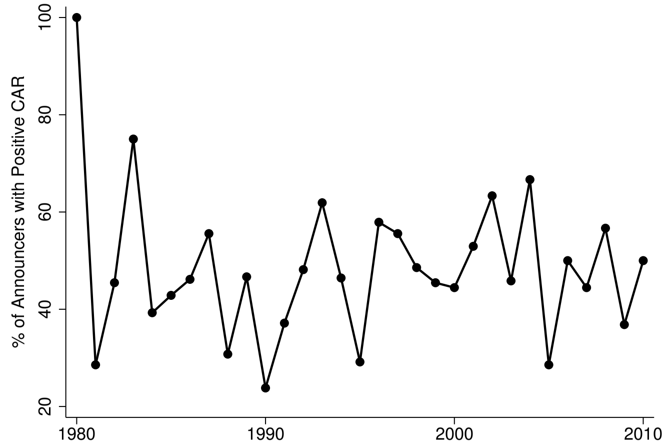

Figure 1A. Average fraction of announcers with positive CAR[-1,+1] – All announcements

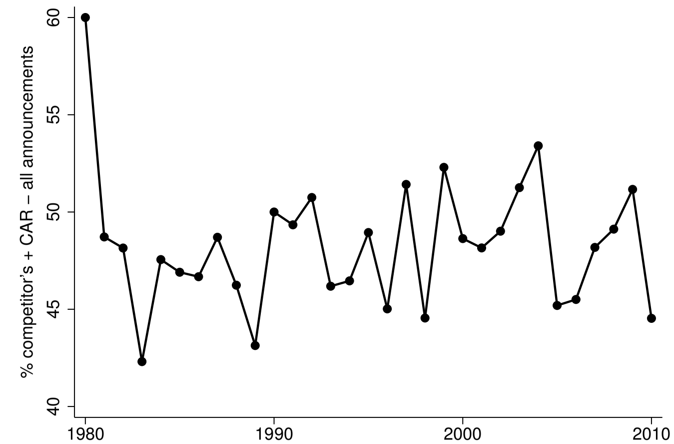

Figure 1B. Average fraction of rivals with positive CAR[-1,+1] – All announcements

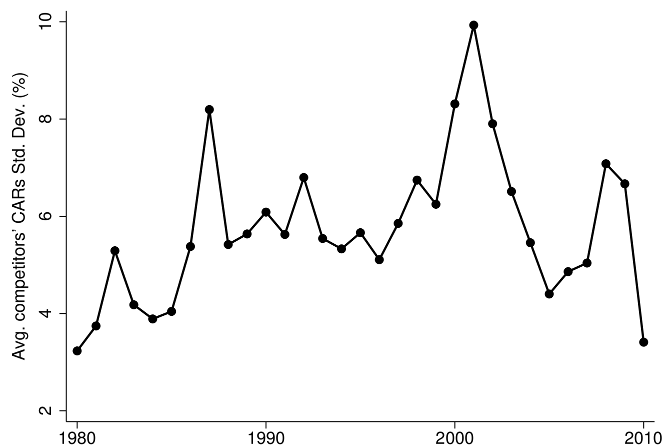

Figure 2. Average within-event standard deviation of rivals' CAR[-1,+1] – All announcements

Table 1: Variable Definitions

This table describes the variable definitions for dependent and independent variables used in our regressions.

Dependent Variable	**Description**
rival $CAR[-1,+1]$	Measures the 3-day cumulative abnormal returns (in % points) for a competing firm centered around a layoff announcement. The cumulative abnormal returns are calculated using the market adjusted return model
Key Independent Variables	
Good News	We classify a layoff announcement as good news if the announcer's CAR$[-1,+1]$ is greater than zero.
Bad News	We classify a layoff announcement as bad news if the announcer's CAR$[-1,+1]$ is less than zero.
Tobin's Q	Measured as the ratio of market value of equity divided by book value of equity. Compustat (csho*prcc)_(at-lt), all measured at time t-1. Final value is winsorized at 1%.
R&D	Dummy variable that indicates that the firm has positive R&D expenses. Based on Compustat variable xrd
Sales growth	Measured as total sales less previous year's total sales divided by previous year's total sales. Compustat (salet-1 -salet-2) / salet-2
Additional Controls	
Leverage	Book value of debt divided by current and long term debt plus shareholders' equity. Compustat (dlc + dltt) / (dlc + dltt + seq). All variables measured at t-1. Final value is winsorized at 1%.

Whited-Wu Index	Measures financial constraints and is calculated following Whited and Wu (2006).
Altman Z score	Measures likelihood of bankruptcy and is calculated following Altman (1968).
RoA	Measured as earnings before interests, taxes, depreciation, and amortization (ebitda) by the book value of total assets. Compustat (sale - cogs) / at, all variables measured at time t-1. Final value is winsorized at 2%.
Cash holdings	Cash plus marketable securities scale by previous year's total assets. Compustat che / at, che is measured at t-1 and at is measured at t-2. Final value is winsorized at 1%.
log(Total Assets)	The natural logarithm of total assets adjusted for inflation. Compustat ln(at/deflator), measured at time t-1. Final value is winsorized at 1%.
Age	Measured as the count of unique firm-level observations from the Compustat Fundamentals Annual Database (limited to one observation per year). Age is measured at time t-1 and winsorized at 1%.
No. of Employees	Total number of employees of the firm in thousands. Compustat emp. Measured at time t-1. Final value is winsorized at 1%.
COGS	Cost of Goods Sold scaled by sales. Based on Compustat cogs/sales. Measured at time t-1. Final value is winsorized at 1%.
SG&A	Selling, General & Administrative Expenses, scaled by sales. Based on Compustat sga/sales . Measured at t-1. Final value is winsorized at 1%.
No. of Segments	Measured as the number of segments reported by the firm in Compustat's Segment Database.

S&P 500	Indicator variable that is equal to 1 if the firm is currently listed in the S&P 500 index.
Layoff Size	Total number of workers announced to be displaced by the firm.
Layoff Ratio	Size of the layoff as a fraction of the firm's total number of employees at period t-1.

Table 2: Distribution of Layoffs across Industries

Sector	**Number of Layoffs**	**Layoff Size**	**Layoff Ratio**	**Ann.**	**Rivals (All)**	**Rivals (S&P 500)**
Manufacturing	550	1,551	4.04%	186	28	5
Mining	22	604	9.16%	11	44	6
Retail Trade	30	3,928	3.90%	19	10	3
Services	52	1,270	6.09%	24	178	12
Transportation, Electric, Gas	2	695	2.19%	2	2	.
Wholesale Trade	2	385	.99%	2	4	1

Table 3: Descriptives

The sample is 676 layoff announcements by 251 unique S&P500 firms in the period 1979-2010 and 25,819 unique firm-year observations of public rivals (based on 3-digit SIC code). All variables are described in table 1. Panel A (B) describes the summary statistics for rivals' characteristics in the "good news" ("bad news") case, i.e., in which announcer's stock return reaction has a positive (negative) 3-day cumulative abnormal return – CAR. The reported levels of significance at the mean t-tests for the differences in mean between rivals and announcers are *, **, and ***, corresponding to 10%, 5%, and 1% statistical significance levels at a two-tail test.

