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Competitors' Stock Price Reaction to Mass Layoff Announcements

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Using data on layoff announcements by S&P 500 firms, we show that layoff announcements mostly contain industrywide news. Competitors' stock price reactions are positively correlated with the announcer's returns. This contagion effect is stronger for competitors whose values depend on growth opportunities. When layoff announcements induce positive stock returns to announcers, competitors with positive R&D see a 1.15% increase in their returns. Conversely, when announcements induce negative reactions to announcers, competitors with high sales growth see a reduction of 1.09% in returns. Our findings suggest that investors perceive layoffs as a change in growth options rather than a change in the competitive environment.

Keywords: Mass Layoffs, Competitors, Firm characteristics.

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Layoff announcements are important corporate events that have, on average, been shown to negatively affect a firm's stock value.[1] Despite an average negative effect, there is substantial heterogeneity in market reactions because layoffs can be either good or bad 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 better understand the industry-specific components of layoff announcements, we investigate their effects on the announcing firm's competitors.

An unexpected mass layoff announcement can affect a firm's competitors in two ways. First, the layoff could be contagious within an industry if the announcement is the result of a systematic shock to the entire industry (e.g. technology shocks, market conditions, customer preferences). In such cases the announcement by one firm will also reveal relevant information about its competitors. Second, the unexpected announcement could signal a strengthening (weakening) of the announcer's position in the industry. In such cases the announcement triggers a redistribution of wealth across firms in the industry. We follow Lang and Stulz (1992) and measure contagion (competitive) effects as a positive (negative) correlation of stock price reactions between the announcing firm and their competitors. We examine these countervailing contagion and competitive effects by decomposing when each effect is strongest following unexpected layoff announcements.

Using an event-study approach, we show that layoff announcements overwhelmingly reveal industry-wide information, i.e., the contagion effects of an announcement dominate the competitive effects. We also find that, on average, 40-50% of announcers see an increase in their stock value following their announcement. This significant variation in the announcer's stock price reaction across events indicates that measuring an average effect for the overall sample may bias our results downward.[2] To avoid such bias, we further explore industry effects in two different settings that are based on the announcer's stock reaction: good news and bad news announcements.[3] The contagion

[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% of the sample reacts in the opposite direction to the remaining sample, we will have a bias towards no results.

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

effects persist and dominate competitive effects irrespective of whether the layoff announcement is good news or bad news for the announcer. In other words, even though there is variation in non-announcers' market responses to a layoff announcement, their average reaction is always positively associated with the announcer's reaction.

Next, we find that competitor characteristics, both within and across events, help to explain their stock price reaction through their expected ability to respond to industry shocks. By controlling for liquidity, size and growth characteristics, we find that the net contagion effects are stronger for growth firms within an industry. That is, when layoff announcements reveal information about industry prospects, competitors whose value depend on growth opportunities are affected the most. Digging deeper, when the layoff announcement is seen as good news for the announcer, competitors with positive investments in R&D respond more positively than other peer firms. In particular, we observe that competitors with positive investment in R&D see a 1.15% cumulative abnormal return (CAR) in the 3-day window around the mass layoff announcement. The effect is strongest in highly competitive (1.19%) and growth-oriented (1.27%) industries. Differently, the effect for other competitors is statistically insignificant. On the other hand, when layoff announcements convey bad news for the announcer, competitors with high sales growth experience the most negative responses. In particular, firms at the top quartile of the sales growth distribution see a CAR of -1.09% in the three-day window around the layoff announcement. Similar to the case with good news, the effect is strongest in highly competitive (-1.16%) and growth-oriented (-1.29%) industries. The impact on low sales growth competitors is not statistically significant for all the mentioned cases. Our results are robust to both event fixed effects models and random effects models where we allow for layoff- and announcer-specific characteristics to impact non-announcer responses. The fact that our results are stronger in less concentrated industries, where we would expect peers to have more similar sets of underlying investments, corroborates the idea that results are mainly due to perceived industry-wide unexpected shocks.

Apart from competitor characteristics, information transfers can also be affected by announcer and layoff characteristics. Using a random effects regression model allows 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. We show that our main results about non-announcer characteristics are robust to the choice of regression model. This corroborates our conclusion that competitor characteristics are important determinants of information transfers in our sample. Moreover, apart from the announcer's CAR, which has a positive and significant coefficient, indicating the importance of contagion effects, no other announcer or layoff characteristics seems to significantly impact competitors' stock reaction.

We also replicate our analysis applying the methodology implemented in the current literature to demonstrate the power of our analysis. We measure competitors' responses to a layoff announcement using a value-weighted and equal-weighted portfolio for all sample announcements. While results are consistent with contagion effects dominating the competitive effects, we fail to find significant average effects of competitor characteristics on portfolio returns. Based on these findings, we conclude that within-event heterogeneity among competitors is more important in explaining their response to the layoff than announcer, event or industry characteristics. Moreover, these results highlight how our empirical approach may address common pitfalls of information transfer studies. The use of a value-weighted portfolio of competitors, while allowing researchers to evaluate an average impact on competitors, washes away any relevant heterogeneity in individual competitor characteristics. This drawback can be particularly costly in industries where non-announcer responses exhibit large cross-sectional variation. Another issue with this commonly used "average" approach is that it does not take into account potential event-specific unobserved effects.[4] This potentially biases the results by considering all sample events to be substantially similar. We overcome these limitations by utilizing event-specific fixed effects while including individual competitors' characteristics. We also split the sample and/or include interactions with respect to announcer's responses whenever it seems appropriate based on our economic intuition.

This paper also contributes to the existing literature on information transfers by studying

[4]Notice that, even though the literature tries to correct the potential correlation across observations in the same industry by working with a value-weighted or equally-weighted portfolio of industry competitors instead of individual competitors, these studies do not address the issue of event specific unobserved effects. In fact, most papers average the competitor responses across all events within the same industry.

the industry effects of layoff announcements. Mass layoff announcements represent a powerful setting to examine 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. This implies that firms will undertake a mass layoff only if they expect that the reasons for adjustment are long-lived. 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.[5] Third, layoffs are unique from other firm-specific news announcements previously 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 information content potentially provide vastly different results.[6] 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 peer characteristics and intra-industry information transfers.

1 Related Literature

A market value represents a consensus expectation of discounted future cash flows for a company. However, forming an accurate consensus is a difficult process due to information asymmetry and uncertainty. As such, markets are constantly revising valuations based on updated information. Announcements by industry peers have proven to be a rich source of information in this process. An extensive literature exists on intra-industry information transfers between peers for many different types of news events. In this literature, the goal is to evaluate the impact of a firm's announcement on the average stock price reaction of its industry competitors, given the industry and announcer characteristics. This methodology has been applied to announcements of bankruptcy (Lang and Stultz (1992) and Ferris, Jayaraman, and Makhija (1997)), mergers (Eckbo (1983)), corporate capital investments (Chen, Ho, and Shih (2007)), financial misrepresentation (Goldman, Peyer, and Stefanescu (2012)), dividend initiations (Howe and Shen (1998)), dividend changes (Firth (1996),

[5]See Merz and Yashiv (2007) and Bazdrech, Belo, and Lin (2013).

[6]Bankruptcy announcements (Lang and Stulz (1992), Ferris, Jayaraman, and Makhija (1997)) financial misrepresentation (Goldman, Peyer, and Stefanescu (2012)), dividends (Firth (1996), Laux, Starks, and Yoon (1998)) and corporate capital investment announcements (Chen, Ho, Shih (2007)).

Laux, Starks, and Yoon (1998)), and security offerings (Szewczyk (1992)) among others. In most cases, the contagion effect dominates, with the competitors' stock price reactions in the same direction as the announcer's stock price reaction (with the exception of corporate capital investment). Unfortunately, the average competitors' stock price reaction delivers only the net impact of the news on competitors, showing only which effect - contagion or competition - predominated and by how much. While this aggregation may solve issues of the potential correlations across competitors, it removes any cross-sectional differences thus inhibiting our understanding of which competitor characteristics predict different reactions. This methodology also threatens to mask results in very heterogeneous industries in which different competitors may have offsetting stock price reactions to the announcer's news.

Another drawback in the literature is that, in most of the cases, the impact of the news on the announcer's stock price is easily determined as either positive (corporate capital investment, dividends) or negative (bankruptcy, financial misrepresentation, security offerings). Differently, in the case of layoff announcements, although the impact of a firm's labor force and its adjustment cost on firm performance is undisputed (Merz and Yashiv (2007), Bazdrech, Belo, and Lin (2013)), the information content of mass layoffs on the announcer is ambiguous. In this sense, before we are able to analyze the impact of the announcement on rivals and the magnitude of contagion and competitive effects, we need to evaluate the informational content of the layoff on the announcer itself. This differential informational content of the announcement generates an even greater reason to investigate the drivers of investor responses at industry peers.

The literature on the impact of mass layoffs has up to now focused mainly on the impact of layoff announcements on the announcer's stock return. Most of the earlier literature (see Worrell, Davidson, and Sharma (1991), Abowd, Milkovich, and Hannon (1990), among others) has found a negative impact of mass layoff announcements on stock returns. However, more recent work by Farber and Hallock (2009) shows that the impact of layoff announcements on the average stock returns of announcers has varied over time, being extremely negative during the 1970s while approaching zero in later periods. This pattern seems to be partially reverted from 2000 on. Hallock, Strain, and Webber (2011) extended the database used by Farber and Hallock (2009) until 2007.

They show that stock price reaction to job loss announcements are less negative in the 1980s and 1990s compared to the 1970s, but the 2000s are not statistically different from the 1970s. In our data, we can also 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.

However, notice that this literature focuses on the average impact of layoff announcements on the announcer's stock return. As we show in this paper, while the impact is **on average** negative, there is a wide dispersion in announcers' stock reactions, varying from -28.95% to $+26.81\%$ in our sample. Moreover, the fraction of announcers with positive 3-day cumulative abnormal returns (CAR) in a given year has been usually above 40% with an upward trend going up to nearly 45% by the end of our sample period, as shown in Figure 1.A. In this sense, even though the average reaction to a layoff announcement may be negative, the informational content of a given announcement can vary significantly from very negative to very positive.

Finally, the literature that looks at the impact of mass layoffs on the announcing firm's competitors is quite small. Studying a sample of 403 layoff announcements, Bhabra, Bhabra, and Boyle (2011) show evidence of intra-industry effects of layoff announcements. They find that information spillover effects are observed for low leverage, high Tobin's q rivals in cases where the layoff announcement contained adverse industry information. Differently, rivals that are large and efficient see a positive return when the layoff announcement did not contain adverse industry information. Although their paper touches on the importance of studying intra-industry information transfers around layoff announcements, we argue that our methodology adds some critical improvements. Even though they deviated from the previous literature by looking at individual competitors instead of aggregating in value weighted portfolios, they do not cluster the standard errors in their regressions, which generates biased estimates due to an omitted variable bias. Moreover, while they divide their sample in terms of the announcing firm's expressed reasons for the mass layoff, they do not divide in terms of the market's reaction to the layoff. While there is some evidence that the announced reasons for the layoff affect investors' reaction to the layoff announcement (Palmon, Sun, and Tang (1997) and Faber and Hallock (2009)), it is far from unambiguous. In fact, in interview data from senior investors and managers, Hallock (2003) shows that investors seem quite skeptical about the actual validity of these announced reasons. Our approach proposes a methodology and a partition of the sample to avoid the problems observed in Bhabra et. al. (2011). In unreported results, we also control for the announced reasons in the analysis in which their coefficients would not be absorbed. Since they are insignificant, we do not report these results here, but they are available upon request.

2 Overall Impact and Decomposition based on Announcer Reaction

As mentioned before, the informational content of a mass layoff is complex, with the potential for either good or bad news for the announcer and the industry. We evaluate the effect on competitors by splitting the sample based on the announcer's stock price reaction. We classify a positive abnormal announcer reaction as the "good news case" and a negative abnormal reaction as the "bad news case". We evaluate the potential impact of competitors' characteristics in these two mutually exclusive cases. Following the analysis by Lang and Stultz (1992), we consider the possibility of contagion and competition effects on peers. The contagion effect, representing industry-wide shocks, is observed when the competitor's stock price reaction is in the same direction as the announcer's. Differently, a competition effect, indicating potential redistribution of market share across competitors, is observed when the competitor's stock price reacts in the opposite direction of the announcer's stock. We discuss the potential impact of different competitor characteristics on their reactions under both the good and bad news cases in the subsequent sections. Table 1 summarizes the discussion. We consider the following vector of competitor characteristics, measured at the start of the period, meant to capture non-announcers' liquidity, size, and growth opportunities: book leverage, cash holdings scaled by assets, the log of total assets, firm age, total number of employees, market-to-book ratio, return on assets, a dummy to indicate R&D expenses, sales growth, number of sectors in which the firm operates, and measures of financial constraint and bankruptcy risk including the Whited-Wu index and Altman's Z-score. We also control for competitors' membership in the S&P 500 index at the time of the announcement. Details about the construction of these variables are described in the next section, as well as in Table 3.

