Essays on Labor and Finance

by

Bharadwaj Kannan

B.A. Honors, Delhi University, 2008

M.A., Christ University, 2010

A thesis submitted to the

Faculty of the Graduate School of the

University of Colorado in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

Department of Finance

2016

This thesis entitled:
Essays on Labor and Finance
written by Bharadwaj Kannan
has been approved for the Department of Finance

Associate Prof. Edward Van Wesep

Assistant Prof. J.Anthony Cookson

Date ____________________

The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

Kannan, Bharadwaj (Ph.D., Finance)

Essays on Labor and Finance

Thesis directed by Associate Prof. Edward Van Wesep

The first chapter presents evidence showing that layoff announcements mostly contain medium and long-run industry-wide news. That is, competitors stock price reactions are positively correlated with the announcer's return. This contagion effect is stronger for competitors whose values depend on growth opportunities. In particular, when a layoff announcement induces positive stock returns to the announcer, competitors with positive R&D see a 1.15% increase in their returns. This effect is stronger in highly competitive technology industries, indicating that the layoff announcements signal new growth opportunities. Conversely, when a layoff announcement induces negative stock returns to the announcer, competitors with high sales growth see a reduction of 1.09% in returns, implying that industry prospects are deteriorating. Our findings suggest that investors perceive layoffs as changes in growth options rather than changes in competitive environment.

The second chapter shows that contrary to popular belief, layoff announcements do not always lead to reduced employment. Using hand-collected data on layoff announcements for S&P 500 firms, I show that 32% of layoffs announced do not lead to employment downsizing. While the market, in the short run, does not react differently to announcements that do and do not lead to downsizing, firms exhibit significantly higher buy-and-hold abnormal returns in the following 300 days when their announcement leads to downsizing. I create a real-time index to predict the probability of a layoff leading to employment shrinkage and show that a simple long-short strategy based on this index will generate abnormal returns of 9.5% – 10.8%. Abnormal returns are strongest in high union coverage industries implying that when firms successfully bargain with workers to downsize, they benefit the most. I find that firms use poor performance and high leverage as sources of commitment to bargaining. Overall, my results suggest that layoff decisions, depending on their type, have important implications for long term performance and corporate policy.

Acknowledgements

I am greatly indebted to my advisor, Roberto Pinheiro, for outstanding guidance. His insight and carefully placed criticism has always pushed me to work harder. Roberto has been a great sounding board and a strong source of support through the ups and downs of my PhD program.

I would also like to thank my co-chair, Edward Van Wesep. Ed's constructive feedback has greatly improved the qualtiy of my work. He has also tried to instill in me the ability to pitch ideas clearly for which I will be forever grateful.

I am also grateful to my committee members: Mattias Nilsson, Tony Cookson and Diego Garcia for insightful and timely comments. My batchmates, Saad Alnahedh, Gustaf Bellstam, Adam Bordeman, Jenni Dinger, Jason Lunn, Michael Manser, and Subhiksha Swamy, have been a great source of encouragement during the last 5 years. Their careful readings and suggestions have greatly benefited my work.

Finally, I would like to thank my parents, Usha and Kannan, and my wife, Pritha. This PhD would not have been possible without their love, support, and understanding. I dedicate this work to them.

Contents

Chapter

Tables

Table

Figures

Figure

Chapter 1

Miners' Canary or Noah's Dove: The Industry Prospects of Layoff Announcements [1]

> "*District 12 uses canaries in their coal mines to warn them of bad air. When the air is bad, the canary stops singing and perhaps dies.*" (Suzanne Collins – "Catching Fire")

> "*When the dove returned to him in the evening, there in its beak was a freshly plucked olive leaf! Then Noah knew that the water had receded from the earth*" (Genesis 8:11)

Layoff announcements are important corporate events that have, on average, been shown to negatively affect a firm's stock value.[2] 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.

[1] This chapter is co-authored with Adam Bordeman and Roberto Pinheiro

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

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.[3] 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.[4] The contagion 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,

[3] 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.

[4] 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.

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.[5] 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 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.[6] 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

[5] 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.

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

sub-samples based on information content potentially provide vastly different results.[7] 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.

1.1 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), 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

[7] 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)).

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 1.1. 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.

1.2 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 1.1 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 1.3.

1.2.1 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).[8] 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.[9] 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 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

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

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

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).

1.2.2 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.[10] As before, we should again expect that these effect would be the strongest in concentrated markets.

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

[10] See Bolton and Scharfstein (1990).

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.[11] On the other hand, large firms may be the most susceptible to rapidly changing tastes due to the challenges of re-tooling.[12]

1.3 Data and Sample Selection

1.3.1 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.[13] Table 1.2 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 for the following keywords: "layoff", "layoffs", "lay-off", "laid off", "restructure", "restructured",

[11] 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.

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

[13] 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.

"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).[14] [15] Details on the construction of the variables are presented in Table 1.3. 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.

1.3.2 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 1.1.

[14] 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

[15] 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).

In Table 1.4, Panels A, B, and C, 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 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 Panels D, E, and F), announcers are bigger, more leveraged, and older.[16] 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 Panels G, H, and I. 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%.

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

1.3.3 Summary Statistics: Competitors

Panels D to I of Table 1.4 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 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 1.2, following a pattern similar to the one observed for announcers in Figure 1.1. Finally, the standard deviation of competitors' reactions have also increased over time – as we can observe in Figure 1.3 – 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).

1.3.4 Summary Statistics: Layoffs - over time and across industries

In Panel J of Table Table1.4, 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 1.5.3, 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 1.5 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 1.6 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.

1.3.5 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.[17] As we can see in Table 1.7, 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 1.7 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.

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

1.4 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 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 1.2 and 1.3, 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:

$$CAR_{it} = \beta * \mathbf{x_{it}} + \gamma * \mathbf{z}_{event} + c_{event} + u_{i,t} \tag{1.1}$$

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 1.3. 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.[18]

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

$$CAR_{i,t} = \theta * w_{i,t} + \eta * \bar{v}_{i,t} + \epsilon_{i,t} \tag{1.2}$$

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.

1.5 Results

1.5.1 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 1.8 show the results for our sample. Our tests are constructed using value-weighted portfolios of competitors with stock returns available

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

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 1.8 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's unique strengths and weaknesses.[19]

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 Panels A-C against the results from Panels D-F and G-I, 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 1.4 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.

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

1.5.2 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 1.8, 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.[20] In other words, the competitive effect will be dominant in industries that are highly concentrated where firms have market 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).[21] 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

[20] See Lang and Stultz (1992).

[21] 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.

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.

1.5.2.1 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 announcements are good news for the announcers. The benchmark results are presented in column 1 of Table 1.9.[22] 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 1.4 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

[22] 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.

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 1.9. 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 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.[23] 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 1.5.3, we consider the subsample of announcements in which the announcer's CAR is

[23] 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.

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.

1.5.2.2 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 1.10. 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.

In columns 2 and 3 of Table 1.10 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 1.9 and 1.10 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.

1.5.3 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 1.11 we implement the alternative approach to breaking down the sample across good and bad news announcements. As discussed in Section 1.4, 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 1.12, 1.13, and 1.14 present three more robustness checks of our results. Table 1.12 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 1.12, our results on R&D investment, market-to-book, and sales growth are preserved, while the results on size are not robust.[24] Similarly, Table 1.13 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 1.14 we replicate the analysis from Tables 1.8 and 1.9 with the subsample of manufacturing firms. As expected, results are qualitatively the same.

1.5.4 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 1.4. 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

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

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 model. If, however, $\lambda \approx 1$, then the data is best modeled through a fixed effects estimation. As we see in Test A in Appendix A, 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 Appendix A, 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 1.15. 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.

1.6 Portfolio Approaches

1.6.1 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.

Table1.16 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 1.16 corroborate the patterns observed in Figures 1.2 and 1.3, that showed a wide variation of competitors' reactions within event.

1.6.2 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 1.17. Results are similar to the ones obtained in Table 1.16 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).

1.6.3 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.

1.7 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.

1.8 Figures and Tables

Figure 1.1: Heterogeneity in Announcer Stock Price Reaction

Note: This figure shows the fraction of announcers with positive 3-day CAR, [-1,+1], for every year in our sample of 676 announcements.

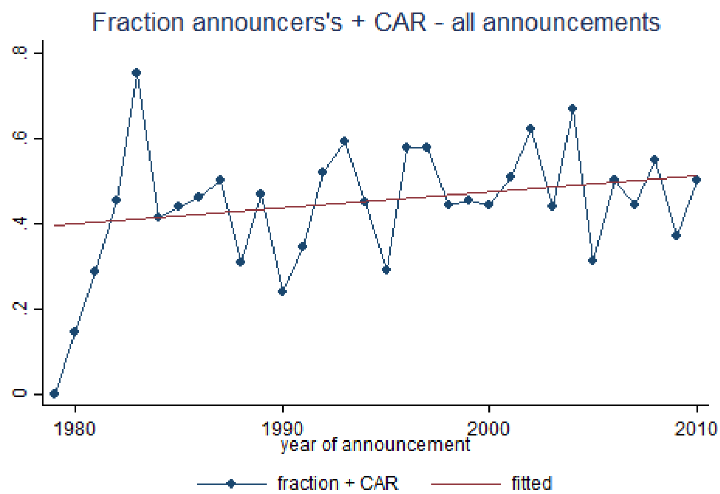


Figure 1.2: Across-Event Heterogeneity in Competitor Stock Price Reaction

Note: This figure shows the fraction of competitors with positive 3-day CAR, [-1,+1], for every year in our sample of 676 announcements.

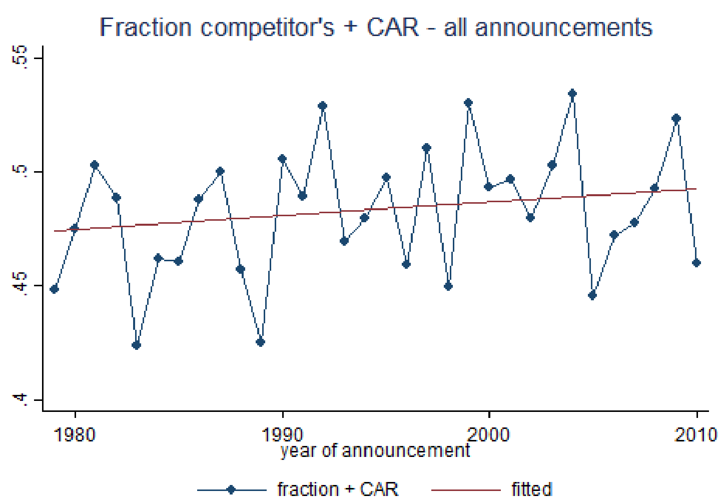


Figure 1.3: Within-Event Heterogeneity in Competitor Stock Price Reaction

Note: This figure shows the average within-event standard deviation of competitors' 3-day CAR, [-1,+1], for every year in our sample of 676 announcements.

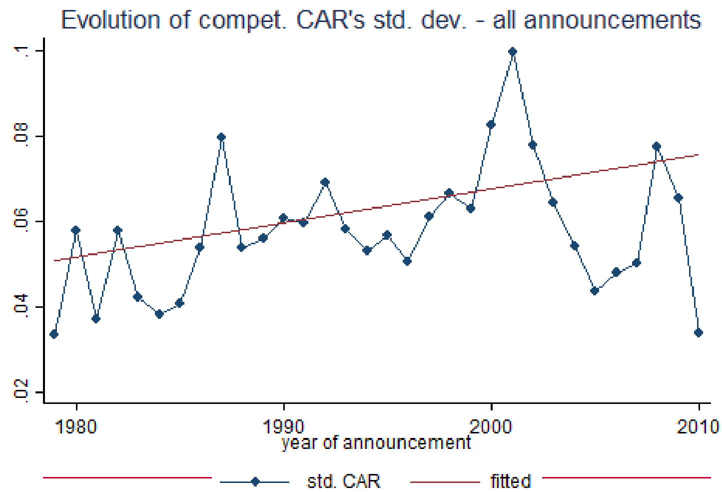


Figure 1.4: Density Plots of Competior Stock Price Reaction and R&D

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

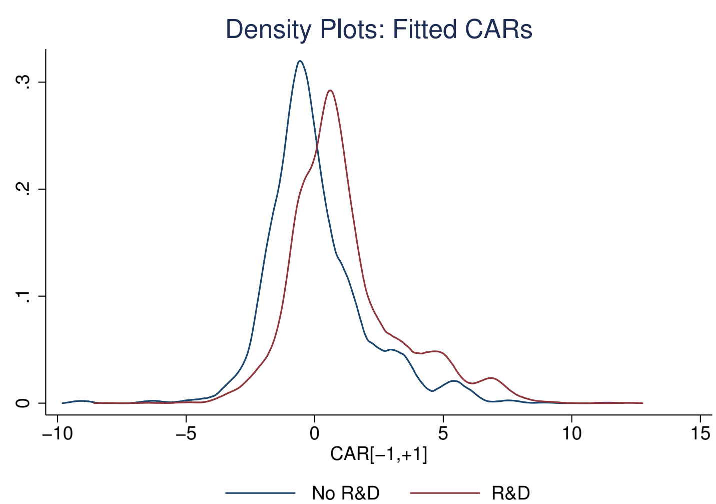


Table 1.1: Expected Impact of Competitor Characteristics for Industry Effects of Layoff Announcements

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 1.2: Sample Construction

A. Competitors

Description	**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

Description	**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 1.3: Variable Definitions

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 model.
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 (sale at (t-1) − sale at (t-2))/(sale at (t-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 1.4: Descriptive Statistics

(a) Announcers: 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

(b) Announcers: 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

(c) Announcers: 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

(d) 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

(e) 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

(f) 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

(g) Only S&P 500 Competitors: 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

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

(h) Only S&P 500 Competitors: 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

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

(i) Only S&P 500 Competitors: 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

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

(j) Layoffs by 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 1.5: Distribution of Layoffs Announcements Over Time and Industry

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 1.6: 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 1.7: Probability of Becoming an Announcer

Note: This table shows 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 control for decade and industry fixed effects. Standard errors are bootstrapped.

	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 1.8: Tests for Average Effects

(a) All annoncements: Competitors' 2-tail tests - Abnormal Returns over the Event window

Note: 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.

(b) All annoncements: Competitors' 2-tail tests - Parametric Statistics with bootstrapped Significance Levels

Note: 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	$\overline{\text{CAR}}$	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.

(c) All annoncements: Competitors' 2-tail tests - Parametric and Non-parametric

Note: 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.

(d) Good News case: Competitors' 2-tail tests - Abnormal Returns over the Event Window

Note: 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	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.

(e) Good News case: Competitors' 2-tail tests - Parametric Statistics with Bootstrapped Significance Levels

Note: 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	$\overline{\text{CAR}}$	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.

(f) Good News case: Competitors' 2-tail tests - Parametric and Non-parametric

Note: 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)	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.

(g) Bad News case: Competitors' 2-tail tests - Abnormal Returns over the Event Window

Note: 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.

(h) Bad News case: Competitors' 2-tail tests - Parametric Statistics with Bootstrapped Significance Levels

Note: 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.

(i) Bad News case: Competitors' 2-tail tests - Parametric and Non-parametric

Note: 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)	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 1.9: Competitors' Stock Return Reaction - Good News Case

Note: 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 1.10: Competitors' Stock Return Reaction - Bad News Case

Note: 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 1.11: Competitors' Stock Return Reaction - Alternative Approach

Note: 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 1.12: Competitors' Stock Return Reaction - Only Statistically Significant Announcements

Note: 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 1.13: Competitors' Stock Return Reaction - Only S&P 500 competitors

Note: 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 1.14: Competitors' Stock Return Reaction - Only Manufacturing Firms

(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 1.15: Competitors' Stock Return Reaction - Random Effects Model

Note: 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 1.16: Portfolio of Competitors - Between Estimators Model

Note: 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	**Good News**	**Bad News**
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 1.17: Weighted Portfolio of Competitors - Weighted Least Squares

Note: 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	**Good News**	**Bad News**
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

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

Chapter 2

Failure to Downsize: Insights from Layoff Announcements and Firm Performance

Firms announcing layoffs are typically assumed to follow through with significant workforce reductions but, in practice, this is often not the case. Using hand-collected data covering 1247 layoff announcements between 1990 and 2010 by S&P 500 firms, I show that nearly 32% of layoffs announced do not lead to a subsequent decline in employment. While the announcements of firms that do and do not lead to employment shrinkage look quite similar, and yield similar short-run cumulative abnormal returns, the subsequent operating and stock performances of these firms differ substantially.

Financial economists have long shown that layoffs tend to occur in the most financially distressed firms (Atanassov and Kim (2009), Hanka (1998), Kang and Shivdasani (1997), Ofek (1993), and Kose et al. (1992)). During periods of distress, liquidity constraints may force firms to lay off employees (and downsize) even if the decision destroys value in the long term. On the other hand, when a firm reorganizes its workforce instead of downsizing, the layoff could be a signal of taking on an opportunity. Consequently, layoff announcements that reorganize a firm's workforce should lead to greater improvements in performance compared to announcements that lead to employment downsizing. However, my results suggest the opposite.

Firms that follow through on downsizing reduce costs, increase cash holdings, and earn an 8.6% buy-and-hold abnormal return over 300 days following the announcement. Firms that fail to follow through, however, lose a –0.93% buy-and-hold abnormal return over 300 days following the announcement. The differences in operating and stock price performance are economically and statistically significant.

It is notable that the market does not appear to react differently to layoff announcements that ultimately result in employment declines compared to those that do not. This may be because the text of both types of announcement is quite similar.[1] I show, however, that whether an announcement leads to employment downsizing at the firm is predictable at the time of the announcement. Downsizers tend to be distressed, with worse operating performance, sales growth, growth opportunities, and severe financial constraints when compared to firms that fail to downsize following their layoff. Based on these characteristics, I create an index that predicts the likelihood of a layoff resulting in workforce reorganization, and show that a simple long-short strategy based on this index generates buy-and-hold abnormal returns of 9.6% over 300 days following the announcement. Importantly, this is a real-time index generated using only available data from the previous five years.[2]

An explanation consistent with my results is that when downsizing is the firm's best option, increasing leverage may be a way to discipline managers to undertake downsizing decisions even though it might not be in their own interest to do so. This control function of debt is more important in organizations that must shrink where managers face greater pressures to invest in uneconomic projects to avoid retrenchment and retain their status (Jensen (1986)). Consistent with this idea, I find that firms announcing downsizing layoffs significantly increased leverage in the year prior to their announcement. At the same time, firms who fail to downsize do not adjust their leverage prior to the announcement.

---

[1] Reorganizing Announcement, 10 October, 2002: *Abbott Laboratories, continuing to feel the effects of federal regulatory scrutiny of several drugs and laboratory-diagnostic products, said it will lay off about 2,000 workers and shut down manufacturing plants and warehouses....*
Downsizing Announcement, 15 November, 2002: *Advanced Micro Devices Inc. said it will cut about 2,000 positions, or 15% of its 13,000-employee global work force, by the end of the second quarter. The job cuts, which were expected, are part of previously announced efforts to reduce costs and help return the chip maker to profitability....*

[2] A potential concern with using firm characteristics to predict layoff type is that the subsequent difference in buy-and-hold returns may be a function of existing firm characteristics and not the layoff itself. To mitigate this issue, I compare long run stock performance between true and false layoff predictions. The difference in long run stock performance is significant only when predictions of layoff type are verified to be accurate. This shows that the long run stock performance result is driven primarily by the type of layoff and not the firm's characteristics.

Increasing leverage may also be an effective way for firms to use financial flexibility to improve their bargaining position with workers (Matsa (2010)). Importantly, when downsizing the workforce is the firm's best option, it is necessary for the firm to commit to the downsizing decision to earn higher returns. By taking on additional debt and thereby increasing the demands on their cash flow, firms can credibly take a tougher stand when negotiating with workers. However, with financial flexibility, a firm cannot credibly bargain with their workforce to downsize. This incentive to renege on a downsizing threat becomes stronger when the firm has greater debt capacity and current performance. Consistent with this idea, I find that the difference in buy-and-hold abnormal returns between firms that do and do not downsize is strongest in high union coverage industries. That is, when firms successfully bargain with workers to downsize, they benefit the most. These firms use high leverage and poor performance as sources of commitment to bargaining.