Panel A: Good News

	Announcers No. Obs 307	**Rivals** No. Obs 11,447	**t-test (Rival - Ann.)**
CAR[-1,+1]	3.46	0.84	-2.621***
	(3.97)	(7.86)	(-11.01)
Tobin's Q	1.73	2.17	0.440***
	(1.17)	(1.75)	(6.12)
R&D	0.87	0.83	-0.0385*
	(0.33)	(0.37)	(-1.99)
Sales Growth	0.03	0.21	0.175***
	(0.19)	(0.52)	(14.93)
RoA	0.14	0.07	-0.076***
	(0.07)	(0.18)	(-17.12)
Cash Holdings	0.12	0.35	0.230***
	(0.17)	(0.38)	(22.10)
COGS	0.64	0.53	-0.111***
	(0.18)	(0.25)	(-10.41)
SG&A	0.22	0.45	0.234***
	(0.14)	(0.38)	(27.25)
Leverage	0.35	0.18	-0.172***
	(0.20)	(0.21)	(-15.17)
Whited Wu Index	-0.43	-0.23	0.206***
	(0.06)	(0.11)	(54.56)
Altman's Z-score	3.72	6.12	2.403***
	(3.68)	(7.58)	(10.85)
Age	37.64	15.08	-22.56***
	(12.65)	(11.91)	(-30.88)
log(Total Assets)	8.89	5.26	-3.634***
	(0.96)	(1.82)	(-63.55)
No. of Segments	5.14	2.47	-2.663***
	(3.14)	(1.55)	(-14.80)
No. of Employees	50,375	5,268	-45,107***
	(37182)	(15458)	(-21.21)
Layoff Size	1,921	-	-
	(3380.85)	-	-
Layoff Ratio	0.05	-	-
	(0.06)	-	-

Panel B: Bad News

	Announcers No. Obs 351	**Rivals** No. Obs 14,372	**t-test** **(Rival - Ann.)**
CAR[-1,+1]	-3.36 (3.71)	-0.35 (6.91)	3.012*** (14.60)
Tobin's Q	1.76 (1.16)	2.29 (1.82)	0.534*** (8.10)
R&D	0.88 (0.33)	0.82 (0.38)	-0.053** (-2.96)
Sales Growth	0.05 (0.25)	0.20 (0.49)	0.145*** (10.28)
RoA	0.15 (0.08)	0.07 (0.17)	-0.077*** (-16.98)
Cash Holdings	0.12 (0.15)	0.35 (0.38)	0.232*** (26.51)
COGS	0.61 (0.20)	0.51 (0.25)	-0.10*** (-9.33)
SG&A	0.25 (0.18)	0.46 (0.38)	0.217*** (21.55)
Leverage	0.33 (0.19)	0.18 (0.21)	-0.153*** (-15.09)
Whited Wu Index	-0.43 (0.07)	-0.23 (0.11)	0.198*** (54.72)
Altman's Z-score	3.91 (3.24)	6.21 (7.62)	2.308*** (12.52)
Age	35.00 (13.11)	14.56 (11.40)	-20.44*** (-28.94)
log(Total Assets)	8.71 (0.97)	5.20 (1.82)	-3.505*** (-64.91)
No. of Segments	4.87 (3.01)	2.48 (1.53)	-2.40*** (-14.88)
No. of Employees	43,808 (34898)	5,009 (15029)	-38,799*** (-20.78)
Layoff Size	1,318 (2388.15)	- -	- -
Layoff Ratio	0.04 (0.05)	- -	- -

Table 4: Probit - Announcer

This table reports the average marginal effects from a probit model where the dependent variable is the likelihood of a firm making a layoff announcement. The independent variables include proxies for growth (Tobin's Q, R&D expense, and Sales Growth), financial health (RoA, Cash Holdings, COGS, SG&A, Leverage, Whited Wu Index, and Altman's Z-score) and size (Age, No. of Segments, log(Total Assets), No. of Employees). We include all the announcers from our main sample, but restrict rivals to the 1,269 unique firms that were listed in the S&P 500 index at some point in the sample period but did not announce a layoff. We also control for decade and industry fixed effects as indicated in each model and bootstrap the standard errors.

Variables	Prob(Anouncer)	Prob(Anouncer)	Prob(Anouncer)	Prob(Anouncer)
Tobin's Q	-0.017***	-0.018***	-0.014***	-0.013**
	(0.005)	(0.006)	(0.005)	(0.005)
R&D	0.028**	0.025*	0.001	-0.001
	(0.014)	(0.014)	(0.015)	(0.015)
Sales Growth	0.001	-0.011	-0.003	-0.013
	(0.017)	(0.018)	(0.021)	(0.023)
RoA	0.113	0.053	0.148*	0.081
	(0.074)	(0.076)	(0.083)	(0.085)
Cash Holdings	-0.068*	-0.044	-0.074*	-0.049
	(0.039)	(0.039)	(0.043)	(0.041)
COGS	0.146***	0.110***	0.109***	0.074**
	(0.034)	(0.039)	(0.032)	(0.034)
SG&A	0.128***	0.110***	0.159***	0.142***
	(0.033)	(0.034)	(0.037)	(0.036)
Leverage	0.077***	0.073***	0.087***	0.084***
	(0.028)	(0.028)	(0.028)	(0.028)
Whited Wu Index	-0.204	-0.248*	-0.247*	-0.279*
	(0.131)	(0.133)	(0.139)	(0.143)
Altman's Z-score	0.003*	0.003*	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Age	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
No. of Segments	0.004**	0.003*	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
log(Total Assets)	0.012	0.013	0.023***	0.024***
	(0.008)	(0.008)	(0.007)	(0.008)
No. of Employees	0.000**	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Year FE		X		X
Industry FE			X	X
Pseudo R-squared	0.14	0.15	0.15	0.16
N	5,080	5,080	5,078	5,078

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5: Probit - Probability of Good News

This table reports the average marginal effects from a probit model where the dependent variable is the likelihood of a good news layoff announcement. A layoff announcement is defined as good news when the announcer has a positive stock price reaction. The independent variables include proxies for growth (Tobin's Q, R&D expense, and Sales Growth), financial health (RoA, Cash Holdings, COGS, SG&A, Leverage, Whited-Wu Index, and Altman's Z-score) and size (Age, No. of Segments, log(Total Assets), No. of Employees). All Announcers are members of the S&P 500 index. We also control for decade and industry fixed effects as indicated in each model and bootstrap the standard errors.