2.1 Announcer's Good News Case

In this case, the mass layoff announcer's stock price reaction is positive. To the extent that we consider workers to be valuable assets to a firm, this positive reaction appears contradictory. There are a few possible explanations for this result. First, the firm may be operating inefficiently, keeping a sub-optimally large labor force. In this case, a reduction of the firm's payroll is welcomed by the market. A second possibility is that the layoff is a positive productivity shock in an oligopolistic product market in which the announcer optimally chooses to cut costs instead of expand production. Finally, we can imagine a positive shock on capital productivity in a market in which capital and labor are substitutes. In terms of our classification of the informational content of the layoff announcement, we would expect the first explanation generating a competitive effect, while the next two would imply a contagion effect. As previously explained, a contagion effect indicates an improvement for the sector, positively affecting peer companies. Differently, a competitive effect indicates that the announcer is now an improved rival, to the detriment of its peers. Although the direction of these effects is the same for all competitors, the magnitude of the effect depends on the rival's characteristics.

In terms of the competitive effect, we expect that large, liquid, growth-oriented competitors are relatively less affected by the layoff announcement. In particular, large firms – proxied by both logarithm of total assets and the number of employees – are expected to be in a better position to face a stronger competitor, all else equal, than their smaller counterparts, due to better access to resources as well as a strong existing sales infrastructure. Moreover, as pointed out by Zingales (1998), size might be a proxy for efficiency, because only efficient firms become big. Larger firms may also have more bargaining power on the product market as well as easier access to financing. In this sense, larger firms have a longer reaction period before they are driven out of the market compared to smaller peers. Similarly, more liquid firms – i.e., firms with large cash holdings and low leverage – are in a better position to face a stronger competitors. Liquid firms have enough resources to implement any necessary investment and are able to face a slow down in cash flows without defaulting on their interest payments, as pointed out by Fresard (2010) and Campello (2006). Even though there is an argument to support that firms may use debt as a commitment to more aggressive behavior in the product market, as pointed out by Brander and Lewis (1986), most empirical evidence has supported the hypothesis that debt weakens a firm competitive position, as suggested by Bolton and Scharfstein (1990).[7] Moreover, growth firms – i.e. firms with high market-to-book, positive R&D expenses, and high sales growth – are in a better shape to face stronger competition, all else equal. Growth firms not only have more growth opportunities to implement in order to face a restructured competitor, but also have lower capital adjustment costs in the short term. Overall, a smaller fraction of their current valuation is attached to short-term performance, as pointed out by Zhang (2005). Finally, we would expect that high cost firms – proxied both by the ratio of costs of goods sold (COGS) over sales, and selling, general, and administrative expenses (SG&A) over sales – as well as struggling firms – captured by the Altman's Z-score and a measure of distance to delisting (following Bakke, Jens, and Whited (2012)) may be more negatively affected by a stronger competitor. Since distance to delisting is not significant, we decide to omit from the tables. Finally, we would like to emphasize that the magnitude of the competitive effect should be greater in more concentrated industries, where competition is likely to be imperfect. In more competitive industries, firms lack market power and have very slim profit margins. Consequently, the fact that any particular competitor has become stronger or weaker should be only a minor impact on any competitor's prospects.

In terms of contagion effect, the picture is less clear. Firms with large cash holdings, high sales growth, high market-to-book, and positive R&D are expected to do well in the case of good industry news, since these firms are more likely to have the resources and knowledge to take advantage of the new growth opportunities.[8] Similarly, firms with a larger labor force as well as firms with a high production cost would benefit from labor-saving growth opportunities in the industry. However, the impact of good industry news on firms with large assets and high leverage is ambiguous. On one hand, firms with more assets may be better able to capture growth opportunities due to their

[7] For empirical evidence on how debt weakens a firm's competitive position, see Khanna and Tice (2000), Zingales (1998), and Chevalier (1995), among others.

[8] See Aghion and Howitt (1992), Abel and Eberly (2012), Fresard (2010), among others.

economies of scale. On the other hand, these firms may be entrenched in current production processes and less adaptable to capitalize on the positive industry news. Similarly, leverage can have a positive impact by scaling up the impact of new growth opportunities on equity. At the same time, leverage can also reduce the possibility that the firm can undertake those growth opportunities due to cash constraints to meet debt obligations as well as increases the agency problem between manager, shareholder, and debt holders that may deter the firm to invest in NPV positive projects (see Myers (1977), Stulz (1990), among others).

2.2 Announcer's Bad News Case

We now consider the case in which a mass layoff is received as bad news for the announcer by investors in the announcing firm. As before, we decompose the effect on non-announcers into two effects: a contagion effect, in which the mass layoff represents some bad news about the industry overall, and a competitive effect, in which the mass layoff conveys that the announcer is now a weaker competitor. We again study the impact of competitors' own characteristics on their stock price reactions to the layoff announcement.

In terms of competitive effect, we expect that firms with greater assets, large cash holdings, positive R&D expenses, and high sales growth benefit the most by the weakened position of the announcer. This indicates that large firms with enough resources and knowledge to implement policies that allow then to steal market share from a weak competitor are in the best position once the competitive redistribution occurs in the sector. However, the effect of the remaining variables is unclear. For example, while firms with high market-to-book may benefit from better growth opportunities, low market-to-book firms, by being distressed firms, may benefit relatively more due to a reduction in the likelihood of bankruptcy. In a similar manner, while a weaker competitor may mean good news for a distressed, highly leveraged rival, high leverage and distress by themselves may also imply that the firm would have a hard time raising funds to take advantage of the excess of demand left by the weakened competitor.[9] As before, we should again expect that these effect would be the strongest in concentrated markets.

[9] See Bolton and Scharfstein (1990).

In terms of a contagion effect, we expect that more liquid firms – proxied both by high cash holdings as well as by low leverage – are the least affected by the bad industry news, since they are less likely to default on payments or face bankruptcy. The effect of other characteristics is ambiguous. For example, if a mass layoff indicates a permanent reduction in demand for the industry, growth firms would proportionally suffer more, since their value comes from future industry opportunities instead of assets in place. However, a literature that tries to explain the value premium puzzle (see Zhang (2005), Kapadia (2011), Campbell, Hilscher, Szilagyi (2008), among others) indicates that this may not be the case, due to higher adjustment costs of capital, as well as a high correlation of human capital costs (due to a higher likelihood of unemployment) paired with the high bankruptcy cost of value firms. Similarly, firms with a greater workforce can downsize their staff without threatening self destruction.[10] On the other hand, large firms may be the most susceptible to rapidly changing tastes due to the challenges of re-tooling.[11]

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 competitors from the same three-digit SIC code.[12] Table 2 outlines our sample selection procedure.

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 mass 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 relating to S&P 500 firms will be reported in the Wall Street Journal. Additionally, since we are primarily concerned with the effect of layoff announcements on competitors, we are not interested in unannounced layoffs. We search Factiva

[10] One way we can control for that is by examining the magnitude of the impact on the announcer's CAR, conditional on the layoff's size.

[11] A leading example of this difficulty of re-tooling for a large firm is the Kodak case.

[12] Even though there are concerns about using SIC codes to identify industries and some alternatives were suggested by the literature (see Hoberg and Phillips (2010)), we decided to use the 3-digit SIC not only to be able to compare our results to previous literature, but also because we wanted a classification that would be likely to be used by investors to identify potential competitors.

for the following keywords: “layoff”, “layoffs”, “lay-off”, “laid off”, “restructure”, “restructured”, “restructuring”, “downsize”, “downsizing”, “downsized”, “plant closure”, and “plant closing”. We collect 2,367 layoff announcements by 502 distinct firms. For each layoff announcement, we document the date of the layoff announcement, the size of the layoff, the reason given for the layoff, and the type of worker laid off.

We obtain firm-specific financial data for announcers and competitors from Compustat. Our sample is restricted to only US firms. Further, we exclude financial firms (SIC 6000-6799) and utility firms (SIC 4610-4991) due to their highly regulated nature, as well as firms without industry classification (SIC 9999). For each firm announcing a mass layoff, we determine a group of competitors based on their classification in the same three-digit SIC code. Our initial sample consists of 2,367 layoff announcements with competing firms. We include additional restrictions 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 dividends announcements within a $[-5, +5]$ window around the layoff announcement date since these concurrent announcements may impact short-run returns. Moreover, we eliminate any competitor that made one of these announcements within the same event window. Second, in order to focus on layoff announcements that bring new information, we eliminate any layoff 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, since there is a clear distinction in 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, 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 announcement effect. Finally, we eliminate any observation in which we have missing values for variables relevant to our analysis. Our final baseline sample consists of 676 layoff announcements by 251 distinct firms and a sample of 3,127 unique competitors, representing 27,379 firm-event observations during our sample period, 1979-2010.

We use lagged independent variables so that we can control for the accounting and financial position of firms prior to the layoff announcement. These include leverage, firm size (measured in terms of the log of total assets), firm age, market-to-book ratio, sales growth, cash holdings, number of employees, R&D, ROA, COGS, SG&A, as well as measures of distress (e.g Altman's Z-score) and measures of financial constraint (e.g. Kaplan-Zingales and Whited-Wu indexes).[13,14] Details on the construction of the variables are presented in Table 3. All our variables are adjusted for inflation (constant 2000 dollars). We also winsorize control variables at the 2% level to reduce the effect of extreme outliers. Our results are robust to changes in the winsorization level.

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 to calculate cumulative abnormal returns. Our pre-event estimation window is up to 200 days long (minimum 3 days) and it ends 101 days before the layoff announcement. We calculate cumulative abnormal returns 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 3 day event window in our analysis. This window choice allows us to compare our results with previous results in the literature.

3.2 Summary Statistics: Announcer and Layoff Characteristics

Before we discuss competitors' characteristics, we summarize the financial characteristics of the announcers in the sample as well as some key characteristics of the layoff announcements. This analysis is important due to the fact that we observe a lot of 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%, as shown in Figure 1.A.

In Table 4, Panel A, we report summary statistics for announcers. We show not only the summary statistics for all announcements, but we also divide across announcements with positive and

[13]Unfortunately Compustat's wage data is quite incomplete, so we are unable to control for wages directly. However, we have indirect controls for labor costs, for both production workers – through COGS – and non-production workers, by SG&A. Moreover, due to the wage-size premium, firm size is also a proxy for the wage bill

[14]Kaplan-Zingales index was constructed by Lamont, Polk, and Saá -Requejo (2001) based on regression coefficient estimates in Kaplan and Zingales (1997). Whited-Wu index is presented in Whited and Wu (2006).

negative stock price reactions. As we can see from the "All Announcements" table, although the mean and the median for the CAR is negative, there is a huge variation across announcers, with CARs varying from −28.95% to +26.81%. Compared to competitors (shown in Panel B), announcers are bigger, more leveraged, and older.[15] This is not surprising since all the announcers are listed in the S&P 500 index at the time of the announcement, while only 11.66% of the competitors are S&P500 members. However, we obtain qualitatively similar results if we restrict our sample to competitors from the S&P 500, presented in Panel C. The differences between announcers and competitors are statistically significant, even after taking into account the clustered nature of the data. In terms of profitability, we see that, although announcers have lower ROA than S&P 500 competitors, they outperform the average/median of the overall competitor group. This result corroborates what has been found in the literature. Analyzing the evolution of mass layoff announcers before and after the layoff, Chen et al. (2001) show that announcers are not under-performers compared to their industry rivals. 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 as well as the fraction of the firm'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 generated good announcer news are slightly larger in number. 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% of the firm's labor force, while the median announcement affects 3%.

3.3 Summary Statistics: Competitors

Panels B and C of Table 4 describe summary statistics for overall and S&P competitors, respectively. Since all of our announcers have been listed in the S&P 500 at the time of the announcement

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

and only a small fraction of the overall sample of competitors are S&P 500 members, it is important for us to distinguish between S&P 500 and non-S&P 500 competitors when studying the contagion and competitive effects of layoff announcements. When compared to non-S&P competitors, S&P 500 competitors are bigger – in terms of employees and total assets – more profitable, more diversified across segments, older, and more leveraged. Another important point to highlight is that competitors' stock price reaction move, on average, in the same direction as the announcer's reaction. This is a first indication that contagion effect dominates the competitive effect. Moreover, the fraction of competitors with positive CARs in 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 competitors' reactions have 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 (2006).