Next, I attempt to rule out three alternative explanations of my results. Firstly, a layoff could be classified as a reorganizing announcement when the announcement follows a merger or an acquisition. In such cases, the lower buy-and-hold abnormal returns earned in the year following the announcement may just be a function of the merger and not the layoff. I rule out this possibility by providing empirical evidence showing that my results are robust to the exclusion of layoff announcements that follow mergers and acquisitions. Secondly, reorganizing announcements may just be delayed downsizing announcements. That is, the firm may not have completed the layoff by the end of the event year when layoff type is classified. However, I rule out this possibility as well by showing that following reorganizing announcements firms do not reduce employment levels for 3 years. Finally, my hand-collected data on layoff announcements might suffer from an attention bias because my sample includes firms that are not currently in the S&P 500.[3] Firms that are currently in the S&P 500 receive greater coverage from the media as well as investors, compared to firms that were previously members of the index or candidates for inclusion. Importantly, I verify that my results are not driven by an attention bias as I find that my results are robust to the exclusion of firms that are not currently in the S&P 500.

[3] All firms in the sample have been listed in the S&P 500 at some point between 1980 and 2014.

In this paper I employ event-study methodologies and a difference-in-difference framework to empirically test changes in long-run performance and corporate policy following layoff announcements. My results are not dependent on the matching methodology employed since I use two alternative matching methodologies (entropy balancing and Abadie-Imbens matching estimator) to generate balanced control groups. Using these approaches, I also provide evidence from placebo tests showing that my results are robust only when a layoff announcement occurs.

The main contribution of this paper is to identify a new distinction in types of layoff announcements and show that the difference is both predictable and economically important. I classify layoff announcements into reorganizing and downsizing types on the basis of observable changes to employment. Previous research has classified heterogeneity in layoff announcements by using the reasons stated in the announcement (e.g., Simintzi (2013) and Palmon et al. (1997)).[4] At the same time, market participants are aware of the fact that firms may attempt to obscure this heterogeneity (Hallock (2003)).[5] There is also the possibility that a firm makes an announcement but does not follow through with it. While such changes will not bias a short-run event study, they will most definitely bias results when testing the long-run effects of layoff announcements. I add a new dimension to the literature by classifying distinct layoff announcements on the basis of observable changes to subsequent employment.

This paper also makes an important contribution to the existing literature by examining the effects of layoffs announcements on long-run firm performance. Research on layoffs and performance has so far largely focused on the short-run market reaction of firms following layoff announcements. Studies have shown that, following a layoff, firms typically experience a negative stock price reaction in the short run.[6] My paper deviates from the literature by examining the effects of layoffs on *long-run* firm performance. In particular, I show that layoff decisions, depending on their type,

[4] Based on reasons stated in the announcement, Simintzi (2013) classifies layoffs into restructuring and negative announcement. Another paper, Palmon, Sun and Tang (1997) also use reasons found in announcements to classify layoffs into demand driven and efficiency enhancing announcements

[5] Hallock (2003) using survey data shows that while some investors are skeptical about the accuracy of the stated reason in announcements, others are skeptical about the amount of information revealed

[6] see Farber and Hallock (2009), Worrell, Davidson, and Sharma (1991), Abowd, Milkovich, and Hannon (1990), among others

have important implications for *long-run* performance and corporate policy.

2.1 Related Literature

There is a growing literature that shows layoff announcements are important decisions for a firm. While layoffs can generate cash flows, there are substantial up-front costs associated with such announcements (Hamermesh and Pfann (1996)). These costs include severance payments, special costs such as mandatory retraining or outplacement services for laid off employees, as well as indirect costs such as loss of employee morale. The current literature has also established that the quality of a firm's labor force is an important factor in determining the overall market value of the firm (Merz and Yashiv (2007), and Belo, Lin, and Bazdrech (2014)). Therefore any adjustments made to the workforce will have an impact on firm value. It is for these reasons that my unique hand collected layoff data provides a powerful setting for a paper.

It has been well documented that employee layoffs are responses to performance declines and financial distress (Atanassov and Kim (2009), Kang and Shivdasani (1997), Ofek (1993) and Kose et al (1992)). For example, Milanez (2013) using data on advanced layoff notices from the WARN Act[7] for California shows that financially constrained firms are more likely to announce layoffs. She also shows that the stock market reacts more negatively in the short run to layoffs at unconstrained firms. Economists have also argued that following increases in leverage, firms are more likely to transfer the increased risk onto their employees. In particular, Ofek (1993) shows that highly levered firms are more likely to respond to performance decline with downsizing. Hanka (1998) argues that irrespective of performance, firms with higher levels of debt are more likely to reduce employment. While most of these papers have focused on layoff announcements that lead to downsizing, I add a new dimension to this literature by also examining layoff decisions that do not lead to downsizing. In another deviation, I show that layoffs are not always a response to poor performance and/or financial distress. Firms also announce layoffs when they are unconstrained

[7] The Worker Adjustment and Retraining Notification (WARN) Act requires firms with more than 100 full-time employees to provide a notice of impending mass layoff events 60 days in advance. The BLS defines a mass layoff as a layoff that affects at least 50 workers at one company and one location

and performing well.

Previous research has also acknowledged the heterogeneity inherent in layoff announcements. The literature so far has focused on the reasons stated in the announcement to distinguish layoffs. Firms cite many reasons for announcing layoffs, including, but not limited to, mergers and acquisitions, cost cutting, demand slump, bankruptcy, change in technology and efficiency. The existing evidence on the impact of these announced reasons for a layoff on investor reaction is mixed. For example, Palmon et al. (1997) and Farber and Hallock (2009) show that the announced reasons have an impact on investor reaction. Simintzi (2013) also uses reasons to classify layoffs into restructuring and negative types. Alternatively, Hallock (2003) shows using survey data that investors are skeptical about the accuracy of reasons provided by firms in their layoff announcements. In this paper, I propose an alternative method to detecting heterogeneity in layoff announcements on the basis of observable changes to subsequent employment.

In terms of the impact of layoffs on performance, the literature has mainly focused on the short run stock price performance following layoff announcements. Cascio, Young and Morris (1997) is one exception that studies the relationship between employment change and firm performance in the long run. The authors show that downsizing firms performed no better than firms that didn't downsize. However when firms downsize and simultaneously restructured assets, they performed better than their competitors. A potential concern with this study is that the paper does not use layoff announcements to examine downsizing. Other papers in this literature have shown that there is a strong negative impact of layoff announcements on short run stock returns (Worrell, Davidson, and Sharma (1991) and Abowd, Milkovich, and Hannon (1990)). However, more recently Farber and Hallock (2009) show that while layoffs have had a strong negative impact on stock prices during the 1970s, there has been a gradual decline in the negative impact in the 1980s and 1990s. Their database was extended by Hallock, Strain, and Webber (2011) who show that market reaction to layoffs after 2000 is similar to reaction in the 1970s. In this paper, I contribute to the existing literature by examining the effect of layoff announcements on long run performance and firm policy.

2.2 Data

This paper uses a unique hand-collected data set on layoff announcements made by firms listed in the S&P 500 index between 1980 and 2014. Prior to collecting layoff announcements, a list of firms in the S&P 500 index at any point between 1980 and 2014 is constructed. Financial firms (SIC 6000-6799) and utility firms (SIC 4610-4991) are excluded from this list since they are highly regulated compared to firms in other industries. There are 994 firms (after excluding financial and utility firms) that were included in the S&P 500 index at some point between 1980 and 2014.

For each of the 994 firms in the sample I use the Factiva database to search for layoff announcements that appear from 1980 to 2014. The search for layoff announcements is restricted to announcements published in the Wall Street Journal archives. A potential concern with collecting announcements from only the Wall Street Journal is that all announcements may not appear in the newspaper. However, this concern is reduced in my setting because the sample only consists of large firms that are either in the S&P 500 index or have been a part of the index at some point during the sample period. Additionally, Farber and Hallock (2009) find that the Wall Street Journal archives contain news articles for even small events for large firms in the economy. Therefore, a layoff being an important news announcement should appear in the newspaper.

An exhaustive list of search terms is created to ensure that all instances of layoff announcements are captured. For each firm in the sample, my algorithm searches for the following keywords in the Wall Street journal archives: *layoff, layoffs, lay off, lay offs, laying off, lay-off, laid off, restructure, restructured, restructures, restructuring, downsize, downsized, downsizes, downsizing, plant closure and plant closing.* I then go through every news article containing these search terms and compile a separate PDF document for each firm containing all instances of its layoff announcements. From each announcement, information on the company, announcement date (date the announcement appears in the Wall Street Journal), layoff size, location, reason for layoff, and type of worker laid off is collected. The nature of the information available in the announcements is heterogeneous. Therefore I do not have complete information on these parameters for all announcements. Additionally news articles from 1980 to 1987 were mainly in the form of newspaper abstracts and hence announcement descriptions for this period is sparse. To alleviate concerns of missing information reported in abstracts, I restrict my sample to layoff announcements between 1990 and 2010.

Firm level financial and accounting data are collected from Compustat. Daily stock returns are collected from CRSP. Firms are required to have non-missing and non-negative values for total assets, sales, shareholder's equity, number of employees, capital expenditures, R&D expenditure, cash and short term investments, cost of goods sold, and sales, general and administrative expenditure.

I also obtain unionization data at the industry level from *http://www.unionstats.com/*. A detailed description of the data can be found in Hirsch and Macpherson (2003). Industry level union data is provided based on census industry classifications (CIC). While union data for 1990 and 1991 are based on 1980-CIC, data for 1992-2003 are based on 1990-CIC and data for 2004-2010 are based on 2000-CIC. A crosswalk for the various CIC and SIC industry classifications can be found at *http://www.census.gov/people/io/methodology/*. Finally, I aggregate union data by year at the 2-digit SIC industry level. Aggregate union data is not available for 15, 17 and 99 2-digit SIC industries.

The final sample used in the main empirical analysis consists of 1,247 layoff announcements between 1990 and 2010 with complete financial, accounting and stock performance information. Of the 1,247 announcements, 398 layoff announcements do not lead to employment downsizing, while the remaining 849 announcements lead to employment downsizing.[8] Additionally, complete data is available for 3,825 observations (firm years) for firms in the sample that never made a layoff announcement during the sample period. A description of the variables used in my empirical analysis is provided in Table 2.1.

[8] A detailed description of this classification approach is provided in the Methodology section

2.3 Methodology

This section describes the basic empirical design, including classification of layoff types, measures of stock performance, and matching methodologies used to construct a control group for difference-in-difference regression specifications.

2.3.1 Classification of Layoff Type

In this paper, I deal with two types of layoff announcements. One, a reorganizing layoff announcement, where the announced layoff does not lead to subsequent employment shrinkage and two, a downsizing layoff announcement, where the announced layoff leads to subsequent employment shrinkage.

To be precise, I classify a layoff announcement as a reorganizing layoff if the annual change in employment for the event-year is less than 10% of the layoff size. In such instances, even though the firm is laying off workers, it is also hiring almost as many workers during the same year. Alternatively, a layoff announcement is classified as a downsizing announcement when the annual change in employment for the event-year is greater than 10% of the layoff size. I also create alternative measures of classification by varying the cut-off percentage of layoff size to 0 and 20 percent.[9]

2.3.2 Short and Long Run Stock Performance

To measure the short-run stock market reaction to layoff announcements I construct average 3-day cumulative abnormal returns (CARs) centered on the day of the announcement. The 3-day CARs are calculated using the following market model in three steps.

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \tag{2.1}$$

where $E(\epsilon_{it} = 0)$ and $var(\epsilon_{it}) = \sigma_\epsilon^2$

$$AR_{it} = R_{it} - \hat{\alpha_i} - \beta_i \hat{R}_{mt} \tag{2.2}$$

[9] Results are presented in Appendix B

$$CAR_i(-1,+1) = \sum_{t=-1}^{+1} AR_{it} \tag{2.3}$$

In equation 2.1, I estimate the market model over a 255 day estimation window, ending 46 days before the event, where R_{it} and R_{mt} are daily returns for firm i and the market respectively. ϵ_{it} is the zero mean disturbance term. α_i, β_i and σ_ϵ^2 are parameters of the market model. Additionally, I use a value-weighted index from CRSP for the market portfolio. Equation 2.2 uses the estimates from the market model to calculate abnormal returns for each time period by firm. Finally, in equation 2.3 I calculate the 3-day CARs by summing over the abnormal returns, AR, for days -1, 0 and +1 for each firm in the sample. The CARs can be averaged over firm or time to be used in cross-sectional tests.

Next, I construct average 300-day buy-and-hold abnormal returns (BHARs) to measure long run stock performance. The 300-day BHARs are calculated using the Fama-French three-factor model as a benchmark. I outline the steps in the construction below.

$$R_{it} = \alpha_i + \beta_{MKT} MKT_{it} + \beta_{HML} HML_{it} + \beta_{SMB} SMB_{it} + \epsilon_{it} \tag{2.4}$$

$$BHAR_i(+2,+300) = \prod_{t=+2}^{300}(1 + R_{i,t}) - \prod_{t=+2}^{300}(1 + R_{benchmark,t}) \tag{2.5}$$

To ensure that any outperformance of the downsizing and reorganizing announcers doesn't result from risk, I begin by controlling for the Fama-French three factors in equation 2.4. Here, R_{it} is the daily returns for firm i in excess of a benchmark, described below. α_i is an intercept that captures the abnormal risk-adjusted return. MKT_{it}, HML_{it}, and SMB_{it}, are the returns on the market, value, and size factors obtained from Kenneth French's Website. Equation 2.5 represents the BHAR calculation for firm i calculated for a 298-day period (+2,300). $R_{benchmark,t}$ represents a value-weighted benchmark portfolio from CRSP.

2.3.3 Entropy Balancing and Difference-in-Difference

In this paper I use entropy balancing (Hainmueller (2011)) as a preprocessing technique to achieve covariate balance for my control group of non announcers with my treated group of firms making layoff announcements. In the absence of a layoff announcement (treatment), the treated group would have behaved similarly to the balanced control group. In particular, I am interested in estimating the average treatment effect on the treated using the difference in mean outcomes between the treatment and reweighted control groups. This is represented by represented by: $E[Y(1)|D = 1] - E[Y(0)|D = 1]$. Under this approach, as shown in Hainmueller (2011), the mean for the balanced control group is estimated by:

$$E[\widehat{Y(0)|D} = 1] = \frac{\sum_{i|D=0} Y_i w_i}{\sum_{i|D=0} w_i} \tag{2.6}$$

where w_i is a weight chosen for each control unit. Weights are determined using the following reweighting scheme:

$$\min_{w_i} H(w) = \sum_{i|D=0} h(w_i) \tag{2.7}$$

subject to balance and normalizing constraints

$$\sum_{1|D=0} w_i c_{ri}(X_i) = m_r \quad \text{with} \quad r \in 1, ..., R \quad \text{and} \tag{2.8}$$

$$\sum_{1|D=0} w_i = 1 \quad \text{and} \tag{2.9}$$

$$w_i \geq 0 \quad \text{for all} \quad i \quad \text{such that} \quad D = 0 \tag{2.10}$$

h() is a distance metric that is measured by $h(w_i) = w_i log(w_i/q_i)$ where w_i is the estimated weight and q_i is the base weight. Equation 3 represents the balance constraints that are imposed by the researcher to balance the moments of the respective covariate distributions between the treated and control groups. In particular, m_r represents the r_{th} moment of a covariate X_i from the treated group while the left hand side represents the covariate moment for the control group. Additionally, the sum of weights is set to 1 and each weight has to be greater than or equal to 0. The non-negativity constraint is imposed because the distance metric is not consistent for negative weights.

Entropy balancing is an alternative to other preprocessing methods such as propensity score matching, coarsened exact matching and nearest neighbor matching. As highlighted in Hainmueller (2011), this method has a number of advantages over other commonly used methods of matching.

First, using entropy balancing, I manage to achieve a high degree of covariate balance on the first three moments for a large set of covariates. Weights are adjusted for my control group to match my treated firms on firm performance measured by return on assets and market to book ratio, leverage, size in terms of log of real assets and log of employees, age, cash holdings, sales growth, financial constraints measured by the Whited-Wu index, and cost of goods sold scaled by assets. The second advantage entropy balancing has is that while it reweights my control group to achieve covariate balance, it maintains the adjusted weights as closely as possible to the base weights of observations so as to prevent loss of information. This way, I am able to use the information available for all firms as opposed to dropping some and generating a matched control group using a method like nearest neighbor matching. Third, the method is fairly versatile and easily lends itself for subsequent estimation of treatment effects. And finally, this method is computationally attractive since the optimization problem to find unit weights is well behaved and globally convex.

For my main econometric tests I adopt a difference-in-differences research design. An important assumption of a difference-in-differences specification is that in the absence of a layoff announcement, the treatment and control group should be relatively similar along observed dimensions that are relevant for treatment. This is because if the two groups differ significantly along observables, then they are likely to differ along unobservables as well. To alleviate this concern, I use a balanced control group using entropy balancing as highlighted above. In implementing the difference-in-differences specifications I use panel regression techniques to control for firms and year fixed effects. I also cluster standard errors at the 2 digit SIC industry level. I include firm and year fixed effects to control for time invariant firm level unobserved factors and time trends in the economy.

2.3.4 Matching estimator approach

In an alternative approach, I use the Abadie and Imbens (2006) estimator following Abadie, Drukker, Herr and Imbens (2004) to report the average treatment effects on the treated (ATET). The central assumption in this methodology is that in the absence of a layoff announcement (treatment), the treated group would have behaved similarly to the matched control group. The matching estimator isolates the treated observations based on my sub-sample of interest and then, from the population of non-treated firms, selects a set of control firms that are best matches for the treated firms. There are three distinct treatment groups in my sample. The first includes all layoff announcements, the second includes only reorganizing announcements and the third group includes only downsizing announcements. Matched controls for each treated group are selected from the group of non-announcers in the sample. I match on ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. For each of these covariates the Abadie-Imbens matching estimator minimizes the Mahalanobis distance between treated and control firms. For each treated firm, the control firm that is nearest in terms of distance is selected. Most of the unobserved heterogeneity for firms should be accounted for by the chosen covariates. Finally, the estimator produces heteroskedastic robust standard errors.

2.4 Results

The section presents results from the main empirical specifications in this paper.

2.4.1 Summary Statistics

This sub section provides evidence on descriptive statistics and highlights the differences in firm characteristics between first, announcers and non-announcers, and second, between reorganizing and downsizing layoff announcements.

Figure 2.1 graphically describes the distribution of layoff announcements reported in Table 2.1. Panel A plots the total number of layoff announcements in any given year, broken down by type. Panel B of figure 1 serves to provide a description of the number of reorganizing and downsizing layoff announcements. Panel B shows that there is a significant number of reorganizing layoffs in all years of the sample.

I present the distribution of average employment levels for announcers across event time in

Figure 2.2. Panel A depicts the distribution of mean logged employment for firms announcing layoffs that lead to downsizing and Panel B describes the distribution of mean logged employment for firms announcing layoffs that do not lead to downsizing. While employment levels drop following a downsizing announcement, employment levels increase relative to a balanced control group following reorganizing announcements.

Table 2.2 reports the distribution of layoff announcements and average number of workers laid-off by year. For the sample period covering 1990-2010, there are 1,247 layoff announcements. Of these, 398 are reorganizing announcements and the remaining 849 are downsizing announcements. On average, each announcement in the sample lays-off 2,070 workers. It is meaningless to compare the absolute number of workers laid-off in different announcements because firms have different levels of human capital. Therefore, a layoff ratio, where the size of the layoff is standardized by the number of employees at the firm, provides a more accurate description of differences in size, if any, between layoff announcements. The average layoff ratio for downsizing announcements is 5.15% and for reorganizing announcements is 5.02% implying that it is not possible to distinguish between the two types of layoffs on the basis of the layoff ratio.