Variables	Prob(Good news)	Prob(Good news)	Prob(Good news)	Prob(Good news)
Tobin's Q	0.003	-0.008	0.004	-0.005
	(0.038)	(0.041)	(0.043)	(0.043)
R&D	0.013	0.028	-0.006	0.009
	(0.072)	(0.080)	(0.071)	(0.083)
Sales Growth	-0.131	-0.103	-0.136	-0.102
	(0.112)	(0.123)	(0.103)	(0.130)
RoA	-0.099	-0.027	-0.216	-0.151
	(0.533)	(0.621)	(0.503)	(0.606)
Cash Holdings	0.337*	0.271	0.359*	0.298
	(0.202)	(0.217)	(0.202)	(0.206)
COGS	-0.005	-0.040	-0.167	-0.232
	(0.388)	(0.519)	(0.376)	(0.473)
SG&A	-0.310	-0.317	-0.357	-0.399
	(0.479)	(0.615)	(0.432)	(0.548)
Leverage	0.048	0.017	0.041	0.013
	(0.143)	(0.169)	(0.143)	(0.163)
Whited-Wu Index	0.294	0.163	0.157	0.115
	(0.804)	(0.937)	(0.816)	(0.865)
Altman's Z-score	0.001	0.002	-0.000	0.000
	(0.018)	(0.020)	(0.015)	(0.012)
Age	0.004	0.003	0.004	0.003
	(0.002)	(0.003)	(0.002)	(0.003)
No. of Segments	0.001	-0.002	0.005	0.003
	(0.008)	(0.010)	(0.009)	(0.010)
log(Total Assets)	0.017	0.001	0.027	0.016
	(0.053)	(0.064)	(0.055)	(0.056)
No. of Employees	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Year FE		X		X
Industry FE			X	X
Pseudo R-squared	0.02	0.04	0.02	0.05
N	604	604	602	602

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6: Tests for Average Effects

Rivals' 2-tail tests: Parametric Statistics with Bootstrapped Significance Levels

The Patell test is the standardized abnormal return test developed by Patell (1976). **Std. C.S. Z** is the standardized cross-sectional test for market model abnormal returns introduced by Boehmer, Masumeci, and Poulsen (1991). **Port. T.S. t** is the time-series standard deviation test, also called the "crude dependence adjustment test" (Brown and Warner (1980)). Finally, the **C.S. St. Dev. t** is the cross-sectional standard deviation test, also suggested by Brown and Warner (1985). Abnormal returns based on the market model.

Panel A – Overall

Days	N	$\overline{\text{CAR}}$	Std. C.S. Z	Port. T.S. t	C.S. St. Dev. t
(-1,+1)	676	-0.12%	-1.636$^{\$}$	-1.129	-1.21
(0,0)	676	-0.06%	-0.36	-0.889	-0.865
(-1,+3)	676	-0.16%	-1.083	-1.148$^{\$}$	-1.258
(-2,+2)	676	-0.02%	-0.366	-0.143	-0.159
(-5,+5)	676	-0.11%	-1.043	-0.524	-0.616

The symbols $^{\$}$, *,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail nonparametric bootstrap of the indicated test.

Panel B – Good News

Days	N	$\overline{\text{CAR}}$	Std. C.S. Z	Port. T.S. t	C.S. St. Dev. t
(-1,+1)	308	0.44%	2.940**	2.894***	3.123**
(0,0)	308	0.18%	2.353**	1.980**	2.082*
(-1,+3)	308	0.48%	2.916**	2.424***	2.736**
(-2,+2)	308	0.54%	2.996**	2.710***	2.972***
(-5,+5)	308	0.50%	1.774$^{\$}$	1.704*	1.974*

The symbols $^{\$}$, *,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail nonparametric bootstrap of the indicated test.

Panel C – Bad News

Days	N	$\overline{\text{CAR}}$	Std. C.S. Z	Port. T.S. t	C.S. St. Dev. t
(-1,+1)	368	-0.60%	-5.147**	-3.844**	-4.264**
(0,0)	368	-0.25%	-2.609**	-2.780**	-2.624**
(-1,+3)	368	-0.70%	-4.158**	-3.480**	-3.864**
(-2,+2)	368	-0.49%	-3.338**	-2.419**	-2.795**
(-5,+5)	368	-0.62%	-3.211**	-2.081**	-2.520*

The symbols $, *,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail nonparametric bootstrap of the indicated test.

Table 7: Tests for Average Effects

Rivals' 2-tail tests: Parametric Statistics with Bootstrapped Significance Levels

Std. C.S. Z is the standardized cross-sectional test for market model abnormal returns introduced by Boehmer, Masumeci, and Poulsen (1991), **Port. T.S. t** is the time-series standard deviation test, also called the "crude dependence adjustment test" (Brown and Warner (1980)). Finally, the **C.S. St. Dev. t** is the cross-sectional standard deviation test, also suggested by Brown and Warner (1985). Abnormal returns based on the market model.

Panel A – High SMHHI – Good News

Days	N	$\overline{\text{CAR}}$	Std. C.S. Z	Port. T.S. t	C.S. St. Dev. t
(-1,+1)	114	-0.04%	0.120	-0.138	-0.173
(-1,0)	1 14	-0.08%	-0.284	-0.352	-0.409
(-1,+3)	114	-0.06%	-0.185	-0.159	-0.191
(-2,+2)	114	-0.18%	-0.903	-0.491	-0.632
(-5,+5)	114	-0.52%	-1.529	-0.958	-1.236

The symbols $, *,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail nonparametric bootstrap of the indicated test.

Panel B – High SMHHI – Bad News

Days	N	$\overline{\text{CAR}}$	Std. C.S. Z	Port. T.S. t	C.S. St. Dev. t
(-1,+1)	131	-0.99%	-3.816***	-4.472***	-3.712***
(-1,0)	131	-0.72%	-2.919***	-3.969**	-3.064**
(-1,+3)	131	-0.95%	-2.893**	-3.333***	-2.721**
(-2,+2)	131	-0.63%	-2.385**	-2.197**	-1.848*
(-5,+5)	131	-0.99%	-2.476**	-2.333**	-2.051*

The symbols $, *,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail nonparametric bootstrap of the indicated test.

Panel C – Low SMHHI – Good News

Days	N	$\overline{\text{CAR}}$	Std. C.S. Z	Port. T.S. t	C.S. St. Dev. t
(-1,+1)	193	0.73%	3.562***	4.401***	4.042***
(-1,0)	193	0.60%	3.642***	4.404***	3.916***
(-1,+3)	193	0.80%	3.730***	3.735***	3.769***
(-2,+2)	193	0.96%	4.420***	4.476***	4.183***
(-5,+5)	193	1.14%	3.613***	3.577***	3.674***

The symbols $^{\$}$, *,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail nonparametric bootstrap of the indicated test.

Panel D – Low SMHHI – Bad News

Days	N	$\overline{\text{CAR}}$	Std. C.S. Z	Port. T.S. t	C.S. St. Dev. t
(-1,+1)	225	-0.40%	-3.338**	-2.272***	-2.491**
(-1,0)	225	-0.16%	-2.081*	-1.137*	-1.168
(-1,+3)	225	-0.53%	-2.895**	-2.327***	-2.611**
(-2,+2)	225	-0.48%	-2.355*	-2.120**	-2.533**
(-5,+5)	225	-0.56%	-2.257*	-1.678**	-2.158*

The symbols $^{\$}$, *,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail nonparametric bootstrap of the indicated test.