3.4 Summary Statistics: Layoffs - over time and across industries

In Panel D of Table 4, we show how layoff announcements are distributed across industries. As expected, the majority of the layoffs occurred in manufacturing (84%) followed by services (8%), and retail (5%). As we show in Section 5.3, our results are qualitatively the same if we restrict our sample to only manufacturing firms. In terms of the average number of competitors, we also see a significant difference across industries, with numbers varying from 187 in services to 2 in mining. Once we restrict to competitors currently members of the S%P 500 index, the numbers drop significantly, but there is still significant variability across industries. In terms of layoff sizes as fractions of the pre-layoff labor force, we see that layoffs vary from .99% of the firm's labor force (in wholesale trade) to 6.73% in services. Finally, in terms of the distribution of layoffs over time, we see in Table 5 that layoffs are spread out across the sample period. Based on initial clustering analysis, we do not find clear time clusters in our sample.

Finally, Table 6 presents the correlation matrix across the relevant variables. It should be noted that there exists significant partial correlation between most pairs of variables. Hence, our rich set of covariates should help us mitigate the possibility of spurious correlation between the explanatory variables and the cumulative abnormal return.

3.5 Summary Statistics: Likelihood of Becoming an Announcer

Finally, in order to take into account the joint effect of the discussed variables, we run a probit on the likelihood of a given firm announcing a mass layoff while controlling for year and industry effects.[16] As we can see in Table 7, the stylized facts presented above are confirmed by the probit. Announcers tend to be larger, older, less efficient (higher COGS and SG&A), and more diversified than their competitors. Moreover, announcers are also more likely to be value firms. Finally, since we collected layoff announcements for all firms that were at 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 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. However, in Table 7 we include all firms that are in the index at any given point, while controlling for current membership using a dummy variable. This dummy of current S&P 500 status loads 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.

4 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 layoff announcements (i.e. Farber and Hallock 2009) and intra-industry information transfers (Madura et al. 1995, Goins and Gruca 2008, Bhabra et al. 2011). We specifically focus on three-day cumulative abnormal returns 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

[16] In order to keep comparability in size, we restrict the competitors to the S&P 500 group. Standard errors are clustered by layoff event.

the "event date" and acknowledge the possibility of information leakage prior to the WSJ release; if anything, leakage should bias against finding robust results.

Prior research has primarily focused on the impact of a news announcement on the average stock price reaction of a value-weighted portfolio of competitors. We identify two econometric concerns with this approach. First, pooling all observations does not allow researchers to evaluate the impact of the announcement across firms within the same industry. Relatedly, it does not take into account potential changes in the dispersion of stock price reaction across competitors within industries. As we observe in Figures 1.B and 2, there is not only a wide dispersion in the reactions of competitors to a particular announcement, but also this dispersion increased throughout the period that we analyze. Second, this approach does not take into account the potential for event-specific unobserved effects. This potentially introduces an omitted variable bias in the results, particularly when studying events with heterogeneous outcomes like mass layoffs announcements.

In order to control for unobserved heterogeneity at the industry and time period levels, we take advantage of the panel-like structure of the data, in which we usually observe several mass layoffs per three-digit SIC industry classification across time where a significant number of the same firms are observed at different time periods. In particular, we run the following model:

$$CAR_{it} = \beta * \mathbf{x_{it}} + \gamma * \mathbf{z}_{event} + c_{event} + u_{i,t} \tag{1}$$

where CAR_{it} is the cumulative abnormal return for competitor i given a layoff announcement in period t by one of its rivals, $\mathbf{z}_{event}$ are event-specific variables such as the characteristics of the announcer and the industry in which the mass 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 competitor and will be included in $x_{i,t}$ are described in Table 3. 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. To evaluate the impact of the interaction between event-specific factors and competitor-specific characteristics, we run fixed effects specifications in subsamples that are broken down according to specific characteristics of announcers and/or the industry in which the mass layoff announcements occur. We partition our sample based on three characteristics: the concentration of the industry, whether the announcer's industry is in the technology sector, and whether the layoff size is above the sample median layoff size. We expect that information transfers are different between events in each subsample and test accordingly. As an alternative approach, we also run fixed effects regressions on overall sample while controlling for the interactions between layoff characteristics and competitor characteristics. Our results are robust to this alternative approach. Furthermore, we implement this alternative approach for some of the robustness checks that depend on smaller subsamples. By using interactions, we increase the sample size, boosting the statistical power of our analysis.

Second, we consider the case in which $Cov(c_{event}, \Omega) = 0$. In this case, we can 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 hypothesis H_0 : St. Dev.$(c_{event}) = 0$ through a Breusch and Pagan test. Since we reject the hypothesis, we omit the pooled 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. We also introduce variables that interact with event-specific and competitor-specific factors. To compare the results obtained for the random effects and fixed effects models, we also present results for the random effects model across sub samples as presented for the fixed effects model.[17]

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 $H_0 : Cov(\Omega, c_{event}) = 0$. Usually, a Hausmann test is used to test random vs. fixed effects models. However, a Hausmann test is only valid under homoscedasticity and cannot include time fixed effects, conditions that are unlikely satisfied in our

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

case. In this sense, we follow Wooldridge (2010) and run the following auxiliary regression:

$$CAR_{i,t} = \theta * w_{i,t} + \eta * \bar{v}_{i,t} + \epsilon_{i,t} \tag{2}$$

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. Even though our results do not reject that a random effects model is best suited for our problem, we decided to also show that our results are qualitatively the same with a fixed effects model, since the assumption $Cov(\Omega, c_{event}) = 0$ is quite strong and not rejecting it does not imply accepting it.

5 Results

5.1 Average Effects

Before we evaluate the effect of competitors' characteristics on their stock price reaction to a rival's layoff announcement, we start looking for an average industry-wide effect of the layoff announcement. In particular, 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 to determine the net effect on competitors. The panels in Table 8 show the results for our sample. Our tests are constructed using value-weighted portfolios of competitors with stock returns available from CRSP. Notice that we create a value-weighted portfolio 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). As a robustness, we also consider the case of equally-weighted portfolios, 1-tail tests, and regular OLS estimates for the abnormal returns. Since all our results are qualitatively the same across these specifications, we omit the robustness tables. Moreover, Table 8 includes 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 unique strengths and weaknesses.[18]

Our results are broken down two ways. First, we break down the abnormal returns within the event window, by looking at the magnitude of the abnormal return in different days within the event window. Second, we separate the results across the announcer's own stock price reaction, by looking at good and bad news cases one at a time. Comparing the results from Panel A against the results from Panels B and C, we can see that while there is no clear net effect in the overall sample, once we break down the sample with respect to the direction of the announcer's stock reaction, we see a clear pattern that indicates that the contagion effect dominates the competitive effect, such that the net effect on the portfolio of competitors moves clearly in the same direction of the announcer's reaction. 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 at least partly unanticipated by the market. These results corroborate the initial results obtained in Table 4 based on the summary statistics. Finally, our results are also robust to focusing only on announcements that have a reaction for the announcer that is statistically significant as well as to focusing on the manufacturing subsample. For brevity, we omit these tables but they are available upon request.

5.2 Fixed Effects Model

In this section, we focus on results from regression models that include a fixed effects specification. Due to the fact that fixed effects models do not allow us to obtain coefficient for announcer and layoff characteristics, as well as the results from the average tests presented in Table 8, showing the importance of distinction between the good and bad news cases, we decided to split our sample across relevant industry and layoff characteristics. We give details in how we construct our subsamples below.

We generate subsamples based on the level of industry concentration because the competitive effect should only affect industries in which competition is imperfect.[19] In other words, the competitive effect will be dominant in industries that are highly concentrated where firms have market

[18] Dutta (2014) discusses the different tests in details.
[19] See Lang and Stultz (1992).

power. We measure the level of industry concentration in terms of the Herfindahl-Hirschman Index (HHI). Based on this measure of industry concentration we classify industries with an HHI score that is above the sample median into the high concentration subsample and those industries that have an HHI score that is lower than the sample median into the low concentration subsample.

We also generate subsamples based on the level of technological intensity in industries. We believe that growth opportunities and the impact of innovation are more important in technology sectors. In this sense, 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).[20] We would expect that in technology industries, a larger fraction of the firm value comes from growth opportunities (e.g. Demers and Lev (2001)), implying that investment in R&D and market-to-book ratio are more important variables, jointly with variables that allow firms to undertake growth opportunities such as cash holdings.

Finally, we also generate subsamples based on layoff size. If the layoff ratio – the fraction of the firm's labor force that has been displaced in the announced layoff – is above the median in our sample then the announcer is classified into the large layoff subsample. Otherwise the announcer is classified into the small layoff subsample.

As an alternative approach, we also run fixed effects regressions on overall sample while controlling for the interactions between layoff characteristics and competitor characteristics. This approach allows us to obtain more robust results, in particular in the cases in which subsamples become significantly smaller than the overall sample. By introducing interactions, we increase the sample size, boosting the statistical power of our analysis.

In each of the following sections we begin our analysis with a note on the benchmark results followed by a discussion on results from subsamples based on industry concentration, technological intensity, and layoff size.

5.2.1 Layoff Announcement is Good News for the Announcer. In this section we present a discussion of our results from a fixed effects model for a sample of competitors where layoff

[20] Due to the fact that we cluster in SIC three-digit industry, we adjusted Loughran and Ritter (1997) accordingly. In particular, we consider tech industries the following SIC three-digit industries: 357, 366, 367, 382, 384, 481, 489, and 737.

announcements are good news for the announcers. The benchmark results are presented in column 1 of Table 9.[21] We find that firms with positive investment in R&D do relatively better, while more diversified firms – measured by the number of segments in which the firm operates – do slightly worse. All other variables, while presenting coefficients with the expected sign, were not statistically significant. In order to properly measure the impact of each variable, we look at the marginal effect of investing in R&D while taking into account the event fixed effects and fixing the other variables at the sample average. Our results indicate that having positive investment in R&D generates a positive average CAR of 1.15% and this increase is statistically different from zero at the 5% level. It also implies a CAR that is statistically bigger than the one of no-R&D firms at the 5% level, even after taking into account the clustering in the data. Figure 3 plots the density functions for the CARs for both firms with and without R&D investment. As we can clearly see, firms with R&D investments have a significantly higher average CAR. In all the mentioned cases, the impact of mass layoff announcements on no-R&D competitors was not statistically different from zero. Similarly, we observe that firms operating in three or fewer sectors have a CAR that is on average 1.05% and this market response is statistically different from zero. Firms that operate in more than three sectors see a CAR that is not statistically different from zero. Although this is a large difference, only a small fraction of competitors – less than 10% – operate in more than three sectors, so our estimates for highly diversified firms are quite noisy.

We present our results for high and low concentration industries in columns 2 and 3 of Table 9. The positive impact of investment in R&D is observed only in the low concentration subsample. This reiterates our belief that our results may not be due to competitive effects but actually due to contagion effects. In particular, we find that positive R&D investment is associated with a +1.19% CAR in the three-window around the mass layoff announcement. Differently, the effect of announcements on no-R&D firms is not statistically different from zero. Finally, we find that the difference in CARs across groups is statistically significant at 5%. Moreover, as shown in column 3, the R&D result is strongest in the technology sector. Competitors with positive R&D in the

[21] In previous versions, we presented robustness checks in which we eliminate announcements that have a stock price reaction close to zero - both by eliminating the 5th. and 6th. decile as well as cutting out the announcements in which the announcer's reaction is within the interval $[-.3\%, .2\%]$. Results were qualitatively equal to the ones presented here, so we decided to omit. The robustness tables are available upon request.

technology sector see a 3-day window CAR of +1.27% and this effect is statistically significant at the 5% level. Differently, we see no impact of layoff announcements on stock returns of no-R&D firms in the same sector.[22] Since the technology sector is not only usually a highly competitive sector but also one in which undertaking growth opportunities depend on previous investment in R&D, our results corroborate the view that investors perceive layoff announcements as news about industry-wide future prospects.

Finally, investment in R&D has a positive and significant impact on the competitor's CAR in layoff announcements that represent a significant fraction of the announcer's labor force (above the median in our sample). If the size of the layoff is positively correlated with the amount of information conveyed (or perceived by the market), it is natural that we expect a larger impact. In Section 5.3, we consider the subsample of announcements in which the announcer's CAR is statistically different from zero as a way to control for the relevance of the information in the announcement. Our results are qualitatively the same in that scenario.