Table 2.3 reports the distribution of layoff announcements and average number of workers laid-off by industry based on the one-digit SIC classification. As outlined previously in the data section, I exclude financial firms (SIC 6000-6799) and utility firms (SIC 4610-4991) from my sample since they are highly regulated compared to firms in other industries. Table 2.3 shows that layoff announcements by type are fairly well distributed across industries.

The differences in firm characteristics for firms based on the decision to layoff and layoff type are reported in Table 2.4. In panel A, firm characteristics are reported for both firms that announce and do not announce layoffs. My sample covers 1247 layoff announcements and 3825 firm years for firms that never announced a layoff between 1990 and 2010. I observe that in comparison to non-announcers, firms announcing layoffs are larger in terms of size and employment levels, younger in age, have higher leverage, lower performance in terms of ROA and market to book ratios. The difference in means for all firm characteristics are statistically significant at the 1% level.[10] In other words, announcers and non-announcers are very different firms.

In panel B of Table 2.4, I highlight the differences between reorganizing and downsizing announcements. 398 of 1,247 layoff announcements do not lead to a significant decline in employment. That is, nearly 32% of the layoffs announced are of the reorganizing type. It appears that firms making reorganizing announcements are healthier than firms who announce downsizing layoffs. That is, these firms have better operating performance and growth opportunities in terms of ROA and market-to-book ratio, are younger in age, and have fewer employees. Additionally reorganizing firms also have greater sales growth and cash holdings compared to downsizing firms. The differences in means for these firm characteristics are also statistically significant.

2.4.2 Who makes a layoff announcement

This section provides evidence on how likely firms are to announce layoffs based on a given set of firm characteristics.

Table 2.5 presents the average marginal effects from a probit model where the dependent variable is the probability of a firm announcing a layoff. Growth indicators, liquidity, change in leverage, and production costs are important factors in determining the probability of making layoff announcements. I show that a one unit increase in sales growth increases the probability of making a layoff announcement by 13.8%. Further, when the change in leverage increases by one unit, the probability of making an announcement increases by 19.4%. Additionally, a unit increase in a firm's cost of goods sold increases the probability of a layoff announcement by 5.9%. These results are consistent with the idea that firms experiencing poor performance and increases in leverage are more likely to announce layoffs to improve performance and reduce costs.

An interesting result here is the coefficient on cash holdings. A one unit increase in cash holdings increases the probability of a layoff announcement by 22.8%. I argue that this is because layoffs are costly and firms increase their cash holdings to meet the expenses of a mass layoff.

[10] The difference in means for Market to Book ratio is statistically significant at the 5% level

Further, I also show that firms which are older, and larger in terms of total assets are more likely to layoff workers.

In Table 2.6, I present the results from the average marginal effects of a probit model where the dependent variable is the probability of announcing a reorganizing layoff as opposed to a downsizing layoff. The sample for this specification includes 385 reorganizing announcements and 834 downsizing announcements.[11] For this test, I exclude firms that never announce layoffs in the sample. Firms announcing reorganizing layoffs have better operating performance and financial health than firms making downsizing layoffs. In particular, based on column 4, I show that a one unit increase in performance, measured by ROA, increases the probability of announcing a reorganizing layoff by 73.1%. At the same time, a one unit increase in change in leverage reduces the probability of a reorganizing layoff by 35.5%. Consistent with this result, I also find that a one unit increase in financial constraints, measured by the Whited-Wu index, reduces the probability of a reorganizing announcement by 76.6%. Additionally, firms with higher sales growth and market to book ratios are also more likely to announce reorganizing layoffs. These results suggest that when faced with the two types of announcement, the downsizing announcement is more likely to be made by a firm with worse performance and financial stability than the firm making the reorganizing announcement. On the other hand, firms are more likely to announce downsizing layoffs when they are performing poorly and are financially constrained.

Industry union coverage is an independent variable that measures the ratio of workers covered by a collective bargaining agreement by the total number of employees within a 2-digit SIC industry. While the coefficient on industry union coverage is not significant, the sign of the coefficient, negative, is in the expected direction. While the sign of the coefficient suggests that firms in industries with greater coverage under a collective bargaining agreement are more likely to commit to downsizing and less likely to reorganize their workforce, results are not statistically significant.

The results presented in Table 2.6 are consistent with the idea that a firm's decision to commit

[11] There are 15 fewer downsizing announcements and 13 fewer reorganizing announcements in this test because industry union coverage is not available for 15, 17 and 99 2-digit SIC industry classifications

to downsizing is dependent on its financial inflexibility and current performance. Firms that are financially constrained and have worse performance are more likely to commit to downsizing.

2.4.3 Layoff Announcements, Stock Performance and Bargaining

This section presents evidence on the short run and long run market reactions to layoff announcements based on their type.

Following methodology laid out in section 2.3.2, I measure the long run stock performance following layoff announcements by calculating buy-and-hold abnormal returns using the Fama-French 3-factor model as a benchmark. I find that following downsizing layoffs from 1990 to 2010, firms on average earn a 300-day buy-and-hold abnormal return of 8.6%. In contrast, following reorganizing announcements, firms on average lose a 300-day buy-and-hold return of –0.93%. This statistically significant difference in buy-and-hold abnormal returns is depicted in Panel B of Figure 3. These results on long run performance suggest that if the layoff type can be identified at the time of the announcement, investors can earn a buy-and-hold return of 9.5% over 300 days by adopting a simple long-short trading strategy.

I next examine whether the market recognizes that these layoff announcements have different implications for future performance. I calculate 3-day cumulative abnormal returns[12] centered around the layoff announcement to measure short run stock price reaction. The 3-day CARs for both reorganizing and downsizing layoff announcements are approximately -0.5%. These results are graphically depicted in Panel A of Figure 2.3. I find no significant difference in the short term stock price reaction around the two types of layoff announcements. This implies that the market does not recognize the heterogeneity in layoff announcements in the short run.

In Figure 2.4, I present evidence on abnormal stock performance following layoff announcements in high union coverage industries.[13] Results on long run performance are strongest in high union coverage industries. That is, if the layoff type can be identified at the time of the

[12] The cumulative abnormal returns are calculated using the market model as a benchmark

[13] High union coverage industries have coverage greater than the median industry union coverage.

announcement, investors can earn a buy-and-hold return of 10.8% over 300 days by adopting a simple long-short trading strategy. This implies that when firms successfully bargain with workers to downsize, they benefit the most.

2.4.4 Real-time Predictions of Layoff Type

The classification of layoff announcement into reorganizing and downsizing layoffs is based on ex-post changes to employment. For investors to be able to trade profitably based on a simple long-short strategy, they need to be able to identify the layoff type at the time of the announcement.

It is notable that the market reaction at the time of the announcement does not distinguish between the two types of announcements even though they have distinct implications for future performance. This may be because the contents of the two types of announcements are very similar. To begin with, there is no distinction in the size of the layoff. In Table 2.2, I show that the average layoff ratio for reorganizing and downsizing announcements are 5.02% and 5.15% respectively. The difference is statistically insignificant. Second, most layoffs are expected to result in subsequent employment shrinkage at the firm. However for layoffs that don't lead to a subsequent decline in employment, I find no evidence in the announcement suggesting that the firm intends to reorganize its workforce.

Alternatively, I show that it is possible to predict the layoff type in real time using prior firm characteristics. I begin with an initial sample of layoff announcements from 1990 to 1994 where I observe the layoff type ex-post. Using a probit regression model for this sample, I next determine the probability of an announcement being of the reorganizing type. The independent variables used to control for firm characteristics in this regression framework include ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. I use the estimates from this model to make out-of-sample predictions of layoff type when announcements occur in 1995. I apply this estimation procedure to the rest of the sample where I run the probit models in five year rolling windows and use the coefficients to successfully predict the type of layoff when an announcement occurs in the sixth year. I classify a layoff announcement as a predicted reorganizing layoff if the estimated probability of a reorganizing layoff is greater than 0.5. If the estimated probability is less than 0.5, the layoff is classified as a downsizing announcement.

Between 1995 and 2010, there are 873 layoff announcements of which 308 layoff announcements have been classified ex-post as reorganizing layoff announcements. The remaining 565 layoffs are downsizing announcements. After estimating the probability of layoff type, there are 175 predicted reorganizing announcements and 698 predicted downsizing announcements in the sample. I find that my model makes accurate predictions for nearly two-thirds of the sample.

Next, I examine the short and long run stock market for announced layoffs based on their predicted type. Panel A of Figure 2.5 plots the average 3-day CARs for layoff announcements divided into quartiles based on the probability that the layoff is of the reorganization type. I find no significant difference in CARs across the quartiles. However, while examining 1-year buy-and-hold abnormal returns following the announcement, I document a significant decline in returns across quartiles. Panel B of Figure 2.5 shows that there is an inverse relationship between the likelihood of the layoff being of the reorganizing type and buy-and-hold abnormal returns. The difference in the average 300-day buy-and-hold abnormal returns between the first and last quartiles of the probability of a reorganizing announcement is 14.5%.

For all downsizing layoffs, classified ex-post, from 1995 to 2010, firms on average earn buy-and-hold abnormal returns of 5.2% in the 300 days following the announcement. In contrast, following actual reorganizing announcements, firms on average lose buy-and-hold returns of -2.2%. I find that the long run stock performance for predicted announcement types is very similar to the returns of the actual layoff type. Predicted downsizing announcements earn buy-and-hold returns of 4.5% and predicted reorganizing announcements lose buy-and-hold abnormal returns of -5.1%. These results suggest that the predicted types of layoff announcements are a good proxy for actual layoff type. I graphically depict these results in Panels C and D of Figure 2.6.

An important concern with using firm characteristics to predict layoff type is that the predictions may be a reflection of the characteristics rather than the layoff itself. To mitigate this concern, I compare true and false predictions of layoff type. A prediction is true if the predicted layoff type is verified to be accurate ex-post. On the other hand, a false prediction is when the predicted layoff type is contradicted ex-post. If the predictions are a function of firm characteristics, the buy-and-hold abnormal returns by layoff type should exhibit similar patterns for true as well as false predictions. The average 300-day buy-and-hold abnormal returns for true downsizing predictions is 6.6% while the same for true reorganizing announcements is -7.6%. On the other hand, I find that false predicted downsizing announcements lose on average -.07% buy-and-hold abnormal returns while false predicted reorganizing layoff announcements lose -2.5% returns. The difference in the results between true and false predictions provide support for the fact that my predictions of layoff type are a function of the layoff and not just firm characteristics. These results are graphically depicted in Figure 2.7.

2.4.5 Results from Difference-in-Difference Specifications

In this section I present results from Tables 7-13 using two alternative matching methodologies to study the impact of layoff announcements on production costs, liquidity, operating performance and leverage.

Panel A in each of these tables presents results based on the entropy balancing matching approach. I use the following regression model:

$$y_{it} = \gamma_i + \zeta_t + post_{it} + (post * treatment)_{it} + e_{it}$$

My results are robust to γ_i, firm fixed effects, and ζ_t, year fixed effects. The variable $post_{it}$ is an indicator that equals one if the observation occurs in the year after the announcement, and is zero if the observation occurs in the year before the announcement.[14] Additionally I cluster standard errors at the 2 digit SIC classification level. The treatment variables used in columns 1, 2 and 3 are all layoff announcements, reorganizing layoff announcements and downsizing layoff announcements

[14] The timing of a layoff announcement and the execution of the layoff may not happen at the same time. To address this concern, I follow Almond and Doyle (2008) and Cookson (2014) and adopt a doughnut strategy with a wide event window (-1,+1) where I exclude the event year. In this way, my specifications accommodate an adjustment period

respectively. Each specification also uses a re-weighted control group of non-announcers that is balanced to the respective treatment groups. The balancing is achieved along the the first three moments of the following covariates measured in the year before an announcement: ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age.

Panel B in Tables 7-13 reports results generated by the Abadie-Imbens matching estimator. As in panel A, the treatment variables in columns 1, 2 and 3 are all layoff announcements, reorganizing layoff announcements and downsizing layoff announcements respectively. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. The covariates used in the matching estimator are identical to those used in the entropy matching approach.

2.4.5.1 Layoff Announcements and Pre-Event Book Leverage

Table 2.7 presents evidence on changes made to book leverage[15] during a pre-event period by firms that subsequently announce layoffs.

In Panel A, firms that announce layoffs to downsize their workforce significantly raise book leverage by 1.4% in the year preceding their announcement. At the same time, firms that announce layoffs and fail to downsize (reorganize) their workforce do not increase leverage prior to their layoff.

Panel B presents the average treatment effect on the treated (ATET) results using the Abadie-Imbens matching estimator. Results are consistent with Panel A. In particular, firms that subsequently announce layoffs to downsize raise leverage by 1.8% in the year before their layoff. Importantly, I also report that the increase in leverage is statistically significant only for event windows prior to the layoff.

These results are consistent with the idea that when downsizing is the firm's best option, increasing leverage could be a way to discipline managers to undertake downsizing decisions even though it might not be in their own interest to do so. Firms also adjust their financial policy to improve their bargaining position with their workforce.

[15] Results are qualitatively similar when market leverage is used in place of book leverage

2.4.5.2 Layoff Announcements and Production Costs

The effect of layoff announcements on production costs is presented in Table 2.8. Production cost is measured by cost of goods sold, scaled by assets. Panel A of Table 2.8 shows that following layoff announcements firms significantly reduce productions costs by 3.4%. This reiterates the fact that since layoffs are expensive, firms undertake such decisions only when there are some cost savings. Based on evidence presented in columns 2 and 3 of Panel A, I find that firms making downsizing layoff announcements are more successful in reducing production costs than firms making reorganizing layoffs. This is because, firms that make downsizing announcements subsequently cut down on labor expenses due to a reduced workforce. On the other hand following reorganizing announcements, most of the laid off workers are replaced with other employees and hence there is little or no savings on labor cost.

Panel B presents the average treatment effect on the treated (ATET) results using the Abadie-Imbens matching estimator. Results are consistent with Panel A. Additionally, I also report that the fall in production costs is statistically significant only for the comparison between years +1 and -1 relative to the layoff but not for alternate event windows before and after the layoff. This implies that the significant reduction in production costs is due to the layoff announcement.

2.4.5.3 Layoff Announcements and Cash Holdings

In Table 2.9, I present the effects of layoff announcements on cash holdings. I measure cash holdings as cash and short term investments scaled by assets. Panel A of Table 2.9 shows that following layoff announcements firms significantly increase cash holdings by 1.8%. Following downsizing announcements firms raise cash holdings more than firms following reorganizing announcements. This result on cash holdings is consistent with results presented on production costs in the previous section. Firms save more cash out of savings from production costs following downsizing announcements. Alternatively firms are unable to raise cash holdings after reorganizing announcements because there is no saving from production costs.

Panel B presents the average treatment effect on the treated (ATET) results using the Abadie-Imbens matching estimator. Results are once again consistent with Panel A. Additionally, I also report that the increase in cash holdings is statistically significant only for the comparison between years +1 and -1 relative to the layoff but not for alternate event windows before and after the layoff. This implies that the significant increases in cash holdings is due to savings in production costs following the layoff announcement.

2.4.5.4 Layoff Announcements and Operating Performance

This subsection examines whether the savings from layoffs extend to improvements in operating performance. I measure operating performance using ROA.[16]

In Table 2.10 the main dependent variable of interest is ROA. I find that following layoff announcements operating performance at the firm falls by 1%. This result is true for both downsizing and reorganizing layoff announcements. Panel B of Table 2.10 presents the average treatment effect on the treated (ATET) results using the Abadie-Imbens matching estimator. It is notable that following downsizing announcements firms fare worse despite generating savings from production costs. This result on ROA following downsizing announcements is statistically significant only for the comparison between years +1 and -1 relative to the layoff but not for alternate event windows before and after the layoff.

In Table 2.11 the main dependent variable of interest is change in ROA. I find that following layoff announcements change in ROA increases by 0.8%. This implies that despite a fall in absolute operating performance firms witness a change in their performance trends after the layoff. Moreover, increases in change in operating performance is greater for firms following downsizing announcements when compared to reorganizing layoffs. Again, Panel B presents the average treatment effect on the treated (ATET) results using the Abadie-Imbens matching estimator. Under this approach, change in ROA increases for both downsizing and reorganizing layoff announcements. These results are statistically significant only for the comparison between years +1 and -1 relative

[16] calculated as EBITDA scaled by assets

to the layoff and not for alternate event windows before and after the layoff.

In Table 2.12 the main dependent variable of interest is sales growth. I find that following layoff announcements sales growth falls by 4.2%. This result is consistent with results on ROA, presented in Table 2.9. Columns 2 and 3 of Panel A report that the decline in sales growth is greater for firms following downsizing announcements when compared to firms following reorganizing layoffs. Panel B reports the average treatment effect on the treated (ATET) results using the Abadie-Imbens matching estimator. Results are consistent with Panel A. I also show that these results are statistically significant only for the comparison between years +1 and -1 relative to the layoff and not for alternate event windows before and after the layoff.

2.4.5.5 Layoff Announcements and Leverage

Table 2.13 presents evidence on the effects of layoff announcements on book leverage. In Panel A, I show that following reorganizing layoff announcements firms significantly raise book leverage by 2.3%. Panel B presents the average treatment effect on the treated (ATET) results using the Abadie-Imbens matching estimator. Results are consistent with Panel A. Additionally, I also report that the increase in leverage following reorganizing announcements is statistically significant only for the comparison between years +1 and -1 relative to the layoff.

A notable result is reported for the comparison between years -2 and -3 relative to the event year. I find that the firms that ultimately commit to downsizing, increase leverage by 1.7% during this pre-event comparison window. This suggests that firms may take on additional leverage to discipline managers or use financial inflexibility to increase their bargaining power with employees and credibly commit to downsizing.

2.5 Robustness and Additional Tests

2.5.1 Reorganizing Layoffs or Delayed Downsizing?

In this paper, I classify layoff announcements into downsizing and reorganizing types based on subsequent changes to employment for the event-year. A potential problem with this classification is that if the layoff occurs very close to the end of the fiscal year, the laid-off employees may not be captured by the annual change in employment variable. Another concern here is that firms may not go through with the decision to layoff immediately. In each of these cases, announcements will be wrongly classified as reorganizing layoffs. To resolve this issue, I present evidence on the effects of layoff announcements on employment levels in Table B.1 in Appendix B. In Panel A, I show that following reorganizing layoff announcements firms significantly raise the log of employees in the following year by 6.5%. On the other hand, following downsizing announcements, firms significantly reduce log of employees by 16.8%. Panel B presents the average treatment effect on the treated (ATET) results using the Abadie-Imbens matching estimator. Results are consistent with Panel A. Additionally, I also report that the results are statistically significant only for the comparison between years +1 and -1 relative to the layoff. These results suggest that the implications of layoffs on employment extends (in the expected direction) beyond the layoff year implying that the methodology classifying layoff type is robust.

2.5.2 Layoff Announcements and Mergers & Acquisitions

When a firm lays off workers after an acquisition, the announcement is highly likely to be classified as a reorganizing announcement because in an acquisition the firm acquires employees as well. In such cases the lower buy-and-hold abnormal returns earned in the year following the announcement may just be a function of the merger and not the layoff. I document that 90 layoff announcements follow merger and acquisitions. I drop these 90 instances and empirically test the robustness of the main results presented in this paper. Figure B.1 in Appendix B, presents evidence on the short and long run stock market performance for actual and predicted layoff types. Results are consistent with the overall sample. I also report the average treatment effect on the treated results using the Abadie-Imbens matching estimator in Table B.2 of Appendix B. Results are once again consistent with the baseline sample used in this paper. This implies that results are not driven by the incidence of mergers and acquisitions in my sample.