Table 8: Rivals' Stock Return Reaction

This table reports our results from a fixed effects regression model with interaction terms that allow for non-linearity based on the direction of the announcer's market reaction. The dependent variable is the rivals' cumulative abnormal return around a 3-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. The sample consists of all rivals in the same 3-digit SIC code as the announcer with valid data. All specifications include the control variables presented in Table 1. Additionally, we control for event fixed effects and cluster standard errors by industry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Good news × Rival's Q	0.320***			0.284***
	(0.114)			(0.110)
Bad news × Rival's Q	-0.177**			-0.132*
	(0.078)			(0.075)
Good news × Rival's R&D		1.310***		1.194***
		(0.268)		(0.241)
Bad news × Rival's R&D		-0.175		-0.103
		(0.228)		(0.212)
Good news × Rival's Sales Growth			0.477*	0.242
			(0.276)	(0.253)
Bad news × Rival's Sales Growth			-0.736***	-0.558***
			(0.226)	(0.211)
Event FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.050	0.048	0.049	0.052
N	25,802	25,802	25,802	25,802

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 9: Rivals' Stock Return Reaction
Tech Industries

This table reports our results from a fixed effects regression model with interaction terms that allow for non-linearity based on the direction of the announcer's market reaction. The dependent variable is the rivals' cumulative abnormal return around a 3-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. The sample consists of only those rivals from tech industries as defined by Loughran and Ritter (1997). All specifications include the control variables presented in Table 1. Additionally, we control for event fixed effects and cluster standard errors by industry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Good news × Rival's Q	0.391***			0.348***
	(0.126)			(0.118)
Bad news × Rival's Q	-0.169*			-0.112
	(0.101)			(0.095)
Good news × Rival's R&D		1.829***		1.625***
		(0.386)		(0.341)
Bad news × Rival's R&D		-0.140		-0.015
		(0.276)		(0.245)
Good news × Rival's Sales Growth			0.508	0.214
			(0.329)	(0.301)
Bad news × Rival's Sales Growth			-0.926***	-0.715***
			(0.291)	(0.263)
Event FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.063	0.060	0.061	0.065
N	18,448	18,448	18,448	18,448

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10: Rivals' Stock Return Reaction
Non-tech Industries

This table reports our results from a fixed effects regression model with interaction terms that allow for non-linearity based on the direction of the announcer's market reaction. The dependent variable is the rivals' cumulative abnormal return around a 3-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. The sample consists of only those rivals *not* from tech industries as defined by Loughran and Ritter (1997). All specifications include the control variables presented in Table 1. Additionally, we control for event fixed effects and cluster standard errors by industry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Good news × Rival's Q	-0.101			-0.119
	(0.137)			(0.140)
Bad news × Rival's Q	-0.163*			-0.165*
	(0.089)			(0.095)
Good news × Rival's R&D		0.427		0.423
		(0.272)		(0.274)
Bad news × Rival's R&D		-0.215		-0.210
		(0.234)		(0.232)
Good news × Rival's Sales Growth			0.255	0.304
			(0.382)	(0.397)
Bad news × Rival's Sales Growth			0.037	0.102
			(0.316)	(0.334)
Event FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.024	0.024	0.024	0.024
N	7,354	7,354	7,354	7,354

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 11: Rivals' Stock Return Reaction
Low SMHHI Industries

This table reports our results from a fixed effects regression model with interaction terms that allow for non-linearity based on the direction of the announcer's market reaction. The dependent variable is the rivals' cumulative abnormal return around a 3-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. The sample consists of only those rivals from industries with low concentration as defined in Azar, Schmalz, and Tecu (2017). All specifications include the control variables presented in Table 1. Additionally, we control for event fixed effects and cluster standard errors by industry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Good news × Rival's Q	0.375**			0.340**
	(0.158)			(0.148)
Bad news × Rival's Q	-0.136*			-0.097
	(0.082)			(0.079)
Good news × Rival's R&D		1.561***		1.433***
		(0.363)		(0.318)
Bad news × Rival's R&D		-0.256		-0.177
		(0.225)		(0.208)
Good news × Rival's Sales Growth			0.474	0.219
			(0.319)	(0.275)
Bad news × Rival's Sales Growth			-0.615***	-0.447**
			(0.224)	(0.206)
Event FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.0541	0.0525	0.0520	0.0558
N	21,611	21,611	21,611	21,611

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 12: Rivals' Stock Return Reaction
High SMHHI Industries

This table reports our results from a fixed effects regression model with interaction terms that allow for non-linearity based on the direction of the announcer's market reaction. The dependent variable is the rivals' cumulative abnormal return around a 3-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. The sample consists of only those rivals from industries with high concentration as defined in Azar, Schmalz, and Tecu (2017). All specifications include the control variables presented in Table 1. Additionally, we control for event fixed effects and cluster standard errors by industry. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	(1)	(2)	(3)	(4)
Good news × Rival's Q	0.029			-0.014
	(0.173)			(0.162)
Bad news × Rival's Q	-0.490**			-0.358**
	(0.202)			(0.178)
Good news × Rival's R&D		0.328		0.273
		(0.394)		(0.386)
Bad news × Rival's R&D		0.177		0.127
		(0.351)		(0.347)
Good news × Rival's Sales Growth			0.651	0.546
			(0.844)	(0.835)
Bad news × Rival's Sales Growth			-1.988***	-1.628***
			(0.656)	(0.584)
Event FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R^2	0.0372	0.0328	0.0392	0.0404
N	4,188	4,188	4,188	4,188

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 13: Rivals' Stock Return Reaction
Random Effects

This table reports our results from a random effects regression model where we explicitly control for announcer traits.The dependent variable is the rivals' cumulative abnormal return around a 3-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. Additional controls include proxies for financial health and size of both the announcer and the peer as well as controls for announcer growth. Column 1 is our benchmark model that include all 21,638 rival-event observations with valid data for 658 layoff announcements. Columns 2 and 3 report our results for the subsample of low and high SMHHI industries as defined by Azar, Schmalz, and Tecu (2017). Columns 4 and 5 report our results for the subsamples of tech and non-tech industries, following the Loughran and Ritter (1997) definition of technology. We cluster standard errors by industry and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	All	Low SMHHI	High SMHHI	Tech	Non-tech
Good news layoff × Rival's Q	0.107	0.142	-0.084	0.211*	-0.202*
	(0.098)	(0.111)	(0.159)	(0.117)	(0.119)
Bad news layoff × Rival's Q	-0.097	-0.062	-0.298*	-0.118	-0.171*
	(0.084)	(0.092)	(0.155)	(0.097)	(0.091)
Good news layoff × Rival's R&D	0.704***	0.860***	0.320	1.608***	0.335
	(0.235)	(0.277)	(0.430)	(0.376)	(0.287)
Bad news layoff × Rival's R&D	-0.114	-0.185	0.380	-0.137	-0.117
	(0.203)	(0.228)	(0.341)	(0.266)	(0.249)
Good news layoff × Rival's Sales Growth	0.059	-0.088	1.172**	0.108	0.078
	(0.332)	(0.350)	(0.546)	(0.334)	(0.368)
Bad news layoff × Rival's Sales Growth	-0.763***	-0.634***	-1.736**	-0.838***	-0.069
	(0.219)	(0.220)	(0.699)	(0.250)	(0.335)
Announcer CAR[-1,+1]	0.105***	0.132***	0.029	0.092***	0.099***
	(0.028)	(0.030)	(0.034)	(0.035)	(0.037)
N	21,638	18,066	3,569	14,634	7,004
Rival variables	Yes	Yes	Yes	Yes	Yes
Announcer variables	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Appendix