5.2.2 Layoff Announcement is Bad News for the Announcer. Here we present a discussion of our results from a fixed effects model for the subsample of competitors where layoff announcements are bad news for the announcers. The benchmark results are presented in column 1 of Table 10. We find that competitors with higher sales growth, cash holdings, and size – measured by the logarithm of total assets – react more negatively to a layoff announcement that is bad news for the announcer, while firms that operate in more segments are relatively more positively affected. The direction of our results on sales growth indicate that value firms suffer less than growth firms. In the context of the contagion effect, these results should indicate that the loss in value of growth opportunities outweigh higher adjustment costs of assets in place. On the other hand, a competitive effect will indicate that a reduction in the likelihood of bankruptcy due to lower competition benefits value/distressed firms more than any potential benefit of increased demand for growth firms. Our results from the industry concentration subsamples will help us show which of these two effects dominate.

[22] In the case of tech industries, although the effect on competitors with positive R&D is statistically significant at 5% level while the effect on no R&D firms is not statistically significant, we are unable to show that the difference between the two is statistically significant since our database is small compared to the overall sample.

In columns 2 and 3 of Table 10 we present our results for high concentration and low concentration industries. Our results on sales growth and cash holdings are found only in low concentration industries. This indicates that announcer bad news in more competitive industries hurt firms with growth opportunities more, indicating that a mass layoff may signal a long term downturn for the sector. This result once again shows that the contagion effect of a layoff announcement dominates the competitive effect.

The negative coefficient on size is harder to interpret. It implies that firms with more capital in place are more negatively affected, indicating potentially that large firms have a harder time to restructure in order to satisfy a change in the market, as well as a potential reduction in demand not only in the long run but also in the short to middle run – which would be in agreement with the negative impact on high sales growth firms as well. Another possible explanation is that size is capturing the effect of higher wages due to the wage-size premium. However, this hypothesis seems less likely due to the fact that the coefficients for both COGS and SG&A are not statistically significant.

Combining the results from Tables 9 and 10 in terms of the number of segments in which a firm operates clearly indicates that diversification allows firms to hedge against the contagion effect – while firms that work in many segments are less positively affected by good news announcements, they are also less negatively affect by negative contagion effects. This seems logical if we consider information transfers to reveal news about firms with similar portfolios of investments.

In terms of the magnitudes of the effects (based on the benchmark model), even after controlling for clustering, being in the top quartile of the size distribution yields a negative average CAR of -0.88% and this decrease is statistically significant at 5%. Differently, firms at the bottom quartile see positive average CARs, although the effect is not statistically significant. Similarly, being in the top quartile of the sales growth distribution implies a negative average CAR of -1.09% and this effect is statistically significant at 5%, while there is no effect at the bottom quartile. Finally, firms that operate in three or fewer segments experience negative CARs of average magnitude -0.359%, while firms that operate in more than three segments have CARs that are not statistically different from zero. However, the difference in CARs across firms that operate in different number of segments is not statistically different from zero.

Considering the magnitude of the effect of announcements on competitors in the low concentration and technology sectors, we observe that the effect for firms in the top quartile of sales growth is even stronger than before – -1.16% and -1.29% in the 3-day CAR, respectively – and statistically significant at 5%. Moreover, the differences in the magnitude of the effects on firms in and out of the top quartile are also statistically significant at 5% in both cases. The result for firms with 3 or more segments is similar to the one in the benchmark case in terms of magnitude – -0.38% and -0.40% in low concentration and technology industries, respectively – but no longer statistically significant.

5.3 Robustness Checks on the Fixed Effects Models

In this subsection, we quickly overview some robustness checks that we did in order to verify the strength of our results. First, in Table 11 we implement the alternative approach to breaking down the sample across good and bad news announcements. As discussed in Section 4, we introduce interactions of layoff and firm characteristics. As we can clearly see in the table, all our results remain. In fact, due to the gain in sample size, our results become even a bit stronger.

Tables 12, 13, and 14 present three more robustness checks of our results. Table 12 focuses on the subsample of announcements in which the stock reaction is statistically different from zero at the 5% level in a two-tail t-test. The idea here is to focus on announcements that have a strong market reaction, reducing the noise in our sample due to announcements that are not considered as particularly newsworthy by investors. As we can see in Table 12, our results on R&D investment, market-to-book, and sales growth are preserved, while the results on size are not robust.[23] Similarly, Table 13 focuses on the subsample of competitors that are currently members of the S&P 500 index. Even though the sample size is reduced significantly, our results on sales growth and investment in R&D are still quite robust. Finally, in Table 14 we replicate the analysis from Tables 8 and 9 with the subsample of manufacturing firms. As expected, results are qualitatively the same.

[23]Even using the interactions of size with + Announcer CAR and − Announcer CAR generated no result

5.4 Random Effects

Next, we consider the possibility that the unobserved characteristics of the event are not correlated to the individual firm characteristics as described in Section 4. If this is true, a random effects model would be more suited for our estimation. We not only present our results, but also test this hypothesis two ways. First, we present a test proposed by Wooldridge (2010) which uses an auxiliary regression that extends the Hausmann test for the case in which the random effects model is not fully efficient. Second, we use the Generalized Least Squares (GLS) transformation using $\lambda = 1 - \sqrt{\frac{\sigma_u^2}{(\sigma_u^2 + T * \sigma_{c_e vent}^2)}}$, where $\sigma_{c_e vent}$ 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 model. If, however, $\lambda \approx 1$, then the data is best modeled through a fixed effects estimation. As we see in Test A in the Appendix, the auxiliary regression test indicates that a random effects model is better suited, while λ is approximately zero, indicating that the random effects model is closer to a pooled OLS than to a fixed effects model. Finally, in order to evaluate the significance of the event-specific variables, we run a Breusch and Pagan (1980) test. The result, presented in Test B in the Appendix, rejects that a pooled OLS test is better suited than the random effects model. Taken together, these tests indicate that a random effects model is the best suited in our case.

We present the results of the random effects estimation in Table 15. One of the main benefits of a random effects model is that we can obtain estimates for the impact of variables that are constant within events. Results for the competitors variables are similar to the ones presented for the fixed effects estimations, corroborating our previous results. In terms of the announcer-specific variables, we observe that many variables are not relevant – so we decided to omit them from the table. From the significant coefficients, we see a positive impact of announcer's size and profitability in the bad news case, as well as a negative effect of profitability in the good news case. These results seem to indicate the presence of competitive effects at some degree. For example, in the bad news case, we can imagine that if a big and profitable firm is cutting down workers, it may be facing some structural problems that it is trying to sort out before it impacts profitability. A similar argument can made for the negative impact of announcer's profitability in the good news case. However, the effects of these variables is small enough, that the overall CAR, once considering the impact of the random effects, is still statistically insignificant even for firms at the top quartile of Announcer ROA in the case of bad news. We have similar results for announcer's size in the bad news case and announcer's profitability in the good news case. In terms of the layoff characteristics, the only important result comes from the fact that announcer's CAR has a positive and significant coefficient, indicating again a pressure towards announcer and competitors to have stock price reactions in the same direction, which corroborates the idea that contagion effects dominate.

6 Portfolio Approaches

6.1 Between Effects Regressions

In this section, we present the results of a between effects regression framework, as presented by Goldman et al. (2012). This framework allows us to test event-level implications while suppressing all rival firm variation within an event. In this sense, the only variation in this model is in average rival characteristics across events. In particular, this model considers an equally-weighted portfolio of competitors, i.e., both the dependent variable and independent variables are event-level averages. In this sense, we only have one observation per event.

Table 16 presents our results. While we see a few event-level characteristics of the rivals as statistically significant, their economic magnitude are rather small. In this sense, average rival characteristics across events are uninformative, i.e., most of the differences in rivals' reactions are differences across firms within any given event. Consequently, the results in Table 16 corroborate the patterns observed in Figures 1.B and 2, that showed a wide variation of competitors' reactions within event.

6.2 Value-Weighted Portfolios of Competitors

In this section, we follow Lang and Stultz (1992) and implement a weighted least squares with weights equal to the reciprocal of the standard deviation of the market model residual for the industry portfolios. In this case, the value-weighted portfolios are created based on the one-year lagged market value for the competitors. The interpretations for the results should be similar to the ones of the between effects regressions, while the estimates may be more precise.

Our results are presented in Table 17. Results are similar to the ones obtained in Table 16 and the results for the competitor's characteristics are even less statistically significant. We interpret these aggregate results as an indication that most of the variability in the competitor's reactions to layoff announcements is seen across competitors within the same event instead of across events (and industries).

6.3 Other Robustness Checks

Our results are robust to different event windows – not only $[-1, +1]$ but also $[-1, +2]$, $[-2, +2]$, $[-5, +5]$, among others. We also repeated our analysis for positive and negative announcer CARs, eliminating the deciles around the mean (5th. and 6th.) as well as announcements that have a reaction too close to zero. All our results are robust to these changes. In order to save space, we omitted these tables. However, they are available upon request. In terms of firm and industry characteristics, we studied the impact of a competitor having characteristics that makes it a likely future announcer as well as a candidate for forced delisting and bankruptcy. These variables are not statistically significant and their inclusion do not affect our results, therefore we decided to omit them from the analysis.

7 Conclusion

In this paper, we examine the impact of mass layoff announcements on the announcer's industry competitors. We show that on average the contagion effect dominates the competitive effect. Consequently, competitors' stock market reaction goes in the same direction as the announcer's reaction. Moreover, competitors characteristics moderate the information transfer between peers, and this moderating effect is conditional on whether the layoff is positive or negative news for the announcer. In particular, our results point towards mass layoffs predominantly conveying news about the medium to long-term prospects of the industry, which manifests in a strong contagion effect for competitors whose value is driven by growth prospects.

In particular, we show that competitors' sales growth, size, number of segments, and R&D investment have a clear impact on the firm's stock price reaction. However, their effects differ in terms of the informational content of the layoff, as well as the characteristics of the industry. In particular, R&D investments have a positive impact on competitor's CAR when the layoff is seen as good announcer news, specially in low concentration and technology industries. This result indicates that R&D is an important factor when unexpected news highlights new growth opportunities are present in highly competitive industries where technological breakthroughs are an important component of the business model. Differently, sales growth have a negative impact on competitor's CAR predominantly during announcer bad news events. This association is quite strong in highly competitive industries.

Finally, we show that methodologies that focus only on the event-level variations, averaging across competitors' characteristics within events, are less suited to capture the variation of stock price reaction across competitors. We show that most of the differences in competitors' reactions to layoff announcements are differences across firms within a given event. Due to the fact that the variation of competitors' reaction to layoff announcements within a given event has been increasing over time, we expect the across-events methodologies to become even less informative for future projects.

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Appendix
Test A: 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 Market-to-Book	-0.033
	(0.227)
Mean Sales Growth	-0.088
	(1.514)
Mean R&D	-0.484
	(0.707)
Mean log(Total Assets)	0.079
	(0.274)
Mean Cash Holdings	1.534
	(2.789)
Mean (No. of Employees)	-0.011
	(0.019)
Mean RoA	4.160
	(4.302)
Mean COGS	5.188*
	(2.900)
Mean SG&A	6.463**
	(2.981)
Additional Controls	**YES**
Competitor Variables	**YES**
Announcer Variables	**YES**
N	27,379
F statistic	1.72
Adj. R^2	0.01

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

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

$$F(14, 675) = 0.95$$
$$Prob > F = 0.5035$$

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

$$\chi^2 = 11.64$$

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

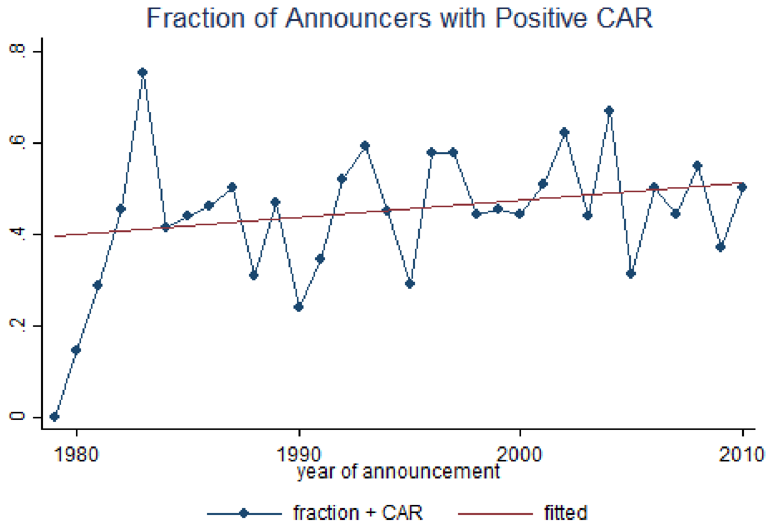

Figure 1.A This figure shows the fraction of announcers with positive CAR[-1,+1] for every year in our sample of 676 announcements.