2.5.3 Downsizing Announcements and Asset Sales

Distressed firms may adopt multiple downsizing strategies to generate cash flows in the short run. While this paper discusses downsizing with respect to layoff announcements, firms may also downsize through asset sales. When a firm downsizes through layoffs and asset sales simultaneously, the higher buy-and-hold abnormal returns in the following year could be explained by asset sales as well. To rule out this alternative explanation I exclude all layoff announcement where the firm also reduces total assets by at least 10%. In doing so, I drop 183 layoff announcements and empirically test the robustness of the main results presented in this paper. Figure B.2 in Appendix B, presents evidence on the short and long run stock market performance for actual and predicted layoff types. I show that results are consistent with the overall sample. I also report the average treatment effect on the treated results using the Abadie-Imbens matching estimator in Table B.3 of Appendix B. Results are once again consistent with the baseline sample used in this paper. This evidence implies that my results for downsizing layoff announcements are not driven by a simultaneous reduction in total assets.

2.5.4 Layoff Announcements and Attention Bias

In this paper I use hand-collected data on layoff announcements by all firms listed in the S&P 500 at some point between 1980 and 2014. It is possible that my data suffers from attention bias because firms that are currently in the S&P 500 receive greater coverage from the media as well as investors, compared to firms that were previously members of the index or candidates for inclusion. Therefore, I might have been more likely to find layoff announcements by firms listed in the index at the time of their announcement. To empirically test that my results are not driven by an attention bias I exclude layoff announcements by firms that were not a part of the S&P 500 at the time of the announcement. I drop 105 layoff announcements. Figure B.3 in Appendix B, presents evidence on the short and long run stock market performance for actual and predicted layoff types. I show that results are consistent with the overall sample. I also report the average treatment effect on the treated results using the Abadie-Imbens matching estimator in Table B.4 of Appendix B. Results are once again consistent with the baseline sample used in this paper. Importantly, this consistency with the baseline sample shows that results are not driven by an attention bias.

2.5.5 Alternative Measure for Layoff Classification

For my main tests, I classify a layoff announcement as a reorganizing layoff if the annual change in employment for the event-year is less than 10% of the layoff size. Alternatively, a layoff announcement is classified as a downsizing announcement when the annual change in employment for the event-year is greater than 10% of the layoff size. To ensure that my results are not dependent on the choice of the 10% cut-off, I create two alternative measures for classifying layoff type by varying the cut-off percentage to 0 and 20 percent. A lower cut-off imposes stronger restrictions for announcements to be classified as reorganizing announcements while a higher cut-off imposes stronger restrictions for announcements to be classified as downsizing announcements. While using a 20% cut-off, there are 825 downsizing and 422 reorganizing layoff announcements. On the other hand, when I use a 0% cut-off, there are 867 downsizing and 380 reorganizing announcements. I present results for the 20% cut-off classification in Figure B.4 and Table B.5 in Appendix B and results for the 0% cut-off classification are reported in Figure B.5 and Table B.6. The results are once again consistent with the main findings. This implies that the evidence presented in this paper is not dependent on the choice of the cut-off percentage to classify layoff type.

2.6 Conclusion

In this paper, I examine the effect of layoff decisions on long-run firm performance. I begin by identifying the heterogeneity inherent in layoff decisions on the basis of changes to employment following a layoff. I document that nearly 32% of all layoffs by S&P 500 firms do not lead to a decline in employment. I show that this heterogeneity has important implications for long-run performance. In particular, layoffs that lead to a decline in employment result in significantly greater buy-and-hold abnormal returns in the year following the announcement compared to firms that fail to downsize following layoffs. Notably, the market fails to distinguish between these layoffs in the short run.

While the market fails to distinguish these layoffs at the time of the announcement, I show that it is possible to predict layoff type in real time using information on prior firm characteristics. Downsizers tend to be distressed, with worse operating performance, sales growth, growth opportunities, and severe financial constraints. I create a real-time index based on these firm characteristics to predict the likelihood of a layoff resulting in workforce reorganization, and show that a simple long-short strategy based off of this index can generate profits for investors.

I also employ a difference-in-differences framework with entropy balancing and a matching estimator approach to show that layoff announcements, depending on their type, have important implications for production costs, liquidity and operating performance. Following downsizing announcements, firms are successful in reducing production costs and generating cash flows compared to firms that fail to downsize following layoffs. Additionally, following downsizing layoffs, firms also witness an improvement in performance trends.

Finally, I show that my results are not driven by alternative explanations such as mergers and acquisitions, asset sales, attention bias and limitations in the classification of layoff type. The main results presented in the paper also survive a battery of placebo tests for pre-layoff and post-layoff event windows.

Overall, the results presented in this paper are consistent with the idea that when downsizing is the firm's best option, increasing leverage may be a way to discipline managers to undertake downsizing decisions even though it might not be in their own interest to do so. Additionally, firms also adjust their financial policy to improve their bargaining position with their workforce. In particular, when downsizing is a value-creating option, financially inflexible firms following poor performance can credibly take a tougher stand when negotiating with workers. Importantly, when firms fail to commit to the downsizing decision, they are significantly worse off. While I show that downsizing firms raise leverage in the year prior to their layoff, the lack of union coverage data at the firm level does not allow me to verify whether firms are successful in increasing bargaining power.

2.7 Figures and Tables

Table 2.1: Variable Definitions

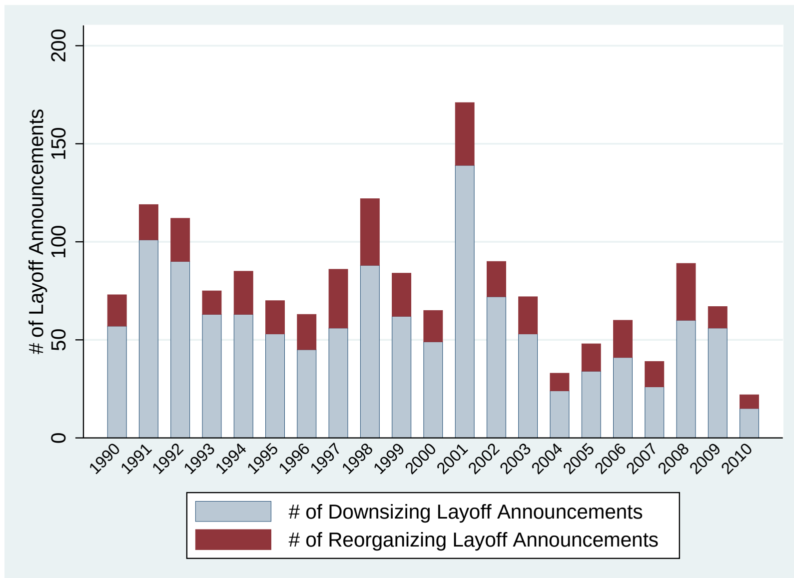
Layoff Classification	**Description**
Downsizing Layoff Announcement	Defined as a layoff announcement where the annual change in employment for the event year is greater than 10% of the number of workers laid-off by the firm. Employment data is from Compustat.
Reorganizing Layoff Announcement	Defined as a layoff announcement where the annual change in employment for the event year is less than 10% of the number of workers laid-off by the firm. Employment data is from Compustat.
Stock Performance Variables	**Description**
CAR (-1,+1)	Measures the 3-day cumulative abnormal returns for a firm centered around it's layoff announcement. The cumulative abnormal returns are calculated using the Market Model as a benchmark.
BHAR (+2,+300)	Measures the one-year buy-and-hold abnormal returns following a layoff announcement. The BHARs are calculated using a characteristics-based matching approach using the Fama-French three factor model as a benchmark.
Firm Characteristics	**Description**
ROA	Measured as the ratio of earnings to book value of assets. Compustat (ebitda)/(at), all measured at time t.
Change in ROA	Measured as the annual change in ROA.
Market-to-Book Ratio	Measured as the ratio of market value of equity to book value of equity. Compustat (csho*prcc_f)/(at-lt), all measured at time t.
Cost of Goods Sold	Measured as the ratio of cost of goods sold scaled by book value of assets. Compustat cogs/at , all measured at time t.
Cash Holding	Cash plus marketable securities scale by previous year's total assets. Compustat che/at, che is measured at t and at is measured at t-1.
Sales Growth	Measured as total sales less previous year's total sales divided by previous year's total sales. Compustat $(sale_t - sale_{t-1})/sale_{t-1}$.

Book 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.
Change in Book Leverage	Measured as the annual change in Book Leverage.
Whited-Wu Index	Measures financial constraints and is calculated following Whited and Wu (2006).
Log of Employees	Measures the natural logarithm of the Total number of employees of the firm. Compustat ln(emp*1000)). Measured at time t.
Log of Assets	The natural logarithm of total assets adjusted for inflation. Compustat ln(at/deflator),measured at time t.
Log of Age	Measured as the natural logarithm of 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.
Industry Union Coverage	Measured as the ratio of number of workers covered by a collective bargaining agreement divided by the total number of workers employed within a 2-digit SIC industry.

Figure 2.1: Distribution of Layoff Announcements by Year

Note: The figures below describe the distribution of layoff announcements by type for a sample of firms listed in S&P 500 between 1980 and 2010. Panel A depicts the total number of layoff announcements while panel B depicts the percentage of layoff announcements by type for any given year.

(a)



(b)

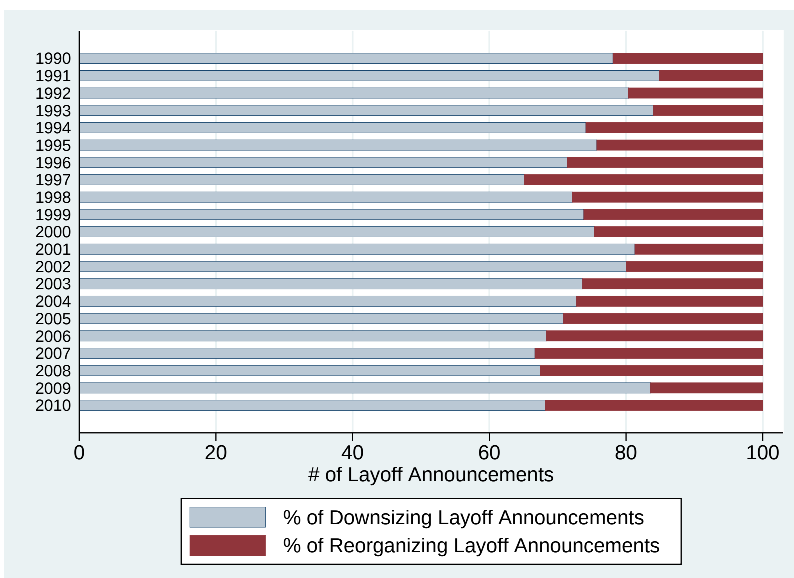
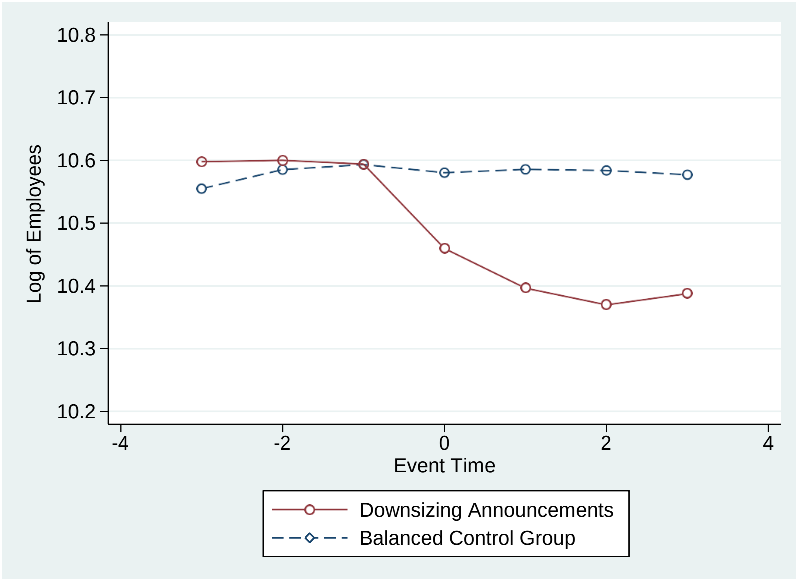


Figure 2.2: Distribution of Employment Levels by Event Time

Note: The figures below describe the distribution of mean logged employment levels by event year for S&P 500 firms that announce layoffs between 1980 and 2010. Panel A depicts the average log of employees for downsizing layoff announcements by event time while panel B depicts the average log of employees for reorganizing layoff announcements by event year.

(a) Downsizing Announcements



(b) Reorganizing Layoffs

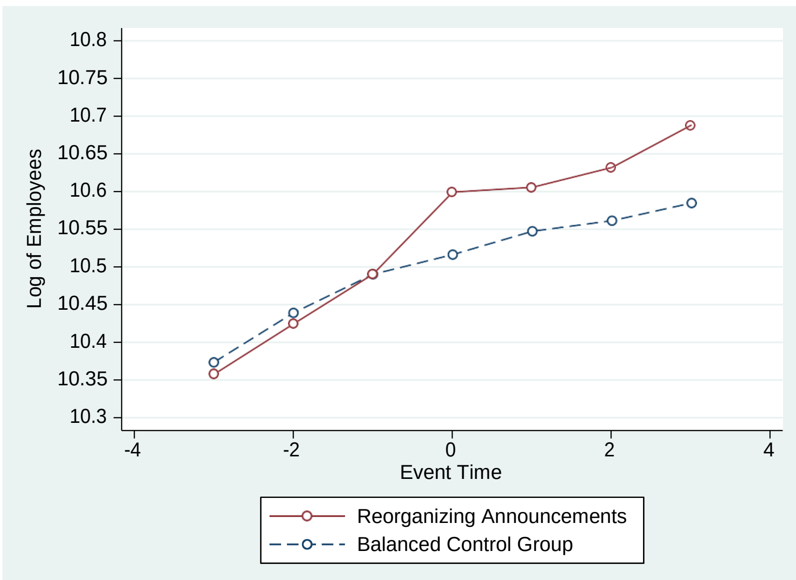
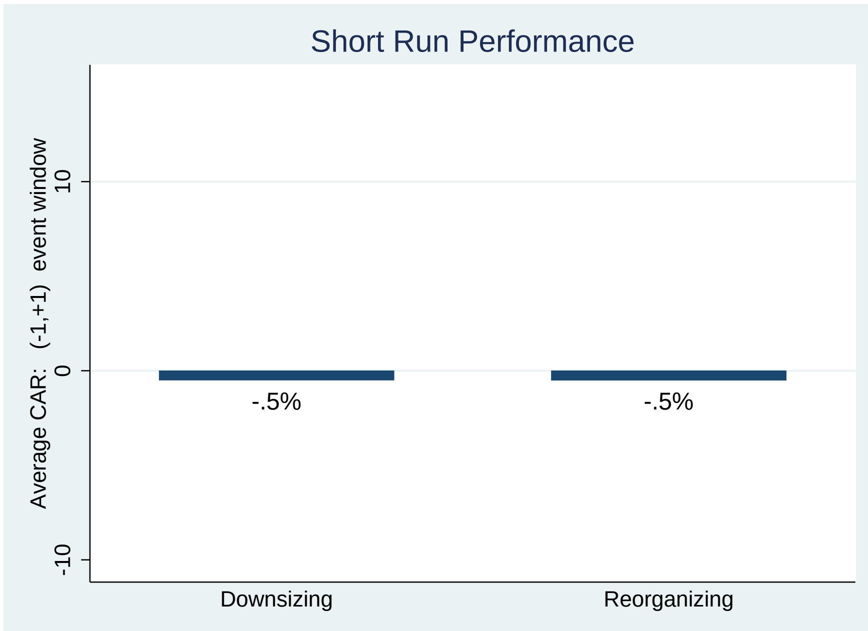


Figure 2.3: Layoff Announcements and Stock Market Performance

Note: The figures below describe the average stock market performance for layoff announcements by type from 1990 to 2010. Panel A plots the average 3-day cumulative abnormal return for downsizing and Reorganizing layoff announcements. The 3-day CARs are calculated using a market model and are centered around the day of the announcement. Panel B depicts the average Buy and Hold abnormal returns for downsizing and Reorganizing layoff announcements. The BHARs are calculated using the Fama French 3 factor model as a benchmark and span a 298-day window, (+2,+300).

(a) Short Run Stock Performance



(b) Long Run Stock Performance

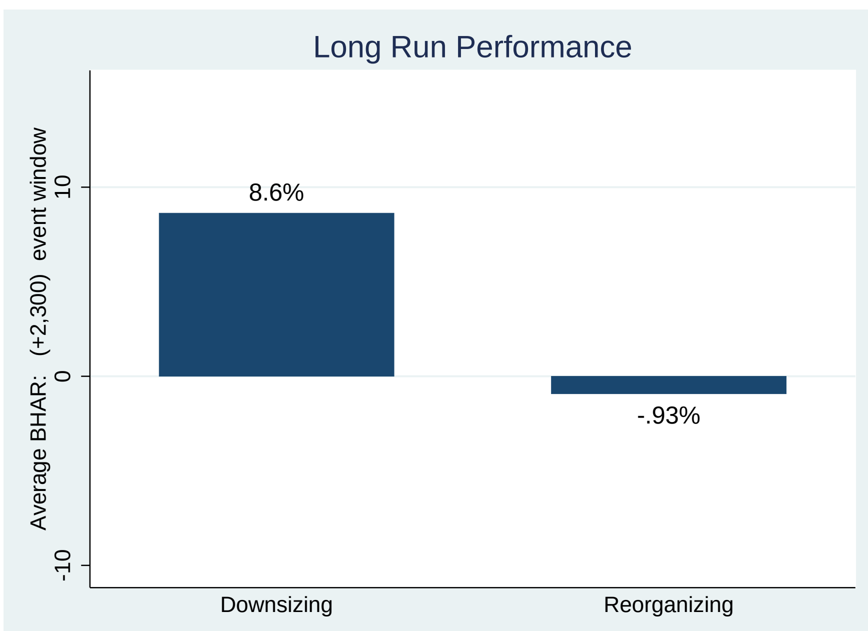
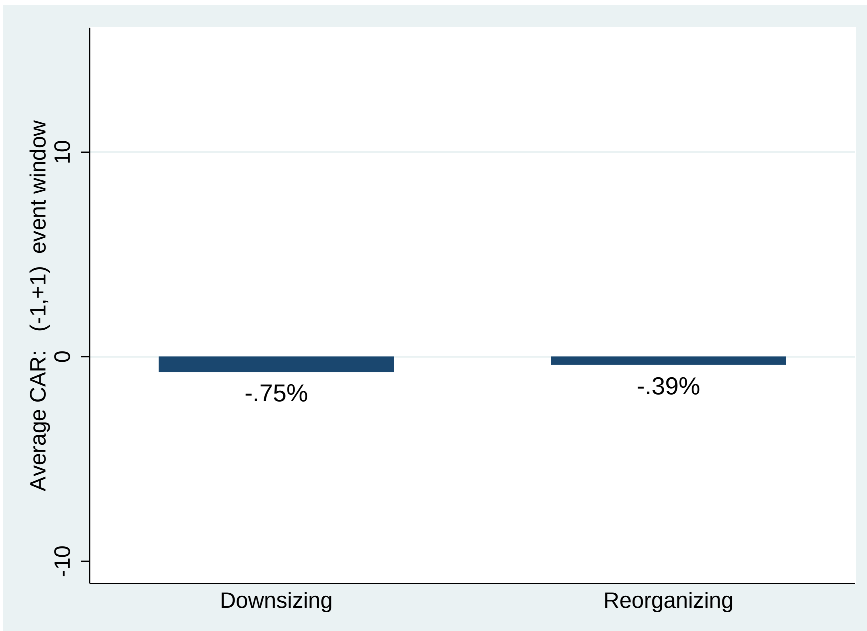


Figure 2.4: Layoff Announcements and Stock Market Performance in High Union Coverage Industries

Note: The figures below describe the average stock market performance in high union coverage industries for layoff announcements by type from 1990 to 2010. Panel A plots the average 3-day cumulative abnormal return for downsizing and Reorganizing layoff announcements. The 3-day CARs are calculated using a market model and are centered around the day of the announcement. Panel B depicts the average Buy and Hold abnormal returns for downsizing and Reorganizing layoff announcements. The BHARs are calculated using the Fama French 3 factor model as a benchmark and span a 298-day window, (+2,+300).