Table A1: Rivals' Stock Return Reaction
S&P 500 Rivals

This table reports our results from a fixed effects regression model with interaction terms that allow for non-linearity based on the direction of the announcer's market reaction. The dependent variable is the rivals' cumulative abnormal return around a 3-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. The sample consists of only those rivals that belong to the S&P 500. Columns 1, 4, and 7 are our benchmark models that include all 2,975 rival-event observations with valid data for 579 layoff announcements. Columns 2, 5, and 8 report our results for the subsample of low SMHHI industries as defined by Azar, Schmalz, and Tecu (2017). Columns 3, 6, and 9 report our results for the subsample of tech industries, following the Loughran and Ritter (1997) definition of tech. We cluster standard errors by industry and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Bench	Low SMHHI	Tech Firms	Bench	Low SMHHI	Tech Firms	Bench	Low SMHHI	Tech Firms
Good news × Rival's Q	0.201	0.382	0.194						
	(0.249)	(0.285)	(0.291)						
Bad news × Rival's Q	0.026	0.172	-0.057						
	(0.204)	(0.194)	(0.256)						
Good news × Rival's R&D				0.754*	1.195***	1.763***			
				(0.437)	(0.435)	(0.620)			
Bad news × Rival's R&D				-0.535*	-0.696**	-0.775			
				(0.310)	(0.334)	(0.669)			
Good news × Rival's Sales Growth							0.349	0.055	0.324
							(1.118)	(1.262)	(1.077)
Bad news × Rival's Sales Growth							-1.841***	-1.970**	-2.128**
							(0.583)	(0.820)	(0.860)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.2724	0.3169	0.3201	0.2725	0.3161	0.3209	0.2756	0.3182	0.3236
N	2,975	2,296	1,420	2,975	2,296	1,420	2,975	2,296	1,420

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A2: Rivals' Stock Return Reaction
Manufacturing Industries

This table reports our results from a fixed effects regression model with interaction terms that allow for non-linearity based on the direction of the announcer's market reaction. The dependent variable is the rivals' cumulative abnormal return around a 3-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. The sample consists of only firms in manufacturing industries. Columns 1, 4, and 7 are our benchmark models that include all 15,283 rival-event observations with valid data for 550 layoff announcements. Columns 2, 5, and 8 report our results for the subsample of low SMHHI industries as defined by Azar, Schmalz, and Tecu (2017). Columns 3, 6, and 9 report our results for the subsample of tech industries, following the Loughran and Ritter (1997) definition of tech. We cluster standard errors by industry and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Bench	Low SMHHI	Tech Firms	Bench	Low SMHHI	Tech Firms	Bench	Low SMHHI	Tech Firms
Good news × Rival's Q	0.111	0.152	0.206*						
	(0.112)	(0.112)	(0.125)						
Bad news × Rival's Q	-0.189**	-0.098	-0.191						
	(0.081)	(0.082)	(0.119)						
Good news × Rival's R&D				0.948***	1.081***	1.826***			
				(0.339)	(0.417)	(0.511)			
Bad news × Rival's R&D				-0.202	-0.326	-0.062			
				(0.224)	(0.283)	(0.447)			
Good news × Rival's Sales Growth							-0.051	-0.081	-0.178
							(0.342)	(0.330)	(0.422)
Bad news × Rival's Sales Growth							-0.758***	-0.421	-1.181**
							(0.292)	(0.320)	(0.468)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0507	0.0541	0.0685	0.0503	0.0542	0.0680	0.0504	0.0535	0.0685
N	15,283	11,934	9,237	15,283	11,934	9,237	15,283	11,934	9,237

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A3: Rivals' Stock Return Reaction
5-day CARs

This table reports our results from a fixed effects regression model with interaction terms that allow for non-linearity based on the direction of the announcer's market reaction. The dependent variable is the rivals' cumulative abnormal return around a 5-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. The sample consists of all rivals with valid data. Columns 1, 4, and 7 are our benchmark models that include all 25,802 rival-event observations with valid data for 658 layoff announcements. Columns 2, 5, and 8 report our results for the subsample of low SMHHI industries as defined by Azar, Schmalz, and Tecu (2017). Columns 3, 6, and 9 report our results for the subsample of tech industries, following the Loughran and Ritter (1997) definition of tech. We cluster standard errors by industry and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Bench	Low SMHHI	Tech Firms	Bench	Low SMHHI	Tech Firms	Bench	Low SMHHI	Tech Firms
Good news × Rival's Q	0.375**	0.438**	0.448***						
	(0.153)	(0.189)	(0.173)						
Bad news × Rival's Q	-0.178*	-0.136	-0.149						
	(0.093)	(0.090)	(0.120)						
Good news × Rival's R&D				1.210***	1.540***	1.894***			
				(0.363)	(0.402)	(0.524)			
Bad news × Rival's R&D				-0.441	-0.629*	-0.515			
				(0.355)	(0.381)	(0.488)			
Good news × Rival's Sales Growth							0.626	0.726	0.655
							(0.407)	(0.498)	(0.494)
Bad news × Rival's Sales Growth							-0.921***	-0.787**	-1.184***
							(0.337)	(0.321)	(0.387)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.041	0.044	0.050	0.040	0.043	0.048	0.041	0.043	0.049
N	25,802	21,611	18,448	25,802	21,611	18,448	25,802	21,611	18,448

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A4: Rivals' Stock Return Reaction
11-day CARs

This table reports our results from a fixed effects regression model with interaction terms that allow for non-linearity based on the direction of the announcer's market reaction. The dependent variable is the rivals' cumulative abnormal return around an 11-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. The sample consists of all rivals with valid data. Columns 1, 4, and 7 are our benchmark models that include all 25,802 rival-event observations with valid data for 658 layoff announcements. Columns 2, 5, and 8 report our results for the subsample of low SMHHI industries as defined by Azar, Schmalz, and Tecu (2017). Columns 3, 6, and 9 report our results for the subsample of tech industries, following the Loughran and Ritter (1997) definition of tech. We cluster standard errors by industry and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Bench	Low SMHHI	Tech Firms	Bench	Low SMHHI	Tech Firms	Bench	Low SMHHI	Tech Firms
Good news × Rival's Q	0.451***	0.503***	0.529***						
	(0.145)	(0.146)	(0.149)						
Bad news × Rival's Q	-0.148	-0.129	-0.108						
	(0.182)	(0.178)	(0.221)						
Good news × Rival's R&D				1.348***	1.553***	1.863***			
				(0.391)	(0.485)	(0.596)			
Bad news × Rival's R&D				-0.359	-0.613	-0.552			
				(0.481)	(0.548)	(0.561)			
Good news × Rival's Sales Growth							0.583	0.843**	0.632
							(0.495)	(0.424)	(0.523)
Bad news × Rival's Sales Growth							-1.532**	-1.579***	-2.015***
							(0.595)	(0.603)	(0.608)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.058	0.062	0.065	0.057	0.061	0.064	0.058	0.062	0.066
N	25,802	21,611	18,448	25,802	21,611	18,448	25,802	21,611	18,448

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A5: Rivals' Stock Return Reaction
Statistically Significant Events

This table reports our results from a fixed effects regression model with interaction terms that allow for non-linearity based on the direction of the announcer's market reaction. The dependent variable is the rivals' cumulative abnormal return around a 3-day event window centered on the event. The independent variables of interest are proxies for rivals' growth opportunities: Tobin's Q, R&D expense, and sales growth. The sample consists of all rivals associated with a layoff event where the cumulative abnormal return for the announcer is statistically significantly different from zero. Columns 1, 4, and 7 are our benchmark models that include all 2,999 rival-event observations with valid data for 86 layoff announcements. Columns 2, 5, and 8 report our results for the subsample of low SMHHI industries as defined by Azar, Schmalz, and Tecu (2017). Columns 3, 6, and 9 report our results for the subsample of tech industries, following the Loughran and Ritter (1997) definition of tech. We cluster standard errors by industry and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