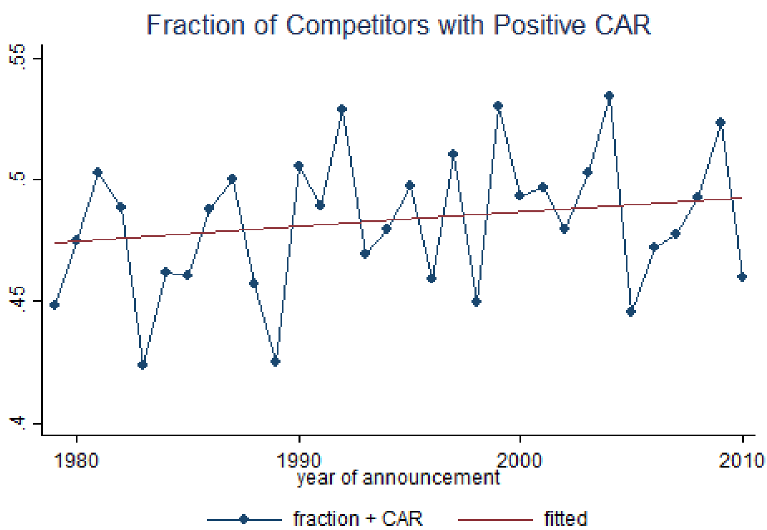

Figure 1.B This figure shows the fraction of competitors with positive CAR[-1,+1] for every year in our sample of 676 announcements.

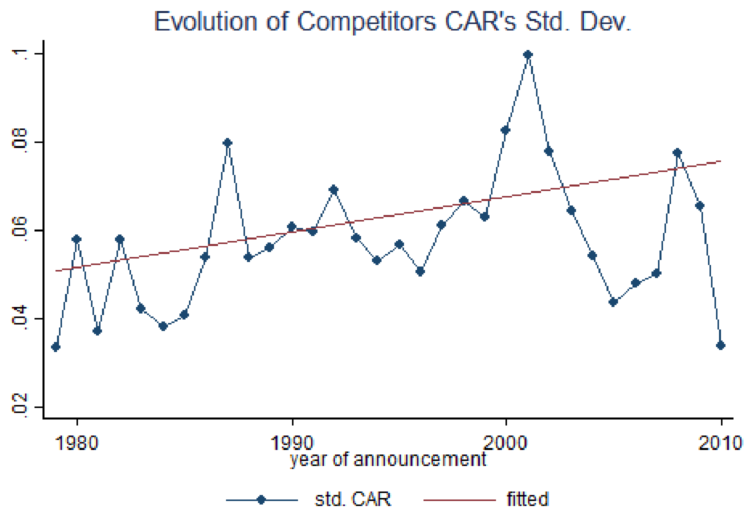

Figure 2 This figure shows the average within-event standard deviation of competitors' CAR[-1,+1] for every year in our sample of 676 announcements.

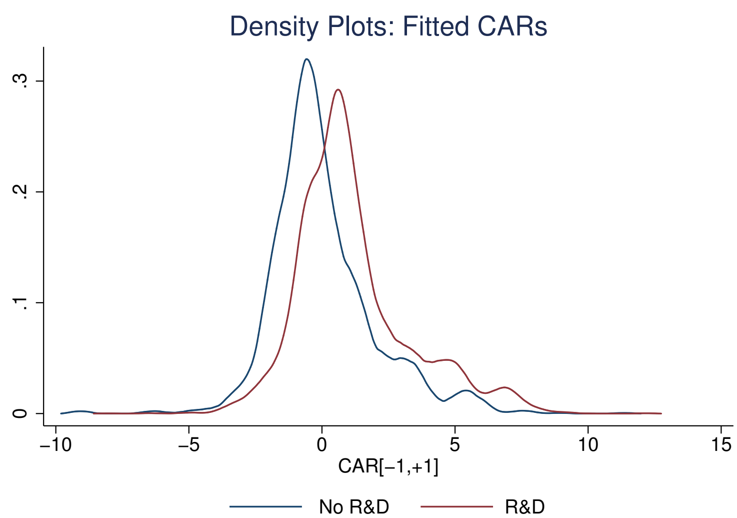

Figure 3 This figure shows the univariate kernel density estimation for competitors' CAR[-1,+1], divided between announcers with positive or zero R&D expenses for our sample of 676 announcements. We assume Epanechnikov kernel functions.

Table 1: Expected effects of Competitor's characteristics on CAR due to Announcer's mass layoff

This table depicts the potential impacts of variables for a contagion effect and a competitive effect. Variable definitions are outlined in Table 3

Variable	**Positive Announcer Shock**		**Negative Announcer Shock**	
	contagion effect	**competitive effect**	**contagion effect**	**competitive effect**
log(Total Assets)	+/-	+	+/-	+
Age	-	0	-	0
Leverage	+/-	-	-	+/-
Book-to-Market	+/-	-	+/-	+/-
Gross Margin	+/-	+/-	-	+/-
Cash Holdings	+	+	+	+
Sales Growth	+	+	+/-	+
Number of Employees	+	+	+/-	+/-
R&D	+	+	+/-	+

Table 2: Sample Construction

A. Competitors

	Firms	Observations
Firms listed in Compustat (1979-2010)	31,654	329,683
Non-US Firms	-5,662	-52,410
Financial firms (SIC 6000 - 6799)	-6,666	-64,999
Utility Firms (SIC 4610 - 4991)	-1,631	-21,738
Obs. missing relevant variables	-1,685	-35,867
Firms with total assets and sales below US$ 1 million	-1,487	-20,254
Negative shareholders' equity	-486	-11,064
Matched to Eventus	-8,572	-31,119
Announcements with likely mistakes in the data	-121	-4,633
Obs. not in AMEX, NYSE, and Nasdaq	-1,839	-21,834
Competitors with incomplete announcer information	-26	-4,119
Layoffs within 5 days of other announcements or 100 days from previous layoffs	-258	-30,148
Announcements by currently not in S&P500	-94	-3888
Layoff size less than 50 workers	-8	-231
Total	**3,127**	**27,379**

B. Announcers

	Announcers	Announcements
Announcers: Total (1979-2010)	502	2,367
Obs. missing relevant variables	-80	-586
Matched to Eventus	-53	-338
Announcements with likely mistakes in the data	-8	-61
Obs. not in AMEX, NYSE, and Nasdaq	-18	-59
Eliminating announcers without competitors	-3	-10
Layoffs within 5 days of other announcements or 100 days from previous layoffs	-51	-546
Announcements by currently not in S&P500	-36	-81
Layoff size less than 50 workers	-2	-10
Total	**251**	**676**

Table 3: Variable Definitions

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

Dependent Variable	**Description**
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 mode
Independent Variables	
S&P 500	Indicator variable that equals 1 if the firm is listed in the S&P 500 index at the time of the layoff announcement
Market-to-Book	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 2%.
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
R&D	Dummy variable that indicates that the firm has positive R&D Expenses. Based on Compustat variable xrd
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 2%.
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 2%.
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 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 2%.
No. of Employees	Total number of employees of the firm in thousands. Compustat emp. Measured at time t-1. Final value is winsorized at 2%.

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%.
No. of Segments	Measured as the number of segments reported by the firm in Compustat's Segment Database.
COGS	Cost of Goods sold scaled by sales. Based on Compustat cogs/sales. Measured at time t-1. Final value is winsorized at 2%.
SG&A	Selling, General & Administrative Expenses, scaled by sales. Based on Compustat sga/sales . Measured at t-1. Final value is winsorized at 2%.
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 4 - Descriptives

The sample is 676 layoff announcements by S&P500 firms in the period 1979-2010 and information about their public 3-digit SIC competitors. It includes information about 3,127 unique competitors and 251 unique announcers. All variables are described in Table 3. Panel A describes the summary statistics for announcer and layoff characteristics in three sub-cases - all announcements, good news, i.e., the cases in which announcer's stock return reaction has a positive 3-day cumulative abnormal return (CAR), and bad news, i.e., the cases in which announcer's stock return reaction has a negative 3-day CAR. Panel B presents the summary statistics for the 3,127 competitors in the sample, also for the three sub-cases presented above. Panel C focuses on the 608 unique competitors that are currently member of the S&P 500 index. The reported levels of significance at the mean t-tests, *, **, and ***, correspond to 10, 5, and 1% statistical significance levels at a two-tail test. While presented results are not clustered on events, clustered results are qualitatively the same. Finally, Panel D shows how the 676 layoff announcements are divided across industrial sectors, as well as how their characteristics in terms of number of displaced workers, fraction of the firms' labor force, and number of distinct announcer, and competitors per announcement vary across industries.

Panel A - Announcers and Layoffs

All Announcements

Variable	Mean	Median	St. Dev.	Min	Max	N
CAR$[-1,+1]$	-0.30	-0.29	5.21	-28.95	26.81	676
Market-to-book	2.79	2.02	2.51	0.30	13.48	676
Sales Growth	0.04	0.02	0.20	-0.42	1.37	676
R&D	0.84	1.00	0.36	0.00	1.00	676
Leverage	0.34	0.33	0.19	0.00	0.87	676
log(Total Assets)	8.72	8.80	0.90	5.89	9.70	676
Age	35.62	37.00	12.74	3.00	51.00	676
Cash Holdings	0.12	0.06	0.16	0.00	1.00	676
No. of Employees	43.27	36.31	30.75	0.84	89.00	676
RoA	0.15	0.15	0.08	-0.26	0.36	676
No. of Segments	5.01	4.00	3.09	1.00	16.00	676
COGS	0.63	0.67	0.19	0.17	1.02	676
SG&A	0.23	0.20	0.15	0.03	1.25	676
Layoff Size	1,562	675	2,587	50	24,600	676
Layoff Ratio	0.05	0.03	0.06	0.00	0.50	676

Good News Case

Variable	Mean	Median	St. Dev.	Min	Max	N
CAR$[-1,+1]$	3.48	2.33	3.95	0.00	26.81	308
Market-to-book	2.76	2.05	2.48	0.30	13.48	308
Sales Growth	0.03	0.01	0.18	-0.42	0.83	308
R&D	0.84	1.00	0.37	0.00	1.00	308
Leverage	0.35	0.34	0.19	0.00	0.87	308
log(Total Assets)	8.80	8.95	0.89	5.89	9.70	308
Age	37.03	39.00	12.44	5.00	51.00	308
Cash Holdings	0.12	0.06	0.16	0.00	1.00	308
No. of Employees	46.05	40.20	31.33	0.84	89.00	308
RoA	0.14	0.14	0.07	-0.20	0.36	308
No. of Segments	5.13	4.00	3.14	1	16	308
COGS	0.64	0.67	0.18	0.17	0.98	308
SG&A	0.22	0.19	0.14	0.03	0.68	308
Layoff Size	1,818	750	2,799	52	24,600	308
Layoff Ratio	0.05	0.03	0.06	0.00	0.50	308

Bad News Case

Variable	Mean	Median	St. Dev.	Min	Max	N
CAR$[-1,+1]$	-3.46	-2.21	3.85	-28.95	-0.00	368
Market-to-book	2.81	2.01	2.54	0.37	13.48	368
Sales Growth	0.05	0.02	0.22	-0.42	1.37	368
R&D	0.85	1.00	0.36	0	1	368
Leverage	0.33	0.33	0.19	0.00	0.87	368
log(Total Assets)	8.65	8.68	0.91	6.11	9.70	368
Age	34.45	36	12.89	3	51	368
Cash Holdings	0.12	0.06	0.15	0.00	0.91	368
No. of Employees	40.94	31.50	30.11	0.86	89.00	368
RoA	0.15	0.15	0.08	-0.26	0.36	368
No. of Segments	4.90	4.00	3.05	1	16	368
COGS	0.61	0.65	0.19	0.17	1.02	368
SG&A	0.24	0.20	0.16	0.03	1.25	368
Layoff Size	1,347	600	2,378	50	20,000	368
Layoff Ratio	0.05	0.03	0.05	0.00	0.33	368

Panel B - Competitors

All Announcements

Variable	Mean	Median	St. Dev.	Min	Max	N
CAR$[-1,+1]$	0.23	-0.12	7.41	-60.40	181.12	27,379
Market-to-book	3.05	2.11	2.79	0.30	13.48	27,379
Sales Growth	0.17	0.08	0.38	-0.42	1.37	27,379
R&D	0.82	1.00	0.39	0	1	27,379
Leverage	0.18	0.09	0.21	0.00	0.87	27,379
log(Total Assets)	5.27	5.01	1.82	1.30	9.70	27,379
Age	14.98	11.00	11.70	2.00	51.00	27,379
Cash Holdings	0.32	0.23	0.29	0.00	1.00	27,379
No. of Employees	5.28	0.69	14.48	0.04	89.00	27,379
RoA	0.08	0.11	0.16	-0.41	0.36	27,379
No. of Segments	2.50	2.00	1.56	1	19	27,379
COGS	0.52	0.53	0.22	0.17	1.11	27,379
SG&A	0.43	0.35	0.30	0.03	1.25	27,379