(a) Short Run Stock Performance



(b) Long Run Stock Performance

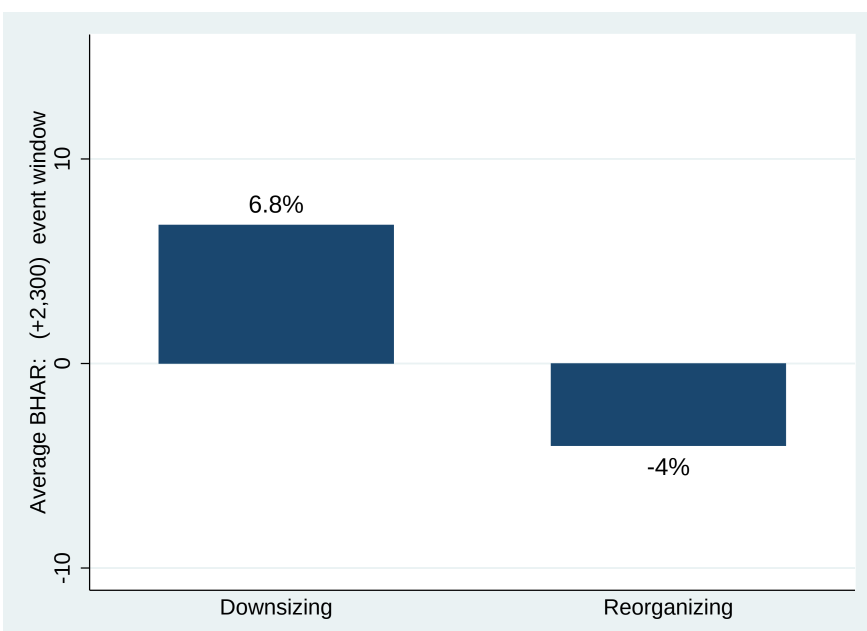
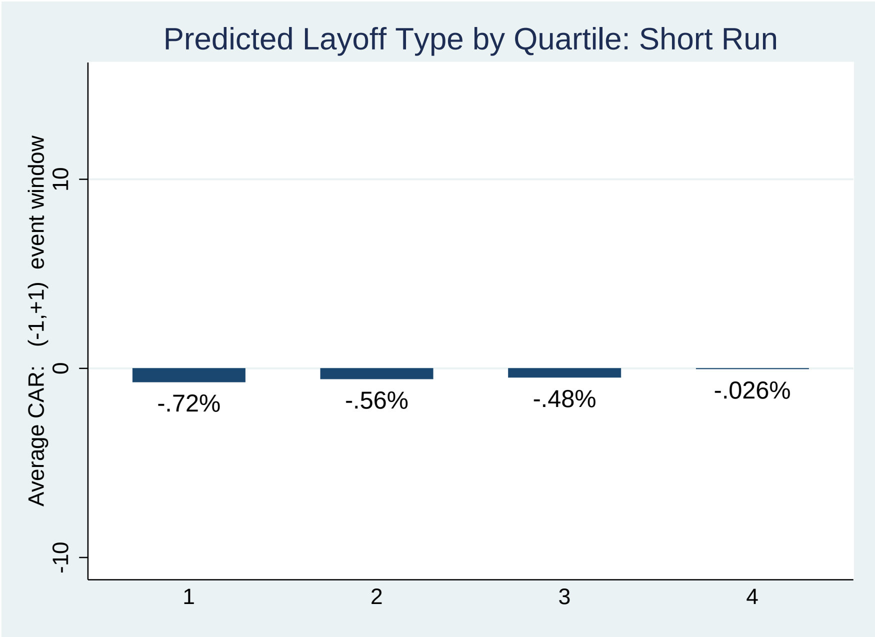


Figure 2.5: Predicting Layoff Type in Real time

Note: The figures below describe the average stock market performance for layoff announcements from 1990 to 2010. Panel A plots the average 3-day cumulative abnormal return for layoff announcements by quartiles of the probability of the layoff being of the employment reorganization type. The 3-day CARs are calculated using a market model and are centered around the day of the announcement. Panel B depicts the average Buy and Hold abnormal returns for layoff announcements by quartiles of the probability of the layoff being of the employment reorganization type. The BHARs are calculated using the Fama French 3 factor model as a benchmark and span a 298-day window, (+2,+300).

(a) Short Run Stock Performance



(b) Long Run Stock Performance

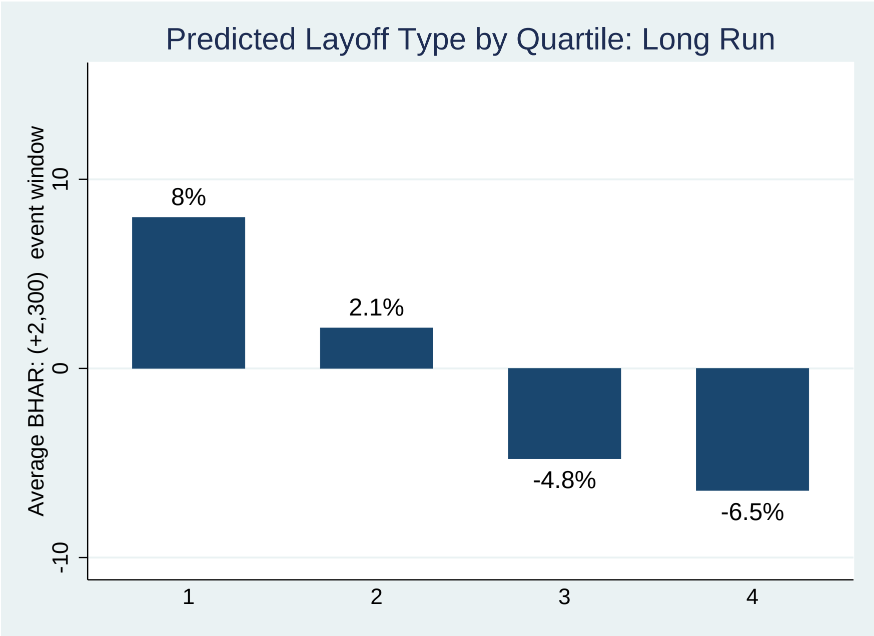
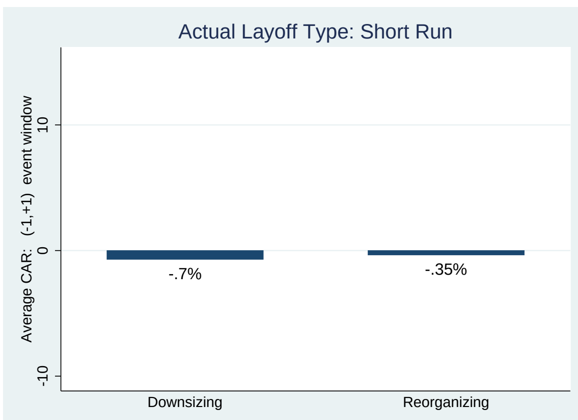


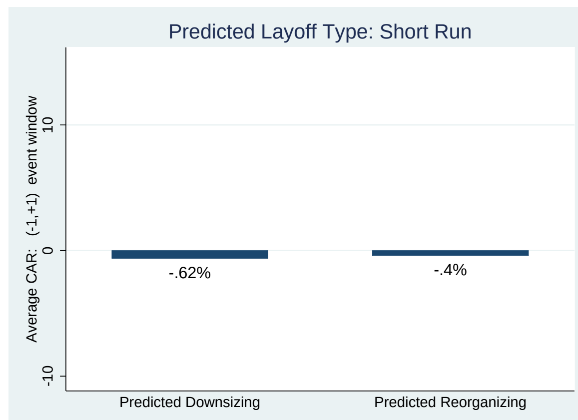
Figure 2.6: Predicted Layoff Type & Stock Returns

Note: The figures below describe the average stock market performance for layoff announcements by type from 1990 to 2010. Panels A and B plot the average 3-day cumulative abnormal return for actual and predicted announcements by layoff type. The 3-day CARs are calculated using a market model and are centered around the day of the announcement. Panels C and D depict the average Buy-and-Hold abnormal returns for actual and predicted announcements by layoff type. The BHARs are calculated using the Fama French 3 factor model as a benchmark and span a 298-day window, (+2,+300).

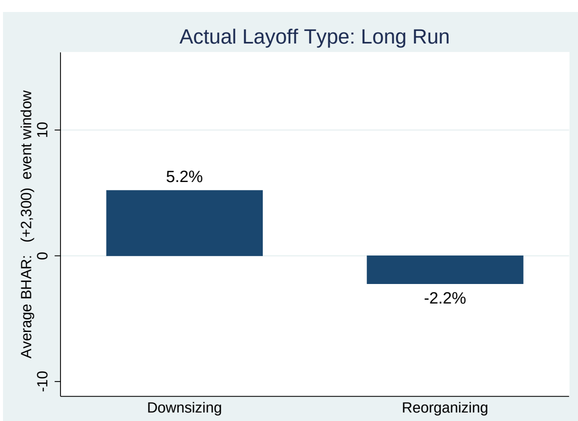
(a) Actual CAR



(b) Predicted CAR



(c) Actual BHAR



(d) Predicted BHAR

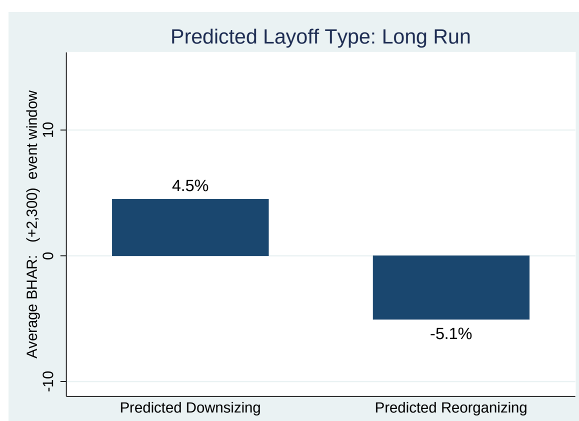
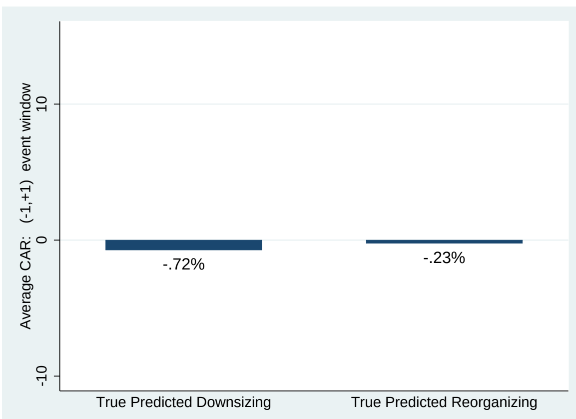


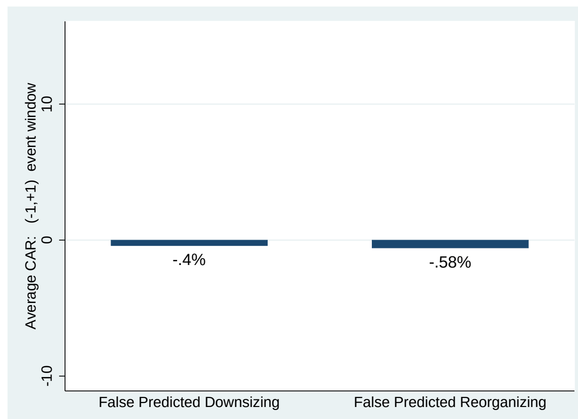
Figure 2.7: True and False Layoff Type Predictions

Note: The figures below describe the average stock market performance for layoff announcements by type from 1990 to 2010. Panels A and B plot the average 3-day cumulative abnormal return for true and false predictions of layoff type. The 3-day CARs are calculated using a market model and are centered around the day of the announcement. Panels C and D depict the average Buy-and-Hold abnormal returns for true and false predictions of layoff type. The BHARs are calculated using the Fama French 3 factor model as a benchmark and span a 298-day window, (+2,+300).

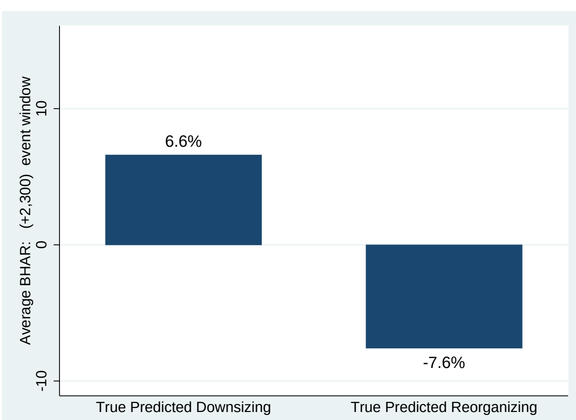
(a) True Predicted CAR



(b) False Predicted CAR



(c) True Predicted BHAR



(d) False Predicted BHAR

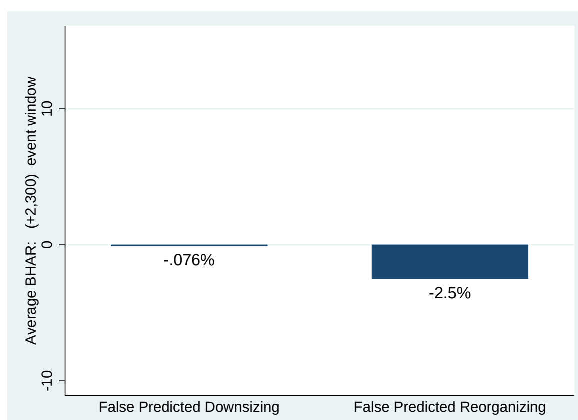


Table 2.2: Layoff Announcements and Affected Employees by Year

	# of Announcements			Average # of Employees laid-off			Layoff Ratio		
Fiscal Year	Downsizing Layoff	Reorganizing Layoff	All	Downsizing Layoff	Reorganizing Layoff	All	Downsizing Layoff	Reorganizing Layoff	All
1990	41	16	57	1638.59	1419.38	1577.05	2.89%	2.01%	2.64%
1991	83	18	101	1156.25	1522.06	1220.36	2.62%	4.38%	2.93%
1992	68	22	90	2018.21	1020.95	1777.49	4.18%	2.54%	3.78%
1993	51	12	63	2997.90	1446.25	2687.57	4.39%	5.73%	4.66%
1994	41	22	63	3709.18	1079.68	2776.13	7.74%	6.49%	7.29%
1995	36	17	53	2387.36	1112.65	1978.49	4.93%	3.68%	4.53%
1996	27	18	45	2776.41	787.00	1980.64	5.02%	3.13%	4.26%
1997	26	30	56	1976.52	1205.14	1562.26	7.06%	5.23%	6.08%
1998	54	34	88	2575.96	2026.09	2367.39	6.89%	7.16%	6.99%
1999	40	22	62	1355.88	1683.33	1468.61	5.17%	10.75%	7.09%
2000	33	16	49	1278.88	1827.94	1458.16	5.45%	5.67%	5.52%
2001	107	32	139	3041.58	2113.30	2830.61	4.86%	7.08%	5.36%
2002	54	18	72	1925.28	1281.39	1754.84	6.97%	3.08%	5.94%
2003	34	19	53	2065.49	831.67	1630.02	7.17%	4.63%	6.27%
2004	15	9	24	2444.00	935.56	1878.33	7.71%	4.65%	6.56%
2005	20	14	34	1740.28	3428.21	2478.75	5.94%	2.87%	4.60%
2006	22	19	41	2953.42	1239.47	2096.45	4.37%	2.78%	3.58%
2007	13	13	26	3128.46	1217.08	2211.00	5.48%	3.18%	4.38%
2008	31	29	60	1313.10	2726.07	1994.36	3.40%	5.46%	4.39%
2009	45	11	56	2915.00	3375.00	3001.79	6.13%	4.04%	5.74%
2010	8	7	15	3467.86	3214.29	3341.07	4.25%	4.34%	4.30%
Total	849	398	1,247	2268.80	1648.91	2070.23	5.15%	5.02%	5.11%

Table 2.3: Layoff Announcements and Affected Employees by Industry

(a) # of Layoffs by Industry

SIC Industry Classification	# of Announcements: Downsizing Layoff	Reorganizing Layoff	All
01-09: Agriculture, Forestry, Mining	0	2	2
10-17: Mining, Construction	32	11	43
20-29: Manufacturing	213	100	313
30-39: Manufacturing	439	149	588
40-48: Transport, Communications	57	44	101
50-51: Trade	35	31	66
70-79: Services	59	50	109
91-99: Public administration	14	11	25
Total	849	398	1,247

(b) Employees Laid-off by Industry

	Average # of Employees laid-off			Layoff Ratio		
SIC Industry Classification	Downsizing Layoffs	Reorganizing Layoffs	All Layoffs	Downsizing Layoffs	Reorganizing Layoffs	All Layoffs
01-09: Agriculture, Forestry, Mining	-	900.00	900.00	-	3.37%	3.37%
10-17: Mining, Construction	610.97	1560.46	865.71	7.35%	16.09%	9.69%
20-29: Manufacturing	1781.39	1652.18	1740.04	4.36%	4.99%	4.56%
30-39: Manufacturing	2402.41	1699.81	2224.93	5.65%	5.93%	5.72%
40-48: Transport, Communications	3936.36	1344.88	2799.29	3.72%	2.40%	3.14%
50-51: Trade	2174.71	2119.21	2149.16	3.35%	2.01%	2.74%
70-79: Services	2490.60	1401.79	1967.97	6.67%	4.97%	5.86%
91-99: Public administration	1552.08	2196.36	1860.22	0.58%	0.74%	0.65%
Total	2268.80	1648.91	2070.23	5.15%	5.02%	5.11%

Table 2.4: Summary Statistics for Firm Characteristics by Layoff and Layoff Type

Note: This table presents average firm characteristics for firms in the sample. Panel A highlights the differences in firm characteristics for announcers and non-announcers and Panel B reports the differences in firm characteristics between Downsizing and Reorganizing layoff announcements.

(a) Summary Statistics for Announcers & Non-Announcers

	Non Announcers		Announcers		Difference of means
Variable	N	mean	N	mean	
ROA	3825	0.1591	1247	0.1420	0.0175***
Leverage	3825	0.3230	1247	0.3800	-0.0570***
Log of Assets	3825	7.6540	1247	9.2160	-1.562***
Market - Book	3825	3.3940	1247	3.1390	0.255**
Log of age	3825	3.0096	1247	3.5020	-0.492***
Cash Holdings	3825	0.1265	1247	0.1070	0.0191***
Sales growth	3825	0.1439	1247	0.0692	0.0747***
WW index	3825	-0.3489	1247	-0.4300	0.0811***
Log of employees	3825	9.1584	1247	10.5600	-1.402***
Cost of goods sold	3825	0.7861	1247	0.6990	0.0869***
RD	3825	0.0192	1247	0.0428	-0.0235***

(b) Summary Statistics for Downsizing & Reorganizing Layoff Announcements

	Downsizing Type		Reorganizing Type		Difference of means
Variable	N	mean	N	mean	
ROA	849	0.1310	398	0.1640	-0.0327***
Leverage	849	0.3920	398	0.3540	0.0380**
Log of Assets	849	9.2390	398	9.1680	0.0705
Market - Book	849	2.7290	398	4.0130	-1.284***
Log of age	849	3.5300	398	3.4420	0.0888*
Cash Holdings	849	0.0971	398	0.1290	-0.0322***
Sales growth	849	0.0475	398	0.1150	-0.0679***
WW index	849	-0.4270	398	-0.4370	0.0105
Log of employees	849	10.5900	398	10.4900	0.103
Cost of goods sold	849	0.7060	398	0.6850	0.0214
RD	849	0.0447	398	0.0386	0.00606*

Table 2.5: Probability of Making a Layoff Announcement

Note: This table reports the average marginal effects from a probit model where the dependent variable is the likelihood of a firm making a layoff announcement. The overall sample consists of firms that make layoff announcements and those that have never made a mass layoff announcement between 1990 and 2010. Each firm in the sample has been listed in the S&P 500 index at some point in time between 1980 and 2014. Independent variables are lagged and winsorized at the 1 percent level. Change in Book Leverage is not available for 5 observations (non-announcers) in the sample. Additionally, standard errors are clustered at the 2 digit SIC classification level.