	Bench	Low SMHHI	Tech Firms	Bench	Low SMHHI	Tech Firms	Bench	Low SMHHI	Tech Firms
Good news × Rival's Q	0.644***	0.868***	0.719***						
	(0.237)	(0.238)	(0.251)						
Bad news × Rival's Q	-0.539**	-0.352	-0.710**						
	(0.241)	(0.257)	(0.287)						
Good news × Rival's R&D				1.625*	2.255	2.800***			
				(0.964)	(1.394)	(0.979)			
Bad news × Rival's R&D				-0.115	-0.292	-0.492			
				(0.534)	(0.718)	(1.465)			
Good news × Rival's Sales Growth							0.927	0.975	0.881
							(0.648)	(0.760)	(0.647)
Bad news × Rival's Sales Growth							-2.369**	-1.437	-3.340***
							(0.924)	(0.930)	(1.274)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.089	0.090	0.093	0.080	0.080	0.081	0.086	0.081	0.088
N	2,999	2,250	2,085	2,999	2,250	2,085	2,999	2,250	2,085

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Internet Appendix to

"Rivals' Growth Prospects & Equity Prices: Evidence from Mass Layoff Announcements"

Test: Random Effects vs. Fixed Effects Estimation

In order to verify if the fixed effects or the random effects model is the most suited for our case, we test the hypothesis $H_0 : Cov(\Omega, c_{event}) = 0$. We follow Wooldridge (2010) and run the following auxiliary regression:

$$CAR_{i,t} = \theta * w_{i,t} + \eta * \bar{v}_{i,t} + \epsilon_{i,t}$$

where are all regressors including time-varying and time-constant regressors and a constant. $\bar{v}_{i,t}$ are the time averages of all time-varying regressors. A joint Wald test on:

$$H_0 : \eta = 0$$

to test if $Cov(\Omega, c_{event}) = 0$. We use cluster- robust standard errors to allow for heteroscedasticity and serial correlation.

Auxiliary Regression - test $Cov(\Omega, c_{event}) = 0$

	Overall
Mean Q	-0.033
	(0.557)
Mean Sales Growth	-2.049
	(1.289)
Mean R&D	-1.053
	(0.849)
Mean log(Total Assets)	0.051
	(0.357)
Mean Cash Holdings	1.140
	(2.182)
Mean (No. of Employees)	0.000
	(0.000)
Mean RoA	6.423
	(4.265)
Mean COGS	2.385
	(2.520)
Mean SG&A	4.797*
	(2.773)
Mean No. of Segments	0.186
	(0.148)
Additional Controls	**YES**
Rival Variables	**YES**
Announcer Variables	**YES**
N	25,802
F statistic	1.35
Adj. R^2	0.004

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Joint Wald Test : $H_0 : \eta = 0$

$$F(15, 657) = 1.14$$
$$Prob > F = 0.3144$$

Therefore, we cannot reject the null hypothesis, i.e., we cannot reject that $Cov(\Omega, c_{event}) = 0$. Based on this test, we have an evidence that Random Effects is better-suited to our data.

Test: Pooled OLS vs. Random Effects

We start by using the Generalized Least Square (GLS) transformation using $\lambda = 1 - \sqrt{\frac{\sigma_u^2}{(\sigma_u^2 + T * \sigma_{c_{event}}^2)}}$, where $\sigma_{c_{event}}$ and σ_u are the standard deviations of the event-specific random variables and idiosyncratic error, respectively, while T is the number of events in the sample. Based on this transformation, the closer λ is from 0, the less important are the event-specific variables and, consequently, a pooled-OLS with clustered standard errors is the most suited models. On the other side, if $\lambda \approx 1$, then the data is best-suited through a fixed-effects estimation.

		λ		
min	**5%**	**median**	**95%**	**max**
0.0067	0.0068	0.0263	0.0993	0.1368

Breusch and Pagan (1980)'s Lagrangian multiplier test for random effects

Finally, in order to evaluate the significance of the event-specific variables, we ran a Breusch and Pagan (1980) test. The result, presented in the table below, rejects that a pooled OLS test is better suited than the random effects model. Therefore, our tests indicate that a random effects model is the best model in our case.

$$CAR_{i,t} = Xb + c_{event} + \epsilon_{i,t}$$

Estimated Results

	Var	**SD**
CAR	47.702	6.907
ϵ	45.521	6.747
$\mathbf{c_{event}}$	.7115	.8435

Test: $Var(c_{event}) = 0$

$$\chi^2 = 11.64$$

$$Prob > \chi^2 = 0.000$$

Table IA.1: Rivals' Stock Return Reaction showing all Controls

This table reports our results from a fixed effects regression model with interaction terms.The dependent variable is the Rivals' cumulative abnormal return around a 3 day event window centered on event. All specifications include the control variables presented in table 1.

	(1)	(2)	(3)	(4)
Good news × Rival's Q	0.320***			0.284***
	(0.114)			(0.110)
Bad news × Rival's Q	-0.177**			-0.132*
	(0.078)			(0.075)
Good news × Rival's R&D		1.310***		1.194***
		(0.268)		(0.241)
Bad news × Rival's R&D		-0.175		-0.103
		(0.228)		(0.212)
Good news × Rival's Sales Growth			0.477*	0.242
			(0.276)	(0.253)
Bad news × Rival's Sales Growth			-0.736***	-0.558***
			(0.226)	(0.211)
Leverage	-0.511	-0.413	-0.396	-0.416
	(0.327)	(0.332)	(0.327)	(0.326)
Whited Wu Index	1.526	1.646	0.656	0.846
	(1.686)	(1.667)	(2.057)	(1.961)
Altman's Z-score	-0.015	-0.007	-0.006	-0.015
	(0.012)	(0.014)	(0.014)	(0.012)
RoA	-0.792	-0.721	-0.853	-0.802
	(0.773)	(0.781)	(0.795)	(0.751)
Cash Holdings	-0.011	-0.046	0.022	0.038
	(0.182)	(0.177)	(0.156)	(0.160)
log(Total Assets)	0.059	0.058	0.023	0.027
	(0.097)	(0.094)	(0.115)	(0.114)
Age	0.004	0.002	0.001	0.001
	(0.006)	(0.006)	(0.007)	(0.007)
No. of Employees	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
COGS	0.161	0.250	0.142	0.294
	(0.365)	(0.373)	(0.398)	(0.365)
SG&A	-0.154	-0.218	-0.137	-0.211
	(0.299)	(0.307)	(0.312)	(0.314)
No. of Segments	-0.011	-0.012	-0.010	-0.012
	(0.029)	(0.029)	(0.030)	(0.028)
S&P 500	-0.025	-0.030	-0.007	-0.078
	(0.191)	(0.173)	(0.174)	(0.191)
Event FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0501	0.0484	0.0486	0.0518
N	25,802	25,802	25,802	25,802

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table IA.2 - Descriptives
S&P 500 Rivals

The sample is 676 layoff announcements by S&P500 firms in the period 1979-2010 and information about their public 3-digit SIC rivals. It includes information about 2,979 rivals currently members of the S&P 500 index and 251 unique announcers. All variables are described in Table 3. Panel A (B) describes the summary statistics for rivals' characteristics in the "good news" ("bad news") case, i.e., the cases in which announcer's stock return reaction has a positive (negative) 3-day cumulative abnormal return – CAR. The reported levels of significance at the mean t-tests for the differences in mean between rivals and announcers are *, **, and ***, corresponding to 10, 5, and 1% statistical significance levels at a two-tail test.