Competitors - Good News Case

Variable	Mean	Median	St. Dev.	Min	Max	N
CAR$[-1,+1]$	0.95	0.27	7.94	-52.64	181.12	12,083
Market-to-book	2.91	2.03	2.68	0.30	13.48	12,083
Sales Growth	0.17	0.08	0.39	-0.42	1.37	12,083
R&D	0.82	1.00	0.39	0.00	1.00	12,083
Leverage	0.18	0.09	0.21	0.00	0.87	12,083
log(Total Assets)	5.29	5.03	1.81	1.30	9.70	12,083
Age	15.18	11	11.92	2	51	12,083
Cash Holdings	0.31	0.23	0.29	0.00	1.00	12,083
No. of Employees	5.33	0.69	14.52	0.04	89.00	12,083
RoA	0.07	0.10	0.16	-0.41	0.36	12,083
No. of Segments	2.50	2.00	1.57	1.00	15.00	12,083
COGS	0.53	0.54	0.22	0.17	1.11	12,083
SG&A	0.43	0.35	0.31	0.03	1.25	12,083

Competitors - Bad News Case

Variable	Mean	Median	St. Dev.	Min	Max	N
CAR$[-1,+1]$	-0.33	-0.42	6.91	-60.40	149.58	15,296
Market-to-book	3.16	2.19	2.88	0.30	13.48	15,296
Sales Growth	0.17	0.09	0.38	-0.42	1.37	15,296
R&D	0.82	1.00	0.39	0	1	15,296
Leverage	0.18	0.10	0.21	0.00	0.87	15,296
log(Total Assets)	5.25	5.00	1.83	1.30	9.70	15,296
Age	14.83	11	11.52	2	51	15,296
Cash Holdings	0.32	0.23	0.29	0.00	1.00	15,296
No. of Employees	5.24	0.68	14.45	0.04	89.00	15,296
RoA	0.08	0.11	0.15	-0.41	0.36	15,296
No. of Segments	2.51	2	1.55	1	19	15,296
COGS	0.51	0.52	0.22	0.17	1.11	15,296
SG&A	0.43	0.36	0.30	0.03	1.25	15,296

Panel C - Competitors - S&P

All Announcements

Variable	Mean	Median	St. Dev.	Min	Max	t-test (Comp. - Ann.)	N
CAR$[-1,+1]$	-0.04	-0.06	4.80	-41.76	43.05	0.257	3,407
Market-to-book	3.80	2.66	3.17	0.30	13.48	1.010***	3,407
Sales Growth	0.09	0.05	0.26	-0.42	1.37	0.0454***	3,407
R&D	0.87	1.00	0.34	0	1	0.0256	3,407
Leverage	0.26	0.24	0.20	0.00	0.87	-0.0835***	3,407
log(Total Assets)	8.45	8.47	1.02	5.02	9.70	-0.263***	3,407
Age	28.98	31.00	14.72	2.00	51.00	-6.647***	3,407
Cash Holdings	0.22	0.13	0.24	0.00	1.00	0.100***	3,407
No. of Employees	30.58	18.59	29.16	0.62	89.00	-12.69***	3,407
RoA	0.16	0.16	0.08	-0.26	0.36	0.0123***	3,407
No. of Segments	3.78	3.00	2.57	1	19	-1.223***	3,407
COGS	0.52	0.54	0.22	0.17	1.11	-0.104***	3,407
SG&A	0.30	0.27	0.18	0.03	1.25	0.0664***	3,407

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Good News Case

Variable	Mean	Median	St. Dev.	Min	Max	t-test (Comp. - Ann.)	N
CAR$[-1,+1]$	1.06	0.58	4.83	-21.97	43.05	-2.424***	1,474
Market-to-book	3.58	2.49	3.05	0.30	13.48	0.819***	1,474
Sales Growth	0.08	0.04	0.26	-0.42	1.37	0.053***	1,474
R&D	0.87	1.00	0.34	0	1	0.031	1,474
Leverage	0.25	0.24	0.20	0.00	0.87	-0.092***	1,474
log(Total Assets)	8.47	8.48	1.00	5.24	9.70	-0.327***	1,474
Age	28.94	31	14.72	2	51	-8.092***	1,474
Cash Holdings	0.22	0.13	0.24	0.00	1.00	0.104***	1,474
No. of Employees	30.78	18.47	29.34	0.62	89.00	-15.27***	1,474
RoA	0.16	0.15	0.08	-0.26	0.36	0.012*	1,474
No. of Segments	3.83	3.00	2.62	1	15	-1.303***	1,474
COGS	0.54	0.56	0.22	0.17	1.11	-0.103***	1,474
SG&A	0.29	0.26	0.18	0.03	1.25	0.068***	1,474

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Bad News Case

Variable	Mean	Median	St. Dev.	Min	Max	t-test (Comp. - Ann.)	N
CAR[-1,+1]	-0.88	-0.53	4.61	-41.76	20.63	2.583***	1,933
Market-to-book	3.96	2.85	3.26	0.30	13.48	1.153***	1,933
Sales Growth	0.09	0.05	0.25	-0.42	1.37	0.039**	1,933
R&D	0.87	1.00	0.34	0	1	0.021	1,933
Leverage	0.26	0.25	0.21	0.00	0.87	-0.077***	1,933
log(Total Assets)	8.44	8.46	1.03	5.02	9.70	-0.209***	1,933
Age	29.01	31	14.73	2	51	-5.439***	1,933
Cash Holdings	0.22	0.13	0.24	0.00	1.00	0.098***	1,933
No. of Employees	30.42	19	29.04	0.62	89.00	-10.51***	1,933
RoA	0.16	0.16	0.08	-0.26	0.36	0.013**	1,933
No. of Segments	3.75	3	2.53	1	19	-1.152***	1,933
COGS	0.51	0.52	0.22	0.17	0.99	-0.103***	1,933
SG&A	0.31	0.28	0.18	0.03	1.15	0.064***	1,933

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel D: Layoffs per Industry – Means

Sector	Number of Layoffs	Layoff Size	Layoff Ratio	Ann.	Comp. (All)	Comp. (S&P 500)
Manufacturing	569	1,543	4.65%	193	29	5
Mining	20	583	7.28%	10	45	5
Retail Trade	31	3,163	6.27%	20	11	3
Services	52	1,270	6.66%	24	187	15
Transportation, Eletric, Gas	2	695	2.19%	2	2	.
Wholesale Trade	2	385	.99%	2	5	2

Table 5: Distribution of layoffs announcements 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	Manufacturing	Mining	Retail	Services	Transp., Eletric, Gas	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 6: Cross-correlation Table

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	
S&P 500	(1)	..													
(-1,+1) CAR	(2)	-0.02***	..												
Leverage	(3)	0.17***	-0.01**	..											
log(Total Assets)	(4)	0.68***	-0.03***	0.28***	..										
Market-to-book	(5)	0.05***	-0.00	-0.04***	-0.02***	..									
Age	(6)	0.49***	-0.02***	0.31***	0.52***	-0.16***	..								
Cash Holdings	(7)	-0.17***	0.01	-0.48***	-0.18***	0.33***	-0.39***	..							
Sales Growth	(8)	-0.10***	-0.02***	-0.11***	-0.04***	0.30***	-0.27***	0.38***	..						
No. of Employees	(9)	0.68***	-0.02***	0.24***	0.65***	-0.03***	0.54***	-0.23***	-0.11***	..					
R&D	(10)	0.06***	0.01***	-0.21***	-0.02***	0.14***	-0.04***	0.23***	0.05***	0.00	..				
RoA	(11)	0.19***	-0.03***	0.11***	0.27***	0.03***	0.22***	-0.19***	0.03***	0.16***	-0.13***	..			
No. of Segments	(12)	0.37***	-0.02***	0.27***	0.40***	-0.14***	0.49***	-0.29***	-0.12***	0.47***	-0.06***	0.13***	..		
COGS	(13)	0.03***	-0.00	0.24***	0.06***	-0.23***	0.21***	-0.27***	-0.09***	0.14***	-0.20***	-0.20***	0.25***	..	
SG&A	(14)	-0.19***	0.03***	-0.35***	-0.30***	0.21***	-0.38***	0.44***	0.12***	-0.23***	0.30***	-0.68***	-0.30***	-0.54***	..

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Probit: Announcer

This table presents the likelihood of a given firm becoming an announcer. Announcers and competitors are firms that were members of the S&P 500 index at some point in our sample period. We include all the announcers in our sample, but restrict competitors to the 1,269 unique firms were at some point in the sample period listed in the S&P 500 index that did not announce a layoff. We control for decade and industry fixed effects and bootstrap the st. errors.

	Announcer	**Announcer**	**Announcer**	**Announcer**
Market-to-Book	-0.039***	-0.040***	-0.036***	-0.037***
	(0.011)	(0.012)	(0.011)	(0.012)
Sales Growth	0.092	0.023	0.048	-0.009
	(0.102)	(0.107)	(0.102)	(0.109)
R&D	-0.007	-0.033	-0.094	-0.108
	(0.065)	(0.067)	(0.078)	(0.078)
Leverage	0.574***	0.577***	0.664***	0.671***
	(0.140)	(0.138)	(0.133)	(0.137)
log(Total Assets)	0.023	0.036	0.062**	0.072**
	(0.028)	(0.031)	(0.032)	(0.035)
Age	0.009***	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Cash Holdings	-0.254	-0.119	-0.219	-0.107
	(0.164)	(0.160)	(0.164)	(0.162)
No. of Employees	0.003***	0.003***	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
RoA	0.745*	0.406	0.716	0.420
	(0.400)	(0.432)	(0.451)	(0.472)
No. of Segments	0.021**	0.021**	0.031***	0.031***
	(0.009)	(0.009)	(0.009)	(0.010)
S&P 500	0.458***	0.459***	0.431***	0.436***
	(0.083)	(0.086)	(0.075)	(0.079)
COGS	1.243***	1.072***	0.987***	0.837***
	(0.237)	(0.236)	(0.268)	(0.282)
SG&A	1.069***	0.994***	1.197***	1.126***
	(0.266)	(0.249)	(0.322)	(0.323)
Industry Fixed Effects	NO	NO	YES	YES
Year Fixed Effects	NO	YES	NO	YES
N	6,405	6,405	6,403	6,403
Pseudo R^2	0.119	0.126	0.129	0.134

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

Table 8 - Tests for average effects

Panel A - All annoncements

Competitors' 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, Musumeci, and Poulsen (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	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.

Competitors' 2-tail tests: Parametric Statistics with bootstrapped significance levels
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, Musumeci, 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.

Days	**N**	$\overline{\textbf{CAR}}$	**Patell Z**	**Std. C.S. Z**	**Port. T.S. t**	**C.S. St. Dev. t**
(-1,+1)	676	-0.12%	-1.832$	-1.636$	-1.129	-1.21
(0,0)	676	-0.06%	-0.431	-0.36	-0.889	-0.865
(-1,+3)	676	-0.16%	-1.164	-1.083	-1.148$	-1.258
(-2,+2)	676	-0.02%	-0.384	-0.366	-0.143	-0.159
(-5,+5)	676	-0.11%	-1.084	-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.

Competitors' 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 for the Announcer

Competitors' 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, Musumeci, and Poulsen (1991). Finally, the **EGLS** presents the estimated generalized least squares test suggested by Sanders and Robins (1991).

Day	**N**	$\overline{\mathbf{AR}}$	**+ : -**	**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.

Competitors' 2-tail tests: Parametric Statistics with bootstrapped significance levels 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, Musumeci, 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)

Days	**N**	$\overline{\mathbf{CAR}}$	**Patell Z**	**Std. C.S. Z**	**Port. T.S. t**	**C.S. St. Dev. t**
(-1,+1)	308	0.44%	3.306**	2.940**	2.894***	3.123**
(0,0)	308	0.18%	2.773*	2.353**	1.980**	2.082*
(-1,+3)	308	0.48%	3.079**	2.916**	2.424***	2.736**
(-2,+2)	308	0.54%	3.156**	2.996**	2.710***	2.972***
(-5,+5)	308	0.50%	1.897$^{\$}$	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.

Competitors' 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

Competitors' 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, Musumeci, 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	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.