Variable	Announcer	Announcer	Announcer	Announcer
Return on Assets	-0.068	-0.036	-0.164	-0.116
	(0.174)	(0.183)	(0.161)	(0.170)
Market to Book ratio	0.000	0.001	0.006	0.006
	(0.004)	(0.003)	(0.004)	(0.004)
Cost of goods sold, scaled by assets	-0.030	-0.018	0.046	0.059*
	(0.027)	(0.024)	(0.034)	(0.030)
Cash Holdings, scaled by assets	0.329***	0.427***	0.151	0.228**
	(0.116)	(0.109)	(0.109)	(0.103)
Sales Growth	-0.137***	-0.178***	-0.107***	-0.138***
	(0.044)	(0.043)	(0.039)	(0.036)
Change in Book Leverage	0.233***	0.202***	0.213***	0.194***
	(0.059)	(0.055)	(0.055)	(0.052)
Whited-Wu index	-0.207**	-0.224***	-0.030	-0.040
	(0.094)	(0.085)	(0.115)	(0.088)
Log of Real Assets	0.076***	0.087***	0.102***	0.133***
	(0.014)	(0.014)	(0.018)	(0.016)
Log of Employees	0.041**	0.030*	0.038*	0.009
	(0.018)	(0.016)	(0.021)	(0.018)
Log of Firm Age	0.086***	0.076***	0.046**	0.048**
	(0.022)	(0.020)	(0.021)	(0.019)
Industry Fixed Effects	No	No	Yes	Yes
Year Fixed Effects	No	Yes	No	Yes
N	5,067	5,067	4,583	4,583
Pseudo R-squared	0.26	0.32	0.37	0.42

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

Table 2.6: Probability of Layoff Type

Note: This table reports the average marginal effects from a probit model where the dependent variable is the likelihood of a layoff being of the Reorganizing type as opposed to a downsizing announcement. A layoff announcement is classified as a downsizing announcement if the number of employees reported by the firm after the layoff is significantly less than the number of employees the firm had in the year prior to the announcement. If not, the layoff is classified as a Reorganizing announcement. Each layoff announcement is by a firm listed in the S&P 500 index at some point in time between 1980 and 2010. All independent variables except industry union coverage are lagged and winsorized at the 1 percent level. Industry union coverage is only lagged. Further industry union coverage is not available for 15, 17 and 99 2-digit SIC codes. Finally, standard errors are clustered at the 2-digit SIC classification level.

Variable	Reorganizing Layoff	Reorganizing Layoff	Reorganizing Layoff	Reorganizing Layoff
Return on Assets	0.593**	0.554**	0.746***	0.731***
	(0.234)	(0.218)	(0.230)	(0.228)
Market to Book ratio	0.020***	0.020***	0.015**	0.017***
	(0.007)	(0.007)	(0.006)	(0.006)
Cost of goods sold, scaled by assets	0.006	-0.006	0.024	0.012
	(0.043)	(0.040)	(0.043)	(0.039)
Cash Holdings, scaled by assets	0.076	0.042	0.043	-0.024
	(0.140)	(0.131)	(0.103)	(0.122)
Sales Growth	0.213**	0.246***	0.220***	0.250***
	(0.093)	(0.091)	(0.084)	(0.088)
Change in Book Leverage	-0.386*	-0.323*	-0.444**	-0.355*
	(0.208)	(0.180)	(0.210)	(0.182)
Whited-Wu index	-0.553**	-0.608***	-0.682**	-0.766***
	(0.271)	(0.180)	(0.307)	(0.157)
Log of Real Assets	-0.012	-0.029	0.017	0.015
	(0.037)	(0.033)	(0.043)	(0.042)
Log of Employees	-0.015	-0.001	-0.084**	-0.080*
	(0.042)	(0.039)	(0.040)	(0.044)
Log of Firm Age	-0.027	-0.041*	0.027	0.015
	(0.030)	(0.023)	(0.024)	(0.021)
Industry Union Coverage	-0.190	-0.086	-0.462	-0.015
	(0.207)	(0.191)	(0.355)	(0.522)
Industry Fixed Effects	No	No	Yes	Yes
Year Fixed Effects	No	Yes	No	Yes
N	1,219	1,219	1,208	1,208
Pseudo R-squared	0.07	0.11	0.13	0.17

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

Table 2.7: Pre-Event (-2,-1) Difference-in-Difference Comparisons of Book Leverage

Note: The dependent variable of interest in this table is Book Leverage. In each panel, the treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Panel A presents results from difference-in-difference regressions. Using entropy balancing I create a re-weighted balanced control group of non-announcers for each treatment group. Balance is achieved along the first three moments of the following covariates for the year before the layoff: ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. In each column, I control for firm and year fixed effects. Additionally, standard errors are clustered at the 2 digit SIC industry classification level. Panel B presents the average treatment effect on the treated (ATET) results. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are identical to Panel A. Finally, heteroskedasticity-consistent standard errors are in parentheses.

(a) Entropy Balancing: (-2,-1)

	All: Book Leverage	Reorganizing: Book Leverage	Downsizing: Book Leverage
Post	0.009***	0.010**	0.009***
	(0.003)	(0.004)	(0.002)
Post x Announcer	0.010**		
	(0.005)		
Post x Restructuring Announcement		0.000	
		(0.008)	
Post x Downsizing Announcement			0.014***
			(0.005)
N	9,594	7,990	8,826
R-squared	0.79	0.82	0.80
Adjusted R-squared	0.7695	0.8023	0.7852

(b) Abadie-Imbens Matching Estimator

	All: Book Leverage	Reorganizing: Book Leverage	Downsizing: Book Leverage
Matching Estimator - ATT: (-3,-2)	0.016***	0.005	0.017***
	(0.006)	(0.009)	(0.006)
Matching Estimator - ATT: (-2,-1)	0.014***	0.006	0.018***
	(0.005)	(0.007)	(0.006)
Matching Estimator - ATT: (-1,+1)	0.002	0.007	-0.002
	(0.008)	(0.011)	(0.009)
Matching Estimator - ATT: (+2,+3)	-0.012*	-0.023**	-0.004
	(0.007)	(0.010)	(0.008)

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

Table 2.8: Difference-in-Difference Comparisons of Production Costs

Note: The dependent variable of interest in this table is COGS/Assets. In each panel, the treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Panel A presents results from difference-in-difference regressions. Using entropy balancing I create a re-weighted balanced control group of non-announcers for each treatment group. Balance is achieved along the first three moments of the following covariates for the year before the layoff: ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. In each column, I control for firm and year fixed effects. Additionally, standard errors are clustered at the 2 digit SIC industry classification level. Panel B presents the average treatment effect on the treated (ATET) results. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are identical to Panel A. Finally, heteroskedasticity-consistent standard errors are in parentheses.

(a) Entropy Balancing: (-1,+1)

	All: COGS/Assets	Reorganizing: COGS/Assets	Downsizing: COGS/Assets
Post	0.003	-0.004	0.007
	(0.007)	(0.007)	(0.008)
Post x Announcer	-0.034***		
	(0.011)		
Post x Reorganizing Announcement		-0.008	
		(0.009)	
Post x Downsizing Announcement			-0.046***
			(0.015)
N	9,594	7,990	8,826
R-squared	0.92	0.95	0.90
Adjusted R-squared	0.9096	0.9502	0.8928

(b) Abadie-Imbens Matching Estimator

	All: COGS/Assets	Reorganizing: COGS/Assets	Downsizing: COGS/Assets
Matching Estimator - ATT: (-1,+1)	-0.033***	-0.015	-0.047***
	(0.010)	(0.012)	(0.012)
Matching Estimator - ATT: (-3,-2)	-0.011	-0.008	-0.009
	(0.008)	(0.011)	(0.010)
Matching Estimator - ATT: (+2,+3)	-0.004	-0.006	-0.002
	(0.008)	(0.012)	(0.010)

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

Table 2.9: Difference-in-Difference Comparisons of Cash Holdings

Note: The dependent variable of interest in this table is cash & short term investments/Assets. In each panel, the treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Panel A presents results from difference-in-difference regressions. Using entropy balancing I create a re-weighted balanced control group of non-announcers for each treatment group. Balance is achieved along the first three moments of the following covariates for the year before the layoff: ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. In each column, I control for firm and year fixed effects. Additionally, standard errors are clustered at the 2 digit SIC industry classification level. Panel B presents the average treatment effect on the treated (ATET) results. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are identical to Panel A. Finally, heteroskedasticity-consistent standard errors are in parentheses.

(a) Entropy Balancing: (-1,+1)

	All: Cash Holdings	Reorganizing: Cash Holdings	Downsizing: Cash Holdings
Post	-0.009*	-0.014**	-0.005
	(0.005)	(0.006)	(0.004)
Post x Announcer	0.018***		
	(0.006)		
Post x Reorganizing Announcement		0.005	
		(0.007)	
Post x Downsizing Announcement			0.023***
			(0.006)
N	9,594	7,990	8,826
R-squared	0.75	0.77	0.76
Adjusted R-squared	0.7267	0.7593	0.7402

(b) Abadie-Imbens Matching Estimator

	All: Cash Holdings	Reorganizing: Cash Holdings	Downsizing: Cash Holdings
Matching Estimator - ATT: (-1,+1)	0.017***	0.010	0.021***
	(0.005)	(0.007)	(0.006)
Matching Estimator - ATT: (-3,-2)	-0.004	0.001	-0.006
	(0.005)	(0.008)	(0.006)
Matching Estimator - ATT: (+2,+3)	0.003	-0.002	0.002
	(0.005)	(0.008)	(0.005)

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

Table 2.10: Difference-in-Difference Comparisons of Firm Performance

Note: The dependent variable of interest in this table is return on assets, ROA. In each panel, the treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Panel A presents results from difference-in-difference regressions. Using entropy balancing I create a re-weighted balanced control group of non-announcers for each treatment group. Balance is achieved along the first three moments of the following covariates for the year before the layoff: ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. In each column, I control for firm and year fixed effects. Additionally, standard errors are clustered at the 2 digit SIC industry classification level. Panel B presents the average treatment effect on the treated (ATET) results. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are identical to Panel A. Finally, heteroskedasticity-consistent standard errors are in parentheses.

(a) Entropy Balancing: (-1,+1)

	All: ROA	Reorganizing: ROA	Downsizing: ROA
Post	-0.001	-0.003	0.000
	(0.002)	(0.002)	(0.002)
Post x Announcer	-0.010***		
	(0.004)		
Post x Reorganizing Announcement		-0.012***	
		(0.005)	
Post x Downsizing Announcement			-0.009**
			(0.003)
N	9,594	7,990	8,826
R-squared	0.65	0.72	0.65
Adjusted R-squared	0.6294	0.7046	0.6265

(b) Abadie-Imbens Matching Estimator

	All: ROA	Reorganizing: ROA	Downsizing: ROA
Matching Estimator - ATT: (-1,+1)	-0.004	0.001	-0.007*
	(0.003)	(0.004)	(0.004)
Matching Estimator - ATT: (-3,-2)	-0.007***	-0.009***	-0.004
	(0.002)	(0.003)	(0.003)
Matching Estimator - ATT: (+2,+3)	-0.001	-0.001	-0.001
	(0.003)	(0.004)	(0.003)

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

Table 2.11: Difference-in-Difference Comparisons of Change in Firm Performance

Note: The dependent variable of interest in this table is change in ROA. In each panel, the treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Panel A presents results from difference-in-difference regressions. Using entropy balancing I create a re-weighted balanced control group of non-announcers for each treatment group. Balance is achieved along the first three moments of the following covariates for the year before the layoff: ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. In each column, I control for firm and year fixed effects. Additionally, standard errors are clustered at the 2 digit SIC industry classification level. Panel B presents the average treatment effect on the treated (ATET) results. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are identical to Panel A. Finally, heteroskedasticity-consistent standard errors are in parentheses.

(a) Entropy Balancing: (-1,+1)

	All: Change in ROA	Reorganizing: Change in ROA	Downsizing: Change in ROA
Post	0.006***	-0.002	0.010***
	(0.001)	(0.002)	(0.002)
Post x Announcer	0.008***		
	(0.003)		
Post x Reorganizing Announcement		0.005	
		(0.003)	
Post x Downsizing Announcement			0.009*
			(0.005)
N	9,594	7,990	8,826
R-squared	0.16	0.22	0.18
Adjusted R-squared	0.0926	0.1613	0.1238

(b) Abadie-Imbens Matching Estimator

	All: Change in ROA	Reorganizing: Change in ROA	Downsizing: Change in ROA
Matching Estimator - ATT: (-1,+1)	0.011***	0.014***	0.010**
	(0.003)	(0.005)	(0.004)
Matching Estimator - ATT: (-3,-2)	-0.006*	-0.009*	-0.004
	(0.004)	(0.005)	(0.004)
Matching Estimator - ATT: (+2,+3)	-0.008**	-0.000	-0.012***
	(0.004)	(0.005)	(0.004)

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

Table 2.12: Difference-in-Difference Comparisons of Sales Growth

Note: The dependent variable of interest in this table is Sales Growth. In each panel, the treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Panel A presents results from difference-in-difference regressions. Using entropy balancing I create a re-weighted balanced control group of non-announcers for each treatment group. Balance is achieved along the first three moments of the following covariates for the year before the layoff: ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. In each column, I control for firm and year fixed effects. Additionally, standard errors are clustered at the 2 digit SIC industry classification level. Panel B presents the average treatment effect on the treated (ATET) results. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are identical to Panel A. Finally, heteroskedasticity-consistent standard errors are in parentheses.

(a) Entropy Balancing: (-1,+1)

	All: Sales Growth	Reorganizing: Sales Growth	Downsizing: Sales Growth
Post	-0.010	-0.040***	0.004
	(0.011)	(0.013)	(0.011)
Post x Announcer	-0.042***		
	(0.015)		
Post x Reorganizing Announcement		-0.025	
		(0.026)	
Post x Downsizing Announcement			-0.049***
			(0.016)
N	9,594	7,990	8,826
R-squared	0.22	0.27	0.24
Adjusted R-squared	0.1648	0.2163	0.1840

(b) Abadie-Imbens Matching Estimator

	All: Sales Growth	Reorganizing: Sales Growth	Downsizing: Sales Growth
Matching Estimator - ATT: (-1,+1)	-0.028**	0.016	-0.048***
	(0.013)	(0.016)	(0.015)
Matching Estimator - ATT: (-3,-2)	0.001	-0.014	0.011
	(0.014)	(0.019)	(0.017)
Matching Estimator - ATT: (+2,+3)	-0.002	-0.019	-0.010
	(0.014)	(0.020)	(0.016)

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

Table 2.13: Difference-in-Difference Comparisons of Book Leverage

Note: The dependent variable of interest in this table is Book Leverage. In each panel, the treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Panel A presents results from difference-in-difference regressions. Using entropy balancing I create a re-weighted balanced control group of non-announcers for each treatment group. Balance is achieved along the first three moments of the following covariates for the year before the layoff: ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. In each column, I control for firm and year fixed effects. Additionally, standard errors are clustered at the 2 digit SIC industry classification level. Panel B presents the average treatment effect on the treated (ATET) results. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are identical to Panel A. Finally, heteroskedasticity-consistent standard errors are in parentheses.

(a) Entropy Balancing: (-1,+1)

	All: Book Leverage	Reorganizing: Book Leverage	Downsizing: Book Leverage
Post	0.009*	0.006	0.011*
	(0.005)	(0.006)	(0.005)
Post x Announcer	0.006		
	(0.006)		
Post x Reorganizing Announcement		0.023**	
		(0.009)	
Post x Downsizing Announcement			-0.002
			(0.008)
N	9,594	7,990	8,826
R-squared	0.78	0.81	0.78
Adjusted R-squared	0.7608	0.8008	0.7675

(b) Abadie-Imbens Matching Estimator

	All: Book Leverage	Reorganizing: Book Leverage	Downsizing: Book Leverage
Matching Estimator - ATT: (-1,+1)	0.002	0.007	-0.002
	(0.008)	(0.011)	(0.009)
Matching Estimator - ATT: (-3,-2)	0.016***	0.005	0.017***
	(0.006)	(0.009)	(0.006)
Matching Estimator - ATT: (+2,+3)	-0.012*	-0.023**	-0.004
	(0.007)	(0.010)	(0.008)

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

Bibliography

[1] Alberto Abadie, David Drukker, Jane Leber Herr, Guido W Imbens, et al. Implementing matching estimators for average treatment effects in stata. Stata journal, 4:290–311, 2004.

[2] Alberto Abadie and Guido W Imbens. Large sample properties of matching estimators for average treatment effects. econometrica, 74(1):235–267, 2006.

[3] Andrew B Abel and Janice C Eberly. Investment, valuation, and growth options. The Quarterly Journal of Finance, 2(01):1250001, 2012.

[4] John M Abowd, George T Milkovich, and John M Hannon. The effects of human resource management decisions on shareholder value. Industrial & Labor Relations Review, 43(3):203S–236S, 1990.

[5] P Aghion and P Howitt. A model of growth through creative destruction. Econometrica, 60(2), 1992.

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

[7] Douglas Almond and Joseph J Doyle Jr. After midnight: A regression discontinuity design in length of postpartum hospital stays. Technical report, National Bureau of Economic Research, 2008.

[8] Julian Atanassov and E Kim. Labor and corporate governance: International evidence from restructuring decisions. The Journal of Finance, 64(1):341–374, 2009.

[9] Tor-Erik Bakke, Candace E Jens, and Toni M Whited. The real effects of delisting: Evidence from a regression discontinuity design. Finance Research Letters, 9(4):183–193, 2012.

[10] Frederico Belo, Xiaoji Lin, and Santiago Bazdresch. Labor hiring, investment, and stock return predictability in the cross section. Journal of Political Economy, 122(1):129–177, 2014.

[11] Ekkehart Boehmer, Jim Masumeci, and Annette B Poulsen. Event-study methodology under conditions of event-induced variance. Journal of financial economics, 30(2):253–272, 1991.

[12] Patrick Bolton and David S Scharfstein. A theory of predation based on agency problems in financial contracting. The American Economic Review, pages 93–106, 1990.

[13] GW Boyle, GS Bhabra, and HS Bhabra. Competitive and contagion effects in corporate layoff announcements. 2011.

[14] James A Brander and Tracy R Lewis. Oligopoly and financial structure: The limited liability effect. The American Economic Review, pages 956–970, 1986.

[15] Trevor Stanley Breusch and Adrian Rodney Pagan. The lagrange multiplier test and its applications to model specification in econometrics. The Review of Economic Studies, 47(1):239–253, 1980.

[16] Stephen J Brown and Jerold B Warner. Measuring security price performance. Journal of financial economics, 8(3):205–258, 1980.

[17] Stephen J Brown and Jerold B Warner. Using daily stock returns: The case of event studies. Journal of financial economics, 14(1):3–31, 1985.

[18] John Y Campbell, Jens Hilscher, and Jan Szilagyi. In search of distress risk. The Journal of Finance, 63(6):2899–2939, 2008.

[19] Murillo Campello. Debt financing: Does it boost or hurt firm performance in product markets? Journal of Financial Economics, 82(1):135–172, 2006.