Panel A: Good News

	Announcers No. Obs 307	**Rivals** No. Obs 1,321	**t-test (Rival - Ann.)**
CAR[-1,+1]	3.46	0.99	-2.473***
	(3.97)	(5.02)	(-9.32)
Tobin's Q	1.73	2.49	0.755***
	(1.17)	(2.00)	(8.48)
R&D	0.87	0.89	0.0135
	(0.33)	(0.32)	(0.64)
Sales Growth	0.03	0.09	0.0621***
	(0.19)	(0.30)	(4.59)
RoA	0.14	0.16	0.0133**
	(0.07)	(0.09)	(2.79)
Cash Holdings	0.12	0.22	0.109***
	(0.17)	(0.26)	(9.04)
COGS	0.64	0.53	-0.114***
	(0.18)	(0.23)	(-9.31)
SG&A	0.22	0.29	0.0725***
	(0.14)	(0.19)	(7.70)
Leverage	0.35	0.26	-0.0932***
	(0.20)	(0.20)	(-7.46)
Whited Wu Index	-0.43	-0.40	0.0344***
	(0.06)	(0.08)	(8.05)
Altman's Z-score	3.72	6.23	2.507***
	(3.68)	(7.12)	(8.73)
Age	37.64	29.04	-8.603***
	(12.65)	(14.80)	(-10.38)
No. of Segments	5.14	3.81	-1.328***
	(3.14)	(2.63)	(-6.87)
log(Total Assets)	8.89	8.55	-0.346***
	(0.96)	(1.06)	(-5.59)
No. of Employees	50,375	32,292	-18,083***
	(37,182)	(33,127)	(-7.83)

Panel B: Bad News

	Announcers	**Rivals**	**t-test**
	No. Obs 351	No. Obs 1,658	**(Rival - Ann.)**
CAR[-1,+1]	-3.36	-0.87	2.496***
	(3.71)	(4.55)	(10.97)
Tobin's Q	1.76	2.55	0.792***
	(1.16)	(1.93)	(9.93)
R&D	0.88	0.87	-0.004
	(0.33)	(0.33)	(-0.18)
Sales Growth	0.05	0.09	0.0325*
	(0.25)	(0.27)	(2.16)
RoA	0.15	0.16	0.0138**
	(0.08)	(0.08)	(2.89)
Cash Holdings	0.12	0.22	0.103***
	(0.15)	(0.26)	(9.99)
COGS	0.61	0.50	-0.110***
	(0.20)	(0.24)	(-9.21)
SG&A	0.25	0.31	0.063***
	(0.18)	(0.19)	(5.92)
Leverage	0.33	0.26	-0.0756***
	(0.19)	(0.20)	(-6.76)
Whited Wu Index	-0.43	-0.40	0.0245***
	(0.07)	(0.07)	(6.20)
Altman's Z-score	3.91	6.04	2.135***
	(3.24)	(6.48)	(9.07)
Age	35.00	29.03	-5.962***
	(13.11)	(14.66)	(-7.58)
No. of Segments	4.87	3.73	-1.142***
	(3.01)	(2.60)	(-6.61)
log(Total Assets)	8.71	8.49	-0.216***
	(0.97)	(1.08)	(-3.70)
No. of Employees	43,809	31,677	-12,132***
	(34,898)	(32,603)	(-5.98)

Table IA.3: Distribution of layoffs over time and industry

This table presents how our sample of 676 mass layoff announcements are distributed across time and across major industrial sectors.

Year	**Manufact.**	**Mining**	**Retail**	**Services**	**Transp.& Util.**	**Wholesale**	**Total**
1979	2						2
1980	7						7
1981	7						7
1982	11						11
1983	8						8
1984	28			1			29
1985	49	1					50
1986	33	4	2				39
1987	10						10
1988	12		1				13
1989	12	1		2			15
1990	19			3			21
1991	32	1	1	1			35
1992	21	4		2			27
1993	22						22
1994	22	1	4	2			29
1995	18		2	3	1		24
1996	15	1	2	1			19
1997	17		1	1			19
1998	30	4	1	1			36
1999	20		2				22
2000	13		1	3		1	18
2001	40		3	8			51
2002	21	2		6			29
2003	17		2	5	1		25
2004	6	1		2			9
2005	12		2	2			16
2006	14		1	1			16
2007	7		1	1			9
2008	23		2	5		1	31
2009	16		1	2			19
2010	5		2	1			8
Total	**569**	**20**	**31**	**52**	**2**	**2**	**676**

Table IA.4 - Tests for average effects
Panel A – All Announcements

Rivals' 2-tail tests: Abnormal Returns over the Event window
Overall

Patell test is the standardized abnormal return test developed by Patell (1976), **Std. C.S. Z** is the standardized cross-sectional test for market model abnormal returns introduced by Boehmer, Masumeci, and Poulsen (1991). Finally, the **EGLS** presents the estimated generalized least squares test suggested by Sanders and Robins (1991).

Day	**N**	$\overline{\textbf{AR}}$	**+ : -**	**Patell Z**	**Std. C.S. Z**	**EGLS Z**
-5	676	0.03%	326:350	-0.028	-0.025	-0.024
-4	676	0.12%	323:353	1.025	0.87	0.777
-3	676	-0.06%	338:338	-0.936	-0.795	-0.723
-2	676	0.12%	342:334	1.845$^{\$}$	1.649$^{\$}$	1.482
-1	676	0.01%	323:353	-0.58	-0.524	-0.491
0	676	-0.06%	340:336	-0.429	-0.36	-0.332
1	676	-0.08%	297:379$^{<<}$	-2.152*	-1.926$^{\$}$	-1.759$^{\$}$
2	676	-0.02%	325:351	0.468	0.441	0.395
3	676	-0.02%	335:341	0.087	0.086	0.078
4	676	-0.06%	331:345	-1.755$^{\$}$	-1.593	-1.482
5	676	-0.10%	297:379$^{<<}$	-1.29	-1.103	-1.064

The symbols $^{\$}$, *,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively. The symbols (, $<$ or), $>$ etc. correspond to $^{\$}$,* and show the direction and significance of the generalized sign test.

Rivals' 2-tail tests: Parametric and Non-parametric

Overall

Prec. Wght CAAR reports the cumulative average abnormal returns weighted by the weights obtained from the Patell (1976) test. Column **+ : -** reports not only the number of securities with positive and negative cumulative abnormal returns, but it also report the generalized sign test suggested by Cowan (1992) that tests the null hypothesis that the fraction of positive CARs is 0.5. **Rank Test Z** reports the non-parametric rank test suggested by Corrado (1989). Column **Jackknife Z** presents the parametric test suggested by Giaccotto and Sfiridis (1996). **EGLS** presents the estimated generalized least squares test suggested by Sanders and Robins (1991), while the column**CDCSI** reports the Collins and Dent (1984) test assuming cross-sectional independence.