Competitors' 2-tail tests: Parametric Statistics with bootstrapped significance levels
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, Musumeci, 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)

Days	N	$\overline{\textbf{CAR}}$	Patell Z	Std. C.S. Z	Port. T.S. t	C.S. St. Dev. t
(-1,+1)	368	-0.60%	-5.508**	-5.147**	-3.844**	-4.264**
(0,0)	368	-0.25%	-3.121**	-2.609**	-2.780**	-2.624**
(-1,+3)	368	-0.70%	-4.395**	-4.158**	-3.480**	-3.864**
(-2,+2)	368	-0.49%	-3.408**	-3.338**	-2.419**	-2.795**
(-5,+5)	368	-0.62%	-3.205**	-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.

Competitors' 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.

Table 9: Competitors' Stock Return Reaction - Good News Case

This table reports our results from a fixed effects regression model for the good news case. In each event analyzed here, the announcers stock market reaction was positive. The dependent variable is the competitors cumulative abnormal return around a 3 day event window centered on event. Column 1 is our benchmark model that includes 12,083 competitor-event observations for 308 layoff announcements. Columns 2 and 3 report our results for competitors in highly and lowly concentrated industries. Industry concentration is measure based on the Herfindahl-Hirschman Index (HHI). High concentration industries have HHI above the median HHI for the sample and low concentration industries report HHI below the sample median. Columns 4 and 5 report our results for competitors in technology and non-technology industries. Column 6 reports results for competitors in large layoff events. A large layoff event is a layoff event where the layoff size is above the median layoff size for the sample. Finally, we control for event fixed effects and cluster standard errors by event.

	Benchmark	**Low HHI**	**High HHI**	**Technology**	**Non-Tech**	**Large Layoff**
Market-to-Book	0.069	0.070	0.063	0.106	-0.089	0.028
	(0.069)	(0.072)	(0.143)	(0.083)	(0.070)	(0.062)
Sales Growth	0.121	0.246	-1.330	0.093	-0.217	0.190
	(0.301)	(0.300)	(0.877)	(0.383)	(0.527)	(0.421)
R&D	1.080***	1.117***	0.788	1.369***	0.378	1.339***
	(0.271)	(0.267)	(0.654)	(0.315)	(0.343)	(0.289)
Leverage	-0.247	-0.345	0.090	0.256	-0.798	0.030
	(0.456)	(0.493)	(1.349)	(0.599)	(0.663)	(0.556)
log(Total Assets)	0.126	0.133	0.039	0.190	-0.049	0.267**
	(0.100)	(0.108)	(0.238)	(0.119)	(0.158)	(0.130)
Age	-0.007	-0.004	-0.026**	-0.002	-0.010	-0.001
	(0.008)	(0.008)	(0.012)	(0.010)	(0.009)	(0.010)
Cash Holdings	0.165	0.009	1.332	0.343	-0.774	0.328
	(0.423)	(0.448)	(1.132)	(0.452)	(1.134)	(0.549)
No. of Employees	-0.008	-0.010*	0.010	-0.021**	0.011*	-0.017**
	(0.006)	(0.006)	(0.013)	(0.009)	(0.006)	(0.008)
RoA	-1.460	-1.198	-2.283	-1.311	-1.927	0.395
	(1.311)	(1.481)	(3.803)	(1.706)	(2.530)	(1.623)
Altman's Z-score	0.022*	0.026**	-0.020	0.018	0.046**	0.014
	(0.012)	(0.013)	(0.042)	(0.014)	(0.019)	(0.017)
No. of Segments	-0.128***	-0.080	-0.312***	-0.117	-0.092**	-0.064
	(0.042)	(0.053)	(0.085)	(0.078)	(0.047)	(0.080)
S&P 500	0.249	0.181	0.691	0.410	0.129	0.075
	(0.237)	(0.279)	(0.483)	(0.354)	(0.382)	(0.355)
COGS	0.159	0.059	1.241	0.527	-0.195	2.199**
	(1.050)	(1.137)	(1.629)	(1.371)	(1.326)	(0.989)
SG&A	0.166	0.424	-2.291	0.496	-0.632	1.723*
	(0.929)	(0.999)	(1.758)	(1.146)	(1.195)	(0.939)
Constant	-0.553	-0.856	1.202	-1.752	1.795	-3.667***
	(1.056)	(1.104)	(2.312)	(1.334)	(1.968)	(1.085)
Events	308	163	145	87	221	132
N	12,083	10,412	1,671	8,839	3,244	6,747
Adj. R^2	0.0484	0.0558	0.0122	0.0633	0.0033	0.0418

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

Table 10: Competitors' Stock Return Reaction - Bad News Case

This table reports our results from a fixed effects regression model for the good news case. In each event analyzed here, the announcer's stock market reaction was negative. The dependent variable is the competitors' cumulative abnormal return around a 3 day event window centered on event. Column 1 reports our benchmark model that includes 15,296 competitor-event observations for 368 layoff announcements. Columns 2 and 3 report our results for competitors in highly and lowly concentrated industries. Industry concentration is measure based on the Herfindahl-Hirschman Index (HHI). High concentration industries have HHI above the median HHI for the sample and low concentration industries report HHI below the sample median. Columns 4 and 5 report our results for competitors in technology and non-technology industries. Column 6 reports results for competitors in large layoff events. A large layoff event is a layoff event where the layoff size is above the median layoff size for the sample. Finally, we control for event fixed effects and cluster standard errors by event.

	Benchmark	Low HHI	High HHI	Technology	Non-Tech	Large Layoff
Market-to-Book	-0.069	-0.073*	0.023	-0.062	-0.089*	-0.084
	(0.043)	(0.044)	(0.122)	(0.053)	(0.053)	(0.056)
Sales Growth	-0.737***	-0.753***	-0.619	-0.936***	0.077	-0.950***
	(0.251)	(0.259)	(0.577)	(0.277)	(0.393)	(0.320)
R&D	-0.099	-0.024	-0.470	-0.103	0.059	-0.112
	(0.210)	(0.248)	(0.483)	(0.266)	(0.232)	(0.287)
Leverage	0.156	0.113	0.717	0.257	-0.037	0.376
	(0.367)	(0.424)	(0.984)	(0.509)	(0.562)	(0.589)
log(Total Assets)	-0.241***	-0.230***	-0.293**	-0.263***	-0.156	-0.284***
	(0.070)	(0.076)	(0.148)	(0.078)	(0.117)	(0.094)
Age	0.004	0.002	0.020*	0.003	0.006	0.004
	(0.006)	(0.007)	(0.012)	(0.009)	(0.009)	(0.009)
Cash Holdings	-0.507*	-0.630*	1.315	-0.694**	0.840	-0.388
	(0.296)	(0.322)	(1.124)	(0.344)	(0.722)	(0.416)
No. of Employees	0.006	0.004	0.016*	0.010	-0.001	0.007
	(0.005)	(0.006)	(0.009)	(0.008)	(0.006)	(0.007)
RoA	0.188	-0.138	2.725	0.088	1.210	-0.766
	(0.920)	(0.964)	(3.396)	(1.238)	(1.246)	(1.196)
Altman's Z-score	-0.003	-0.002	-0.020	-0.004	0.002	-0.024
	(0.015)	(0.015)	(0.052)	(0.018)	(0.019)	(0.017)
No. of Segments	0.080**	0.081*	0.084	0.132**	0.017	0.094*
	(0.037)	(0.042)	(0.073)	(0.055)	(0.042)	(0.055)
S&P 500	-0.016	0.062	-0.631	-0.069	0.061	0.180
	(0.238)	(0.266)	(0.444)	(0.347)	(0.292)	(0.365)
COGS	0.455	0.478	0.399	0.316	0.954	0.488
	(0.600)	(0.605)	(3.292)	(0.808)	(0.807)	(0.778)
SG&A	0.233	0.114	0.759	0.292	0.169	-0.026
	(0.625)	(0.601)	(3.666)	(0.786)	(0.970)	(0.753)
Constant	0.869	0.933	-0.066	1.033	-0.238	1.304
	(0.674)	(0.694)	(3.579)	(0.854)	(1.041)	(0.813)
Events	368	195	173	103	265	159
N	15,296	13,255	2,041	10,834	4,462	9,188
Adj. R^2	0.0487	0.0560	0.0021	0.0604	0.0247	0.0638

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

Table 11: Competitors' Stock Return Reaction
Alternative Approach

This table reports our results from a fixed effects regression model with interaction terms.The dependent variable is the competitors' cumulative abnormal return around a 3 day event window centered on event. Column 1 is our benchmark model that includes 27,379 competitor-event observations for 676 layoff announcements. Columns 2 reports our results for competitors in competitive industries. Industry concentration is measure based on the Herfindahl-Hirschman Index (HHI). High concentration industries have HHI above the median HHI for the sample and low concentration industries report HHI below the sample median. Columns 3 reports our results for competitors in technology industries. We control for event fixed effects and cluster standard errors by event.

	Benchmark	**Low HHI**	**Technology**
+ Ann. CAR × Comp. Market-to-Book	0.080	0.085	0.116
	(0.067)	(0.073)	(0.084)
- Ann. CAR × Comp. Market-to-Book	-0.077**	-0.084*	-0.070
	(0.037)	(0.044)	(0.049)
+ Ann. CAR × Comp. Sales Growth	0.271	0.406	0.287
	(0.330)	(0.345)	(0.371)
- Ann. CAR × Comp. Sales Growth	-0.862***	-0.878***	-1.112***
	(0.221)	(0.249)	(0.262)
+ Ann. CAR × Comp. R&D	1.168***	1.251***	1.492***
	(0.256)	(0.272)	(0.331)
- Ann. CAR × Comp. R&D	-0.173	-0.134	-0.206
	(0.192)	(0.235)	(0.262)
+ Ann. CAR × Comp. log(Total Assets)	0.066	0.069	0.120
	(0.076)	(0.082)	(0.100)
- Ann. CAR × Comp. log(Total Assets)	-0.192***	-0.179***	-0.205***
	(0.058)	(0.064)	(0.071)
+ Ann. CAR × Comp. No. of Segments	-0.163***	-0.122**	-0.168**
	(0.047)	(0.055)	(0.080)
- Ann. CAR × Comp. No. of Segments	0.108***	0.114***	0.172***
	(0.037)	(0.042)	(0.062)
Leverage	-0.043	-0.117	0.238
	(0.314)	(0.333)	(0.377)
Cash Holdings	-0.199	-0.338	-0.200
	(0.274)	(0.257)	(0.292)
No. of Employees	-0.000	-0.002	-0.003
	(0.004)	(0.004)	(0.006)
RoA	-0.521	-0.586	-0.508
	(0.815)	(0.847)	(0.992)
Constant	0.265	0.181	-0.243
	(0.653)	(0.670)	(0.834)
Events	676	358	190
N	27,379	23,667	19,673
Adj. R^2	0.0551	0.0625	0.0698

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

Table 12: Competitors' Stock Return Reaction
Only st. signif. announcements

This table reports our results from a fixed effects regression model with interaction terms. Our sample is restricted to announcements in which the announcer's stock price reaction is statistically different from zero. The dependent variable is the competitors' cumulative abnormal return around a 3 day event window centered on event. Column 1 is our benchmark model that includes 3,186 competitor-event observations for 89 layoff announcements. Columns 2 reports our results for competitors in competitive industries. Industry concentration is measure based on the Herfindahl-Hirschman Index (HHI). High concentration industries have HHI above the median HHI for the sample and low concentration industries report HHI below the sample median. Columns 3 reports our results for competitors in technology industries. Column 4 reports results for competitors in large layoff events. A large layoff event is a layoff event where the layoff size is above the median layoff size for the sample. Finally, we control for event fixed effects and cluster standard errors by event.