[20] Wayne F Cascio, Clifford E Young, and James R Morris. Financial consequences of employment-change decisions in major us corporations. Academy of management Journal, 40(5):1175–1189, 1997.

[21] Thomas J Chemmanur, Yingmei Cheng, and Tianming Zhang. Human capital, capital structure, and employee pay: An empirical analysis. Journal of Financial Economics, 110(2):478–502, 2013.

[22] Peter Chen, Vikas Mehrotra, Ranjini Sivakumar, and W Yu Wayne. Layoffs, shareholders' wealth, and corporate performance. Journal of Empirical Finance, 8(2):171–199, 2001.

[23] Sheng-Syan Chen, Lan-Chih Ho, and Yi-Cheng Shih. Intra-lndustry effects of corporate capital investment announcements. Financial Management, 36(2):1–21, 2007.

[24] Judith A Chevalier. Capital structure and product-market competition: Empirical evidence from the supermarket industry. The American Economic Review, pages 415–435, 1995.

[25] Daniel W Collins and Warren T Dent. A comparison of alternative testing methodologies used in capital market research. Journal of accounting research, pages 48–84, 1984.

[26] J Anthony Cookson. Anticipated entry and entry deterrence: Evidence from the american casino industry. Available at SSRN 2368674, 2014.

[27] Charles J Corrado. A nonparametric test for abnormal security-price performance in event studies. Journal of financial economics, 23(2):385–395, 1989.

[28] Arnold Richard Cowan. Nonparametric event study tests. Review of Quantitative Finance and Accounting, 2(4):343–358, 1992.

[29] Elizabeth Demers and Baruch Lev. A rude awakening: Internet shakeout in 2000. Review of Accounting Studies, 6(2-3):331–359, 2001.

[30] David J Denis and Timothy A Kruse. Managerial discipline and corporate restructuring following performance declines. Journal of Financial Economics, 55(3):391–424, 2000.

[31] Anupam Dutta. Parametric and nonparametric event study tests: A review. International Business Research, 7(12):136, 2014.

[32] B Espen Eckbo. Horizontal mergers, collusion, and stockholder wealth. Journal of financial Economics, 11(1):241–273, 1983.

[33] Alex Edmans. Does the stock market fully value intangibles? employee satisfaction and equity prices. Journal of Financial Economics, 101(3):621–640, 2011.

[34] Henry S Farber and Kevin F Hallock. The changing relationship between job loss announcements and stock prices: 1970–1999. Labour Economics, 16(1):1–11, 2009.

[35] Stephen P Ferris, Narayanan Jayaraman, and Anil K Makhija. The response of competitors to announcements of bankruptcy: An empirical examination of contagion and competitive effects. Journal of corporate finance, 3(4):367–395, 1997.

[36] Michael Firth et al. Dividend changes, abnormal returns, and intra-industry firm valuations. Journal of financial and Quantitative Analysis, 31(2), 1996.

[37] Laurent Fresard. Financial strength and product market behavior: The real effects of corporate cash holdings. The Journal of finance, 65(3):1097–1122, 2010.

[38] Carmelo Giaccotto and James M Sfiridis. Hypothesis testing in event studies: The case of variance changes. Journal of Economics and Business, 48(4):349–370, 1996.

[39] Sheila Goins and Thomas S Gruca. Understanding competitive and contagion effects of layoff announcements. Corporate Reputation Review, 11(1):12–34, 2008.

[40] Eitan Goldman, Urs Peyer, and Irina Stefanescu. Financial misrepresentation and its impact on rivals. Financial Management, 41(4):915–945, 2012.

[41] Charles J Hadlock and Joshua R Pierce. New evidence on measuring financial constraints: Moving beyond the kz index. Review of Financial studies, 23(5):1909–1940, 2010.

[42] Jens Hainmueller. Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. Political Analysis, 20(1):25–46, 2012.

[43] Kevin F Hallock. A descriptive analysis of layoffs in large us firms using archival and interview data: 1970–2002. Unpublished paper, Department of Economics, University of Illinois, 2003.

[44] Kevin F Hallock and Farzad Mashayekhi. Are formal corporate news announcements still newsworthy? evidence from three decades of us data on earnings, splits, and dividends. 2003.

[45] Kevin F Hallock, Michael R Strain, and Douglas Webber. Job loss and effects on firms and workers. 2011.

[46] Daniel S Hamermesh and Gerard A Pfann. Adjustment costs in factor demand. Journal of Economic Literature, 34(3):1264–1292, 1996.

[47] Gordon Hanka. Debt and the terms of employment. Journal of Financial Economics, 48(3):245–282, 1998.

[48] Barry T Hirsch and David A Macpherson. Union membership and coverage database from the current population survey: Note. Industrial & labor relations review, 56(2):349–354, 2003.

[49] Gerard Hoberg and Gordon Phillips. Product market synergies and competition in mergers and acquisitions: A text-based analysis. Review of Financial Studies, 23(10):3773–3811, 2010.

[50] John S Howe and Yang-pin Shen. Information associated with dividend initiations: Firm-specific or industry-wide? Financial Management, pages 17–26, 1998.

[51] Michael C Jensen. Agency cost of free cash flow, corporate finance, and takeovers. Corporate Finance, and Takeovers. American Economic Review, 76(2), 1986.

[52] Kose John, Larry HP Lang, and Jeffry Netter. The voluntary restructuring of large firms in response to performance decline. The Journal of Finance, 47(3):891–917, 1992.

[53] Jun-Koo Kang and Anil Shivdasani. Corporate restructuring during performance declines in japan. Journal of Financial Economics, 46(1):29–65, 1997.

[54] Nishad Kapadia. Tracking down distress risk. Journal of Financial Economics, 102(1):167–182, 2011.

[55] Steven N Kaplan and Luigi Zingales. Do financing constraints explain why investment is correlated with cash flow? Technical report, National Bureau of Economic Research, 1995.

[56] Naveen Khanna and Sheri Tice. Strategic responses of incumbents to new entry: The effect of ownership structure, capital structure, and focus. Review of financial studies, 13(3):749–779, 2000.

[57] SP Kothari and Jerold B Warner. Measuring long-horizon security price performance. Journal of Financial Economics, 43(3):301–339, 1997.

[58] Owen Lamont, Christopher Polk, and Jesús Saaá-Requejo. Financial constraints and stock returns. Review of financial studies, 14(2):529–554, 2001.

[59] Larry HP Lang and ReneM Stulz. Contagion and competitive intra-industry effects of bankruptcy announcements: An empirical analysis. Journal of financial economics, 32(1):45–60, 1992.

[60] Paul Laux, Laura T Starks, and Pyung Sig Yoon. The relative importance of competition and contagion in intra-industry information transfers: An investigation of dividend announcements. Financial Management, pages 5–16, 1998.

[61] Tim Loughran and Jay R Ritter. The operating performance of firms conducting seasoned equity offerings. The journal of finance, 52(5):1823–1850, 1997.

[62] A Craig MacKinlay. Event studies in economics and finance. Journal of economic literature, 35(1):13–39, 1997.

[63] Jeff Madura, Aigbe Akhigbe, and Kenneth S Bartunek. Intra-industry effects of bank layoff announcements. Review of Financial Economics, 4(2):187–195, 1995.

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

[65] Monika Merz, Eran Yashiv, et al. Labor and the market value of the firm. American Economic Review, 97(4):1419–1431, 2007.

[66] Anna Milanez. The human capital costs of financial constraint. Technical report, mimeo, 2013.

[67] Stewart C Myers. Determinants of corporate borrowing. Journal of financial economics, 5(2):147–175, 1977.

[68] Eli Ofek. Capital structure and firm response to poor performance: An empirical analysis. Journal of financial economics, 34(1):3–30, 1993.

[69] Oded Palmon, Huey-Lian Sun, and Alex P Tang. Layoff announcements: Stock market impact and financial performance. Financial management, pages 54–68, 1997.

[70] James M Patell. Corporate forecasts of earnings per share and stock price behavior: Empirical test. Journal of accounting research, pages 246–276, 1976.

[71] Ralph W Sanders Jr and Russell P Robins. Discriminating between wealth and information effects in event studies in accounting and finance research. Review of Quantitative Finance and Accounting, 1(3):307–329, 1991.

[72] Myron Scholes and Joseph Williams. Estimating betas from nonsynchronous data. Journal of financial economics, 5(3):309–327, 1977.

[73] Elena Simintzi. Strategic investments: Evidence from restructuring announcements. Available at SSRN 2024146, 2013.

[74] ReneéM Stulz. Managerial discretion and optimal financing policies. Journal of financial Economics, 26(1):3–27, 1990.

[75] Samuel H Szewczyk. The intra-industry transfer of information inferred from announcements of corporate security offerings. The Journal of Finance, 47(5):1935–1945, 1992.

[76] Robert H Topel. Equilibrium earnings, turnover, and unemployment: New evidence. Journal of Labor Economics, pages 500–522, 1984.

[77] Toni M Whited and Guojun Wu. Financial constraints risk. Review of Financial Studies, 19(2):531–559, 2006.

[78] Jeffrey M Wooldridge. Econometric analysis of cross section and panel data. MIT press, 2010.

[79] Dan L Worrell, Wallace N Davidson, and Varinder M Sharma. Layoff announcements and stockholder wealth. Academy of management Journal, 34(3):662–678, 1991.

[80] Lu Zhang. The value premium. The Journal of Finance, 60(1):67–103, 2005.

[81] Luigi Zingales. Survival of the fittest or the fattest? exit and financing in the trucking industry. The Journal of Finance, 53(3):905–938, 1998.

Appendix A

Chapter 1: Fixed Effects Vs Random Effects Vs Pooled OLS Estimation

Table A.1: 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.

Table A.2: Pooled OLS vs. Random Effects Estimation

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

$$\chi^2 = 11.64$$

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

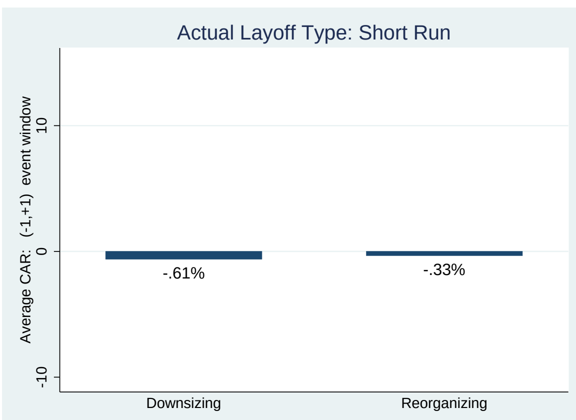
Appendix B

Chapter 2: Robustness Tests

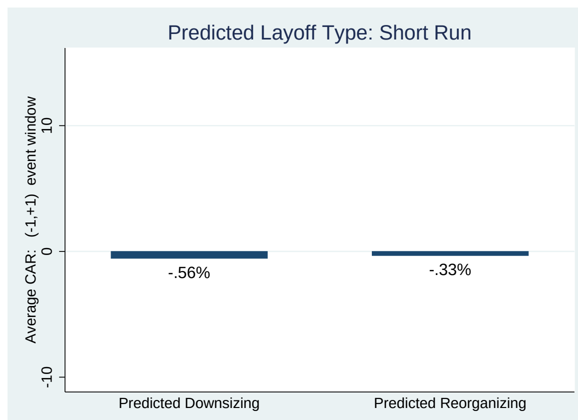
Figure B.1: Predicting Layoff Type in Real Time excluding Announcements following Mergers and Acquisitions

Note: The figures below describe the average stock market performance for layoff announcements by type from 1990 to 2010. The sample excludes layoff announcements that follow mergers and acquisitions. Panels A and B plot the average 3-day cumulative abnormal return for actual and predicted announcements by layoff type. The 3-day CARs are calculated using a market model and are centered around the day of the announcement. Panels C and D depict the average Buy-and-Hold abnormal returns for actual and predicted announcements by layoff type. The BHARs are calculated using the Fama French 3 factor model as a benchmark and span a 298-day window, (+2,+300).

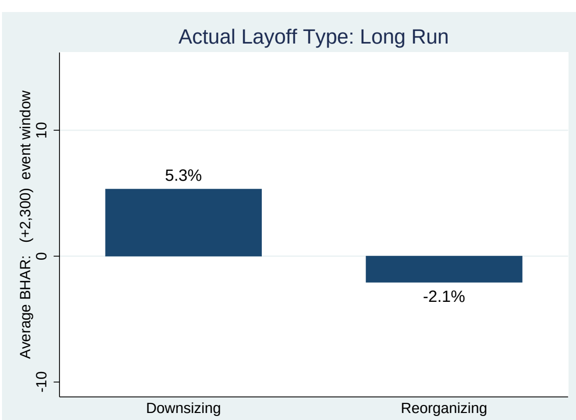
(a) Actual CAR



(b) Predicted CAR



(c) Actual BHAR



(d) Predicted BHAR

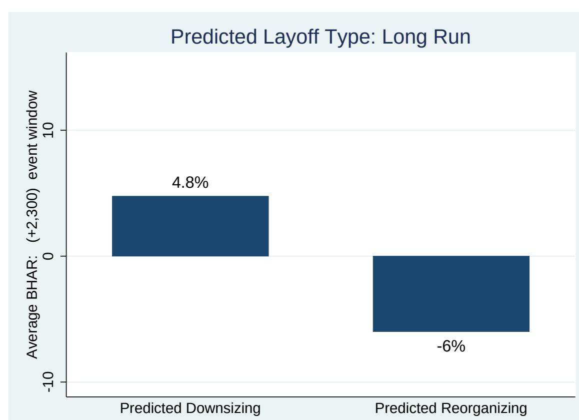
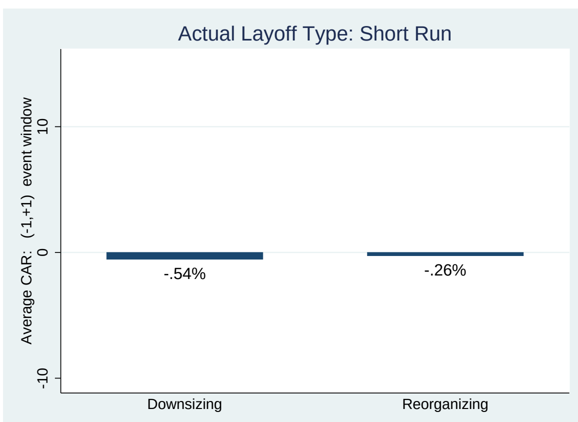


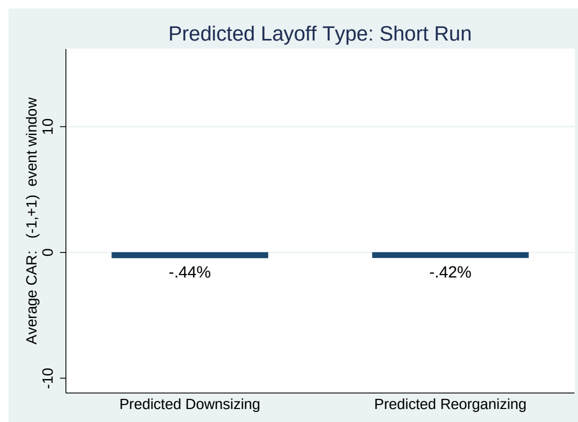
Figure B.2: Predicting Layoff Type in Real Time Excluding Layoff Announcements that Coincide with Asset Sales

Note: The figures below describe the average stock market performance for layoff announcements by type from 1990 to 2010. The sample excludes layoff announcements by firms that also reduce total assets by at least 10%. Panels A and B plot the average 3-day cumulative abnormal return for actual and predicted announcements by layoff type. The 3-day CARs are calculated using a market model and are centered around the day of the announcement. Panels C and D depict the average Buy-and-Hold abnormal returns for actual and predicted announcements by layoff type. The BHARs are calculated using the Fama French 3 factor model as a benchmark and span a 298-day window, (+2,+300).

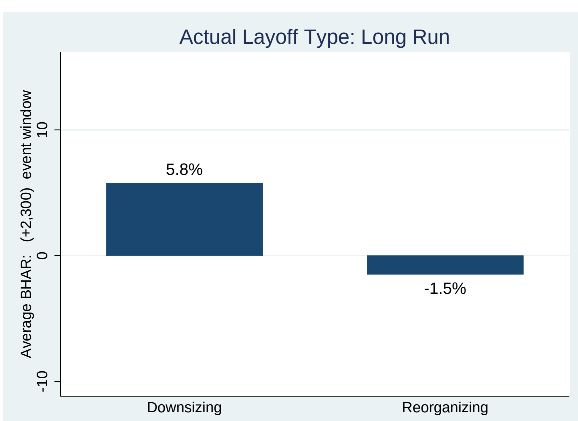
(a) Actual CAR



(b) Predicted CAR



(c) Actual BHAR



(d) Predicted BHAR

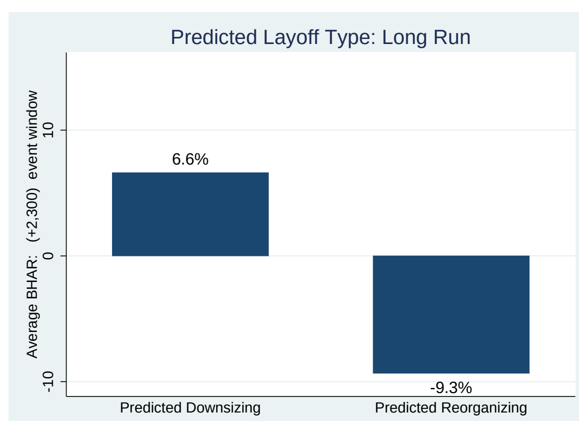
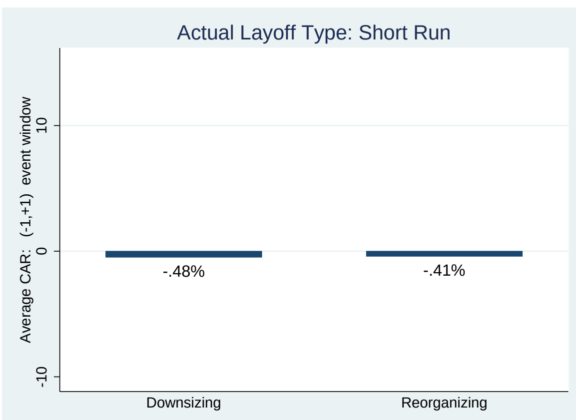


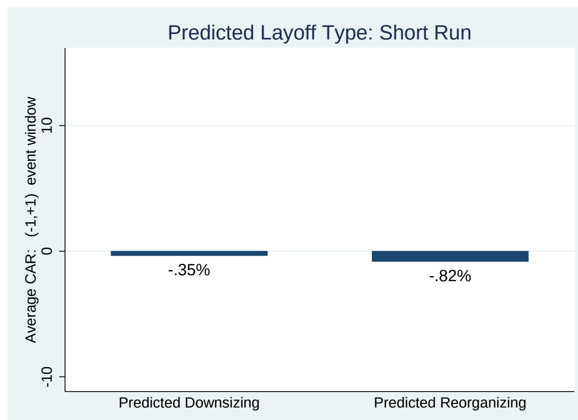
Figure B.3: Predicting Layoff Type in Real Time Excluding Layoff Announcements By Firms Not Currently in the S&P 500

Note: The figures below describe the average stock market performance for layoff announcements by type from 1990 to 2010. The sample excludes layoff announcements by firms that were not listed in the S&P 500 at the time of the announcement. Panels A and B plot the average 3-day cumulative abnormal return for actual and predicted announcements by layoff type. The 3-day CARs are calculated using a market model and are centered around the day of the announcement. Panels C and D depict the average Buy-and-Hold abnormal returns for actual and predicted announcements by layoff type. The BHARs are calculated using the Fama French 3 factor model as a benchmark and span a 298-day window, (+2,+300).