Days	N	$\overline{\text{CAR}}$	Prec. Wght CAAR	+ : -	EGLS Z	CDCSI Z	Rank Test Z	Jackknife Z
(-1,+1)	676	-0.12%	-0.25%	311:365	-1.522	$-1.675^{\$}$	-1.550	-1.707$
(0,0)	676	-0.06%	-0.01%	340:336	-0.332	0.104	-0.024	-0.212
(-1,+3)	676	-0.16%	-0.17%	$310{:}366^{(}$	- 0.997	-0.684	-1.250	-1.328
(-2,+2)	676	-0.02%	-0.07%	329:347	-0.335	-0.381	-0.846	-0.696
(-5,+5)	676	-0.11%	-0.28%	321:355	-0.987	-1.038	$-1.684^{\$}$	-1.321

The symbols $^{\$}$,*,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail test. The symbols (, < or), > etc. correspond to $^{\$}$,* and show the direction and significance of the generalized sign test.

Panel B - Good News

Rivals' 2-tail tests: Abnormal Returns over the Event window Good News

Patell test is the standardized abnormal return test developed by Patell (1976), **Std. C.S. Z** is the standardized cross-sectional test for market model abnormal returns introduced by Boehmer et al. (1991). Finally, the **EGLS** presents the estimated generalized least squares test suggested by Sanders and Robins (1991).

Day	**N**	$\overline{\textbf{AR}}$	**+ : -**	**Patell Z**	**Std. C.S. Z**	**EGLS Z**
-5	308	-0.07%	144:164	-1.252	-1.004	-1.015
-4	308	0.26%	151:157	2.259*	1.726$^{\$}$	1.547
-3	308	-0.05%	157:151	-0.388	-0.331	-0.314
-2	308	0.05%	153:155	0.784	0.712	0.669
-1	308	0.17%	158:150	1.905$^{\$}$	1.625	1.559
0	308	0.18%	169:139$^{>}$	2.759**	2.353*	2.274*
1	308	0.10%	159:149	1.061	0.885	0.809
2	308	0.04%	155:153	0.589	0.565	0.521
3	308	0.00%	154:154	0.601	0.551	0.494
4	308	-0.03%	148:160	-0.639	-0.603	-0.553
5	308	-0.14%	129:179$^{<}$	-1.386	-1.223	-1.159

The symbols $^{\$}$, *,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively.The symbols $(, <$ or $), >$ etc. correspond to $^{\$}$,* and show the direction and significance of the generalized sign test.

Rivals' 2-tail tests: Parametric and Non-parametric

Good News

Prec. Wght CAAR reports the cumulative average abnormal returns weighted by the weights obtained from the Patell (1976) test. Column **+ : -** reports not only the number of securities with positive and negative cumulative abnormal returns, but it also report the generalized sign test suggested by Cowan (1992) that tests the null hypothesis that the fraction of positive CARs is 0.5. **Rank Test Z** reports the non-parametric rank test suggested by Corrado (1989). column**Jackknife Z** presents the parametric test suggested by Giaccotto and Sfiridis (1996). **EGLS** presents the estimated generalized least squares test suggested by Sanders and Robins (1991), while the column**CDCSI** reports the Collins and Dent (1984) test assuming cross-sectional independence.

Days	**N**	$\overline{\textbf{CAR}}$	**Prec. Wght CAAR**	**+ : -**	**EGLS Z**	**CDCSI Z**	**Rank Test Z**	**Jackknife Z**
(-1,+1)	308	0.44%	0.61%	167:141$^{)}$	2.809**	2.294*	2.962**	2.426*
(0,0)	308	0.18%	0.32%	169:139$^{>}$	2.274*	2.219*	2.211*	2.028*
(-1,+3)	308	0.48%	0.80%	170:138$^{>}$	2.775**	2.770**	2.694**	2.238*
(-2,+2)	308	0.54%	0.80%	171:137$^{>}$	2.807**	2.698**	2.52*	2.26*
(-5,+5)	308	0.50%	0.72%	163:145	1.736$^{\$}$	1.666$^{\$}$	1.327	1.17

The symbols $^{\$,*,**}$, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail test. The symbols $(, <$ or $), >$ etc. correspond to $^{\$,*}$ and show the direction and significance of the generalized sign test.

Panel C - Bad News for the Announcer

Rivals' 2-tail tests: Abnormal Returns over the Event window Bad News

Patell test is the standardized abnormal return test developed by Patell (1976), **Std. C.S. Z** is the standardized cross-sectional test for market model abnormal returns introduced by Boehmer et al. (1991). Finally, the **EGLS** presents the estimated generalized least squares test suggested by Sanders and Robins (1991).

Day	N	$\overline{\text{AR}}$	+ : -	Patell Z	Std. C.S. Z	EGLS Z
-5	368	0.11%	182:186	1.107	1.1	0.987
-4	368	0.01%	172:196	-0.677	-0.644	-0.574
-3	368	-0.07%	181:187	-0.913	-0.772	-0.679
-2	368	0.18%	189:179	1.784$	1.571	1.367
-1	368	-0.12%	165:203(	-2.528*	-2.437*	-2.230*
0	368	-0.25%	171:197	-3.105**	-2.609**	-2.322*
1	368	-0.23%	138:230<<<	-3.888***	-3.774***	-3.445***
2	368	-0.07%	170:198	0.095	0.089	0.078
3	368	-0.03%	181:187	-0.432	-0.452	-0.417
4	368	-0.08%	183:185	-1.794$	-1.58	-1.483
5	368	-0.07%	168:200	-0.481	-0.4	-0.392

The symbols $, *,**, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively. The symbols (, < or), > etc. correspond to $,* and show the direction and significance of the generalized sign test.

Rivals' 2-tail tests: Parametric and Non-parametric

Bad News

Prec. Wght CAAR reports the cumulative average abnormal returns weighted by the weights obtained from the Patell (1976) test. Column **+ : -** reports not only the number of securities with positive and negative cumulative abnormal returns, but it also report the generalized sign test suggested by Cowan (1992) that tests the null hypothesis that the fraction of positive CARs is 0.5. **Rank Test Z** reports the non-parametric rank test suggested by Corrado (1989). column**Jackknife Z** presents the parametric test suggested by Giaccotto and Sfiridis (1996). **EGLS** presents the estimated generalized least squares test suggested by Sanders and Robins (1991), while the column **CDCSI** reports the Collins and Dent (1984) test assuming cross-sectional independence.

Days	N	$\overline{\text{CAR}}$	Prec. Wght CAAR	+ : -	EGLS Z	CDCSI Z	Rank Test Z	Jackknife Z
(-1,+1)	368	-0.60%	-0.93%	144:224$^{<<<}$	-4.651***	-4.448***	-4.390***	-4.674***
(0,0)	368	-0.25%	-0.28%	171:197	-2.322*	-1.792$^{\$}$	-1.818$^{\$}$	-2.114*
(-1,+3)	368	-0.70%	-0.93%	140:228$^{<<<}$	-3.707***	-3.355***	-3.787***	-4.001***
(-2,+2)	368	-0.49%	-0.75%	158:210$^{<}$	-2.991**	-2.985**	-3.112**	-3.197**
(-5,+5)	368	-0.62%	-1.08%	158:210$^{<}$	-2.942**	-3.023**	-3.240**	-2.908**

The symbols $^{\$,*,**}$, and *** denote statistical significance at the 0.10, 0.05, 0.01 and 0.001 levels, respectively, using a two-tail test. The symbols (, < or), > etc. correspond to $^{\$,*}$ and show the direction and significance of the generalized sign test.

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