	Benchmark	**Low HHI**	**Technology**	**Large Layoff**
+ Ann. CAR × Comp. Market-to-Book	0.234**	0.257**	0.249*	0.221
	(0.119)	(0.117)	(0.133)	(0.140)
- Ann. CAR × Comp. Market-to-Book	-0.094	-0.173	-0.140	-0.152
	(0.108)	(0.127)	(0.173)	(0.114)
+ Ann. CAR × Comp. Sales Growth	1.191	1.235*	1.258*	1.631***
	(0.753)	(0.652)	(0.683)	(0.575)
- Ann. CAR × Comp. Sales Growth	-2.957***	-3.107**	-3.926**	-3.263***
	(1.036)	(1.274)	(1.549)	(1.188)
+ Ann. CAR × Comp. R&D	1.604*	1.926**	2.207**	1.771**
	(0.830)	(0.783)	(0.896)	(0.694)
- Ann. CAR × Comp. R&D	-0.280	-0.463	-1.057	-0.583
	(0.574)	(0.803)	(1.348)	(0.632)
Leverage	-0.875	-1.017	-0.195	-0.432
	(1.101)	(1.204)	(1.455)	(1.306)
log(Total Assets)	0.019	0.140	0.215	0.148
	(0.216)	(0.232)	(0.256)	(0.249)
Cash Holdings	0.123	0.191	0.476	0.306
	(0.963)	(1.021)	(1.054)	(1.024)
RoA	-0.452	-1.145	-1.635	-1.905
	(2.551)	(2.794)	(3.657)	(3.090)
Controls	YES	YES	YES	YES
Events	89	42	24	58
N	3,186	2,654	2,214	2,443
Adj. R^2	0.1081	0.1232	0.1180	0.1250

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

Table 13: Competitors' Stock Return Reaction
Only S&P 500 competitors

This table reports our results from a fixed effects regression model with interaction terms. Our sample is restricted to only competitors that are members of the S&P 500 index at the moment of the announcement. The dependent variable is the competitors' cumulative abnormal return around a 3 day event window centered on event. Column 1 is our benchmark model that includes 3,407 competitor-event observations for 608 layoff announcements. Columns 2 reports our results for competitors in competitive industries. Industry concentration is measure based on the Herfindahl-Hirschman Index (HHI). High concentration industries have HHI above the median HHI for the sample and low concentration industries report HHI below the sample median. Columns 3 reports our results for competitors in technology industries. Column 4 reports results for competitors in large layoff events. A large layoff event is a layoff event where the layoff size is above the median layoff size for the sample. Finally, we control for event fixed effects and cluster standard errors by event.

	Benchmark	**Low HHI**	**Technology**	**Large Layoff**
+ Ann. CAR × Comp. Market-to-Book	-0.096	-0.110	-0.152	-0.190*
	(0.088)	(0.095)	(0.118)	(0.113)
- Ann. CAR × Comp. Market-to-Book	-0.009	-0.003	-0.002	-0.065
	(0.078)	(0.082)	(0.108)	(0.097)
+ Ann. CAR × Comp. Sales Growth	0.912	0.951	1.138	1.889*
	(1.183)	(1.162)	(1.326)	(1.045)
- Ann. CAR × Comp. Sales Growth	-2.747***	-3.007***	-3.398***	-3.706***
	(0.802)	(0.853)	(0.987)	(1.052)
+ Ann. CAR × Comp. R&D	1.597***	1.908***	2.708***	1.871***
	(0.412)	(0.475)	(0.671)	(0.565)
- Ann. CAR × Comp. R&D	-0.582	-0.430	-0.347	-0.805
	(0.411)	(0.433)	(0.743)	(0.597)
Leverage	0.884	0.616	1.167	0.926
	(0.574)	(0.611)	(0.826)	(0.773)
log(Total Assets)	0.130	0.094	0.269	0.347
	(0.172)	(0.187)	(0.252)	(0.253)
Cash Holdings	-0.735	-0.935*	-1.151*	-0.454
	(0.546)	(0.548)	(0.665)	(0.724)
RoA	1.954	1.989	3.305	3.531
	(1.919)	(2.124)	(2.560)	(2.656)
Controls	YES	YES	YES	YES
Events	608	357	188	265
N	3,407	2,864	1,734	1,842
Adj. R^2	0.2439	0.2653	0.2884	0.2493

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

Table 14: Competitors' Stock Return Reaction
Manufacturing

This table reports our results from a fixed effects regression model for the subsample restricted to the manufacturing sector. Panel A presents the good news case, while Panel B presents the bad news case. Specifications in panels A and B follow the models presented in tables 9 and 10, respectively.

A. Good News Case

	Benchmark	**Low HHI**	**High HHI**	**Technology**	**Non-Tech**	**Large Layoff**
Market-to-Book	-0.024	-0.031	0.041	0.022	-0.108	-0.040
	(0.065)	(0.067)	(0.154)	(0.075)	(0.077)	(0.076)
Sales Growth	-0.300	-0.048	-1.681	-0.450	-0.121	-0.687
	(0.396)	(0.389)	(1.044)	(0.462)	(0.704)	(0.535)
R&D	0.809***	0.768***	0.931	1.561***	0.407	1.128**
	(0.283)	(0.288)	(0.725)	(0.504)	(0.353)	(0.462)
log(Total Assets)	0.051	0.045	0.048	0.088	-0.049	0.118
	(0.097)	(0.099)	(0.258)	(0.100)	(0.170)	(0.115)
Cash Holdings	0.406	0.178	1.455	0.879	-0.987	1.048
	(0.543)	(0.557)	(1.300)	(0.584)	(1.207)	(0.742)
RoA	-1.539	-0.992	-3.688	0.606	-5.754**	-0.123
	(1.558)	(1.756)	(4.442)	(1.771)	(2.879)	(2.187)
No. of Segments	-0.100**	-0.019	-0.387***	-0.037	-0.124***	-0.025
	(0.045)	(0.050)	(0.090)	(0.083)	(0.047)	(0.080)
Controls	YES	YES	YES	YES	YES	YES
Events	258	133	125	69	189	108
N	7,388	5,939	1,449	4,823	2,565	3,871
Adj. R^2	0.0382	0.0444	0.0242	0.0575	0.0051	0.0257

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

B. Bad News Case

	Benchmark	**Low HHI**	**High HHI**	**Technology**	**Non-Tech**	**Large Layoff**
Market-to-Book	-0.098***	-0.106***	0.013	-0.088**	-0.104*	-0.111**
	(0.034)	(0.036)	(0.123)	(0.043)	(0.053)	(0.048)
Sales Growth	-0.755**	-0.799**	-0.312	-1.324***	0.244	-1.238**
	(0.359)	(0.378)	(0.627)	(0.456)	(0.421)	(0.482)
R&D	-0.182	-0.034	-0.593	-0.453	0.007	-0.245
	(0.245)	(0.287)	(0.530)	(0.530)	(0.244)	(0.422)
log(Total Assets)	-0.271***	-0.241**	-0.399**	-0.369***	-0.119	-0.317**
	(0.080)	(0.094)	(0.167)	(0.111)	(0.086)	(0.125)
Cash Holdings	-0.022	-0.227	1.458	-0.430	0.741	0.635
	(0.429)	(0.459)	(1.220)	(0.511)	(0.727)	(0.594)
RoA	2.470**	2.258*	3.289	3.241*	1.423	2.168
	(1.184)	(1.360)	(4.493)	(1.885)	(1.314)	(1.708)
No. of Segments	0.077*	0.070	0.096	0.130**	0.025	0.069
	(0.042)	(0.043)	(0.072)	(0.062)	(0.045)	(0.054)
Controls	YES	YES	YES	YES	YES	YES
Events	311	159	152	77	234	128
N	9,029	7,177	1,852	5,159	3,870	4,695
Adj. R^2	0.0466	0.0569	-0.0007	0.0664	0.0216	0.0674

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

Table 15: Competitors' Stock Return Reaction
Random Effects

This table reports our results from a random effects regression model.The dependent variable is the competitors' cumulative abnormal return around a 3 day event window centered on event. Column 1 is our benchmark model that includes 27,379 competitor-event observations for 676 layoff announcements. Columns 2 reports our results for the subsample in which announcer's stock reactions were positive. Columns 3 reports our results for the subsample in which announcer's stock reactions were negative. We include all the competitor's controls presented in tables 9 and 10. We control for event fixed effects and cluster standard errors by event.

	Overall	**Good News**	**Bad News**
Market-to-Book	-0.011	0.061	-0.060
	(0.040)	(0.071)	(0.042)
Sales Growth	-0.382*	0.039	-0.783***
	(0.225)	(0.321)	(0.240)
R&D	0.368**	0.946***	-0.042
	(0.152)	(0.234)	(0.180)
log(Total Assets)	-0.080	0.157	-0.259***
	(0.063)	(0.102)	(0.069)
Cash Holdings	-0.153	0.239	-0.477
	(0.266)	(0.435)	(0.317)
RoA	-0.297	-1.537	0.448
	(0.804)	(1.422)	(0.914)
No. of Segments	0.001	-0.103**	0.078**
	(0.028)	(0.040)	(0.035)
Ann. CAR$[-1,+1]$	0.116***	0.155***	0.093*
	(0.031)	(0.030)	(0.055)
Ann. log(Total Assets)	0.203	-0.050	0.349**
	(0.134)	(0.176)	(0.176)
Ann. RoA	0.414	-6.541**	5.537**
	(1.938)	(2.617)	(2.515)
Ann. SG&A	2.277	-4.362*	6.480***
	(1.785)	(2.597)	(2.145)
Controls	YES	YES	YES
Announcer and Layoff Variables	YES	YES	YES
Events	676	308	368
N	27,379	12,083	15,296

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

Table 16: Portfolio of Competitors
Between Estimators Model

This table reports our results from a between effects regression model. The dependent variable is the equally weighted competitors' cumulative abnormal return around a 3 day event window centered on event. Both the dependent and independent variables represent an equally-weighted portfolio of competitors. That is, each variable represents an event level average. Column 1 is our benchmark model that includes 676 equally weighted competitors for 676 layoff announcements. Column 2 reports results for the good news case where the announcer's stock market reaction was positive. Column 3 reports results for the bad news case where the announcer's stock market reaction was negative. In each of the three models reported in this table, we control for announcer characteristics and decade indicator dummies.

	Overall	**Positive CAR**	**Negative CAR**
Port. Market-to-Book	-0.178	0.071	-0.257
	(0.129)	(0.222)	(0.168)
Port. Sales Growth	-1.207	-0.528	-2.017*
	(0.965)	(2.179)	(1.179)
Fraction Comp. R&D	0.473	0.694	0.177
	(0.370)	(0.566)	(0.612)
Port. log(Total Assets)	-0.068	0.248	-0.374*
	(0.127)	(0.214)	(0.192)
Port. Age	-0.008	-0.010	0.002
	(0.028)	(0.045)	(0.042)
Port. Cash Holdings	2.699**	-0.983	5.383**
	(1.298)	(3.099)	(2.312)
Port. RoA	6.918**	-2.935	11.292**
	(3.292)	(6.438)	(4.688)
Ann. CAR[-1,+1]	0.115***	0.132***	0.077*
	(0.019)	(0.033)	(0.040)
Ann. Market-to-Book	0.083	0.121	0.045
	(0.061)	(0.088)	(0.070)
Ann. Sales Growth	-1.519**	-0.646	-1.919***
	(0.595)	(0.791)	(0.723)
Controls	YES	YES	YES
Announcer & Layoff Variables	YES	YES	YES
Decade Dummies	YES	YES	YES
N	676	308	368
Adj. R^2	0.1076	0.0343	0.1208

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

Table 17: Weighted Portfolio of Competitors
Weighted Least Squares

This table reports our results from a weighted least squares regression model. The dependent variable is the value weighted competitors' cumulative abnormal return around a 3 day event window centered on event. Both the dependent and independent variables represent a value-weighted portfolio of competitors. The weights used to construct this sample are equal to the reciprocal of the standard deviation of the market model residual from the industry portfolios. Column 1 is our benchmark model that includes 676 value weighted competitors for 676 layoff announcements. Column 2 reports results for the good news case where the announcer's stock market reaction was positive. Column 3 reports results for the bad news case where the announcer's stock market reaction was negative. In each of the three models reported in this table, we control for announcer characteristics and decade indicator dummies.

	Overall	**Positive CAR**	**Negative CAR**
Port. Market-to-Book	-0.110	0.004	-0.2003*
	(0.076)	(0.101)	(0.1159)
Port. Sales Growth	-0.486	1.229	-2.3046
	(1.088)	(1.855)	(1.6224)
Fraction Comp. R&D	0.399	0.364	0.2581
	(0.469)	(0.507)	(0.7067)
log(Total Assets)	-0.188	0.145	-0.5223**
	(0.183)	(0.326)	(0.2510)
Port. Cash Holdings	3.823**	2.700	5.2179**
	(1.546)	(2.320)	(2.0773)
Port. RoA	3.834	-0.285	6.6797*
	(2.694)	(5.500)	(3.3592)
Ann. CAR[-1,+1]	0.133***	0.131**	0.1298***
	(0.027)	(0.061)	(0.0369)
Ann. Market-to-Book	0.005	-0.013	0.0005
	(0.058)	(0.082)	(0.0809)
Ann. Sales Growth	-1.292**	-0.136	-2.0762**
	(0.628)	(1.042)	(0.8538)
Ann. log(Total Assets)	0.357*	0.443	0.2502
	(0.198)	(0.270)	(0.2367)
Ann. No. of Employees	-0.012**	-0.013*	-0.0094
	(0.005)	(0.007)	(0.0058)
Controls	YES	YES	YES
Announcer & Layoff Variables	YES	YES	YES
Decade Dummies	YES	YES	YES
Industry Clusters	83	65	70
N	676	308	368
F statistic	4.39	2.55	6.28
Adj. R^2	0.0899	-0.0063	0.1172

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