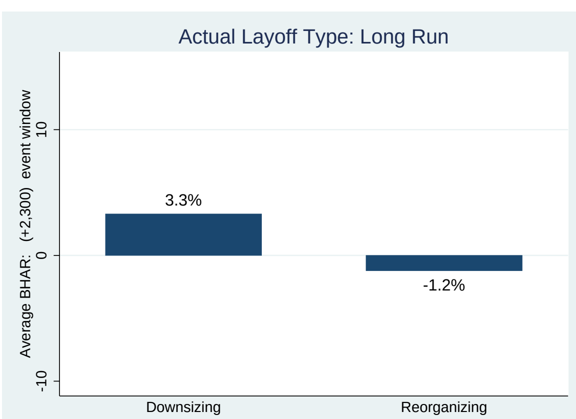
(a) Actual CAR



(b) Predicted CAR



(c) Actual BHAR



(d) Predicted BHAR

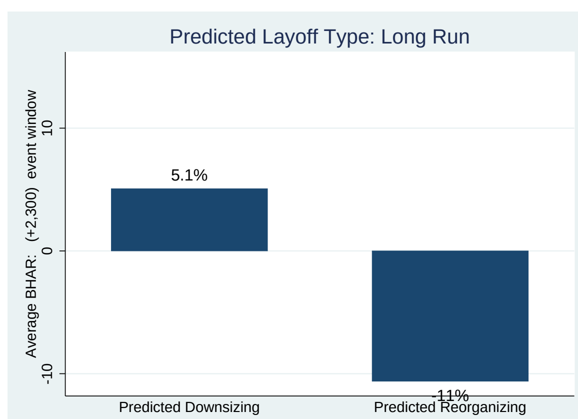
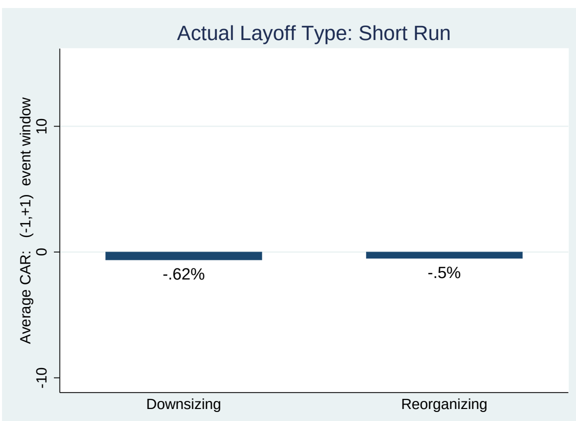


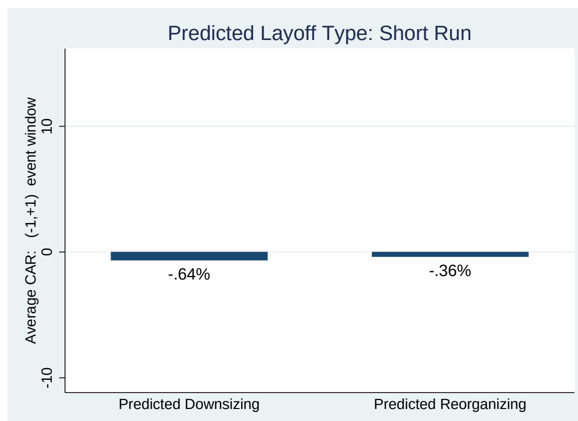
Figure B.4: Predicting Layoff Type in Real Time when Layoff Announcements are Classified Using an Alternative Cut-off (20%)

Note: The figures below describe the average stock market performance for layoff announcements by type from 1990 to 2010. In this sample, I classify a layoff announcement as a reorganizing layoff if the annual change in employment for the event-year is less than 20% of the layoff size. The announcement is classified as a downsizing announcement if the annual change in employment is greater than 20% of the layoff size. Panels A and B plot the average 3-day cumulative abnormal return for actual and predicted announcements by layoff type. The 3-day CARs are calculated using a market model and are centered around the day of the announcement. Panels C and D depict the average Buy-and-Hold abnormal returns for actual and predicted announcements by layoff type. The BHARs are calculated using the Fama French 3 factor model as a benchmark and span a 298-day window, (+2,+300).

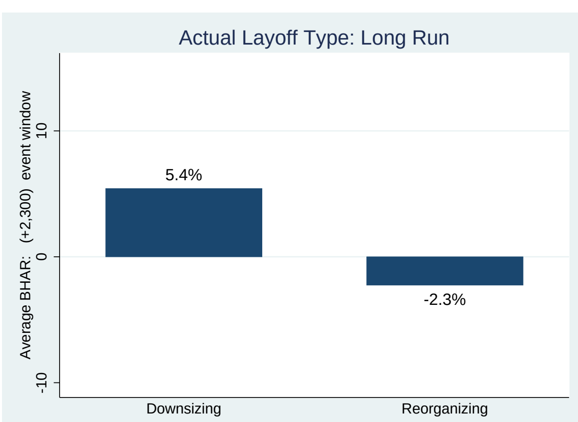
(a) Actual CAR



(b) Predicted CAR



(c) Actual BHAR



(d) Predicted BHAR

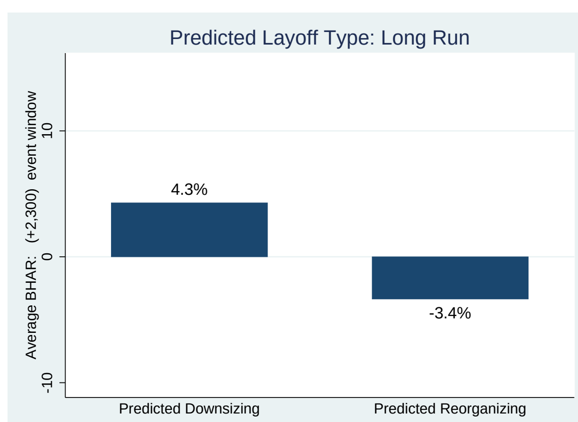
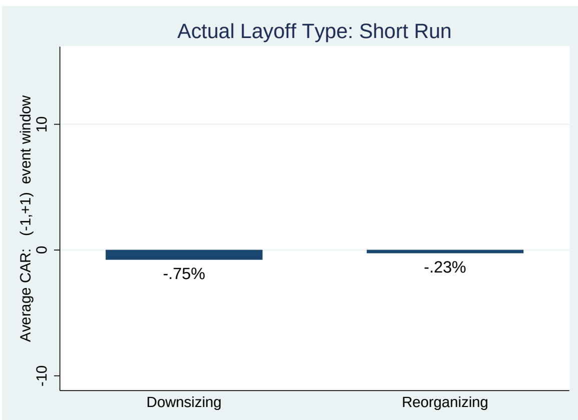


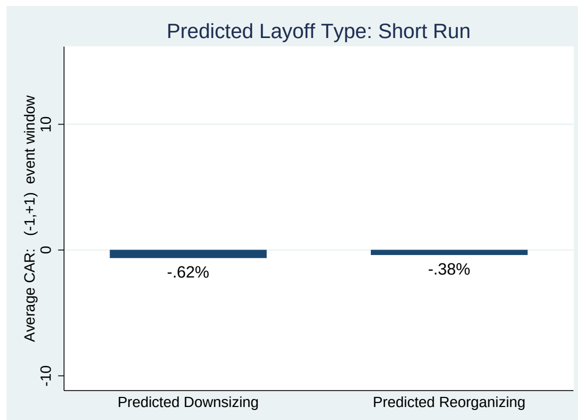
Figure B.5: Predicting Layoff Type in Real Time when Layoff Announcements are Classified Using an Alternative Cut-off (0%)

Note: The figures below describe the average stock market performance for layoff announcements by type from 1990 to 2010. In this sample I classify a layoff announcement as a reorganizing layoff if the annual change in employment for the event-year is less than the layoff size. The announcement is classified as a downsizing announcement if the annual change in employment is greater than the layoff size. Panels A and B plot the average 3-day cumulative abnormal return for actual and predicted announcements by layoff type. The 3-day CARs are calculated using a market model and are centered around the day of the announcement. Panels C and D depict the average Buy-and-Hold abnormal returns for actual and predicted announcements by layoff type. The BHARs are calculated using the Fama French 3 factor model as a benchmark and span a 298-day window, (+2,+300).

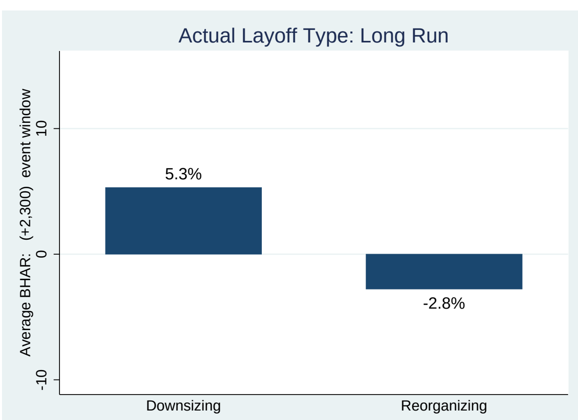
(a) Actual CAR



(b) Predicted CAR



(c) Actual BHAR



(d) Predicted BHAR

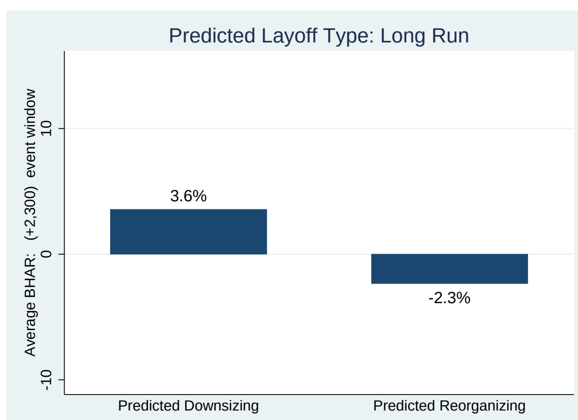


Table B.1: Difference-in-Difference Comparisons of Employee Strength

Note: The dependent variable of interest in this table is Log of Employees. In each panel, the treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Panel A presents results from difference-in-difference regressions. Using entropy balancing I create a re-weighted balanced control group of non-announcers for each treatment group. Balance is achieved along the first three moments of the following covariates for the year before the layoff: ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. In each column, I control for firm and year fixed effects. Additionally, standard errors are clustered at the 2 digit SIC industry classification level. Panel B presents the average treatment effect on the treated (ATET) results. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are identical to Panel A. Finally, heteroskedasticity-consistent standard errors are in parentheses.

(a) Entropy Balancing: (-1,+1)

	All: Log of Employees	Reorganizing: Log of Employees	Downsizing: Log of Employees
Post	-0.005	0.037	-0.026
	(0.026)	(0.029)	(0.024)
Post x Announcer	-0.093***		
	(0.032)		
Post x Reorganizing Announcement		0.065**	
		(0.029)	
Post x Downsizing Announcement			-0.168***
			(0.032)
N	9,594	7,990	8,826
R-squared	0.93	0.95	0.94
Adjusted R-squared	0.9271	0.9412	0.9340

(b) Abadie-Imbens Matching Estimator

	All: Log of Employees	Reorganizing: Log of Employees	Downsizing: Log of Employees
Matching Estimator - ATT: (-1,+1)	-0.100***	0.085***	-0.184***
	(0.019)	(0.026)	(0.020)
Matching Estimator - ATT: (-3,-2)	-0.005	0.009	-0.015
	(0.011)	(0.015)	(0.013)
Matching Estimator - ATT: (+2,+3)	0.008	-0.002	0.006
	(0.013)	(0.018)	(0.015)

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

Table B.2: Difference-in-Difference Comparisons of Key Variables Following Exclusion of Announcements Following Mergers and Acquisitions

Note: This table presents the average treatment effect on the treated (ATET) results for the key variables of interest in this paper for a sample that exclude layoff announcements that follow mergers and acquisitions. The treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are measured for the year before the layoff and include ROA, market-to-book ratio, cost of goods sold, cash holding, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. Heteroskedasticity-consistent standard errors are reported in parentheses.

	All Layoffs	Reorganizing Layoffs	Downsizing Layoffs
Book Leverage - ATT: (-2,-1)	0.014***	0.004	0.019***
	(0.005)	(0.007)	(0.006)
Book Leverage - ATT: (-1,+1)	0.001	0.007	-0.003
	(0.008)	(0.012)	(0.010)
Cost of Goods Sold - ATT: (-1,+1)	-0.035***	-0.021	-0.048***
	(0.010)	(0.013)	(0.012)
Cash Holdings - ATT: (-1,+1)	0.017***	0.008	0.022***
	(0.005)	(0.008)	(0.006)
ROA - ATT: (-1,+1)	-0.005	0.000	-0.007*
	(0.003)	(0.005)	(0.004)
Change in ROA - ATT: (-1,+1)	0.011***	0.014***	0.009**
	(0.003)	(0.005)	(0.004)
Sales Growth - ATT: (-1,+1)	-0.029**	0.019	-0.052***
	(0.013)	(0.017)	(0.015)
Log of Employees - ATT: (-1,+1)	-0.101***	0.090***	-0.184***
	(0.019)	(0.027)	(0.020)

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

Table B.3: Difference-in-Difference Comparisons of Key Variables following Exclusion of Layoff Announcements that Coincide with Asset Sales

Note: This table presents the average treatment effect on the treated (ATET) results for the key variables of interest in this paper for a sample that excludes layoff announcements by firms that also reduce total assets by at least 10%. The treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are measured for the year before the layoff and include ROA, market-to-book ratio, cost of goods sold, cash holdings, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. Heteroskedasticity-consistent standard errors are reported in parentheses.

	All Layoffs	Reorganizing Layoffs	Downsizing Layoffs
Book Leverage - ATT: (-2,-1)	0.013**	0.004	0.018**
	(0.006)	(0.007)	(0.007)
Book Leverage - ATT: (-1,+1)	0.001	0.007	-0.005
	(0.008)	(0.012)	(0.010)
Cost of Goods Sold - ATT: (-1,+1)	-0.030***	-0.022*	-0.042***
	(0.010)	(0.013)	(0.012)
Cash Holdings - ATT: (-1,+1)	0.017***	0.010	0.021***
	(0.005)	(0.008)	(0.006)
ROA - ATT: (-1,+1)	-0.004	0.002	-0.008*
	(0.003)	(0.005)	(0.004)
Change in ROA - ATT: (-1,+1)	0.010***	0.016***	0.007*
	(0.003)	(0.005)	(0.004)
Sales Growth - ATT: (-1,+1)	-0.012	0.032**	-0.034**
	(0.013)	(0.016)	(0.016)
Log of Employees - ATT: (-1,+1)	-0.048***	0.107***	-0.131***
	(0.018)	(0.026)	(0.019)

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

Table B.4: Difference-in-Difference Comparisons of Key Variables Following Exclusion of Announcements by Firms Not Currently in the S&P 500

Note: This table presents the average treatment effect on the treated (ATET) results for the key variables of interest in this paper for a sample that excludes layoff announcements by firms that were not listed in the S&P 500 at the time of the announcement. The treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are measured for the year before the layoff and include ROA, market-to-book ratio, cost of goods sold, cash holding, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. Heteroskedasticity-consistent standard errors are reported in parentheses.

	All Layoffs	Reorganizing Layoffs	Downsizing Layoffs
Book Leverage - ATT: (-2,-1)	0.016***	0.004	0.021***
	(0.005)	(0.007)	(0.007)
Book Leverage - ATT: (-1,+1)	0.004	0.005	-0.001
	(0.008)	(0.011)	(0.010)
Cost of Goods Sold - ATT: (-1,+1)	-0.031***	-0.014	-0.048***
	(0.010)	(0.012)	(0.013)
Cash Holdings - ATT: (-1,+1)	0.016***	0.007	0.021***
	(0.005)	(0.007)	(0.006)
ROA - ATT: (-1,+1)	-0.004	0.001	-0.007
	(0.004)	(0.005)	(0.004)
Change in ROA - ATT: (-1,+1)	0.011***	0.013***	0.010**
	(0.003)	(0.005)	(0.004)
Sales Growth - ATT: (-1,+1)	-0.027**	0.011	-0.045***
	(0.013)	(0.016)	(0.016)
Log of Employees - ATT: (-1,+1)	-0.098***	0.078***	-0.178***
	(0.019)	(0.028)	(0.021)

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

Table B.5: Difference-in-Difference Comparisons of Key Variables when Layoff Announcements are Classified Using an Alternative Cut-off (20%)

Note: This table presents the average treatment effect on the treated (ATET) results for the key variables of interest in this paper for a sample in which layoff type is classified using an alternative cut-off. I classify a layoff announcement as a reorganizing layoff if the annual change in employment for the event-year is less than 20% of the layoff size. The announcement is classified as a downsizing announcement if the annual change in employment is greater than 20% of the layoff size. The treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are measured for the year before the layoff and include ROA, market-to-book ratio, cost of goods sold, cash holding, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. Heteroskedasticity-consistent standard errors are reported in parentheses.

	All Layoffs	Reorganizing Layoffs	Downsizing Layoffs
Book Leverage - ATT: (-2,-1)	0.014***	0.007	0.018***
	(0.005)	(0.007)	(0.006)
Book Leverage - ATT: (-1,+1)	0.002	0.007	-0.002
	(0.008)	(0.011)	(0.009)
Cost of Goods Sold - ATT: (-1,+1)	-0.033***	-0.017	-0.047***
	(0.010)	(0.012)	(0.012)
Cash Holdings - ATT: (-1,+1)	0.017***	0.011	0.021***
	(0.005)	(0.007)	(0.006)
ROA - ATT: (-1,+1)	-0.004	0.000	-0.006
	(0.003)	(0.004)	(0.004)
Change in ROA - ATT: (-1,+1)	0.011***	0.015***	0.010**
	(0.003)	(0.004)	(0.004)
Sales Growth - ATT: (-1,+1)	-0.028**	0.006	-0.045***
	(0.013)	(0.016)	(0.015)
Log of Employees - ATT: (-1,+1)	-0.100***	0.071***	-0.188***
	(0.019)	(0.026)	(0.020)

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

Table B.6: Difference-in-Difference Comparisons Of Key Variables when Layoff Announcements are Classified Using an Alternative Cut-off (0%)

Note: This table presents the average treatment effect on the treated (ATET) results for the key variables of interest in this paper for a sample in which layoff type is classified using an alternative cut-off. I classify a layoff announcement as a reorganizing layoff if the annual change in employment for the event-year is less than the layoff size. The announcement is classified as a downsizing announcement if the annual change in employment is greater than the layoff size. The treatment groups in columns 1, 2 and 3 are all layoffs, reorganizing announcements and downsizing announcements respectively. Using the Abadie-Imbens matching estimator I select one matched control for each treated firm. Matching covariates are measured for the year before the layoff and include ROA, market-to-book ratio, cost of goods sold, cash holding, sales growth, book leverage, Whited-Wu index, log of assets, log of employees and log of firm age. Heteroskedasticity-consistent standard errors are reported in parentheses.

	All Layoffs	Reorganizing Layoffs	Downsizing Layoffs
Book Leverage - ATT: (-2,-1)	0.014***	0.006	0.018***
	(0.005)	(0.007)	(0.006)
Book Leverage - ATT: (-1,+1)	0.002	0.011	-0.003
	(0.008)	(0.011)	(0.009)
Cost of Goods Sold - ATT: (-1,+1)	-0.033***	-0.017	-0.046***
	(0.010)	(0.013)	(0.012)
Cash Holdings - ATT: (-1,+1)	0.017***	0.012	0.021***
	(0.005)	(0.007)	(0.005)
ROA - ATT: (-1,+1)	-0.004	0.001	-0.007
	(0.003)	(0.004)	(0.004)
Change in ROA - ATT: (-1,+1)	0.011***	0.013***	0.010**
	(0.003)	(0.005)	(0.004)
Sales Growth - ATT: (-1,+1)	-0.028**	0.023	-0.050***
	(0.013)	(0.016)	(0.015)
Log of Employees - ATT: (-1,+1)	-0.100***	0.094***	-0.178***
	(0.019)	(0.026)	(0.020)

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