The Timing of Mass Layoff Episodes: Evidence from U.S. Microdata

Alison Weingarden

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Abstract

This paper studies employment decisions at a large number of U.S. companies over the 2007–2012 period, during and after the Great Recession. To this end, I build a panel dataset that matches publicly-listed companies' financial reports to their announced layoff episodes. Using limited dependent variable regressions, I find that layoffs respond to accumulated changes in a company's financial conditions. While recent financial changes have the largest impacts on layoff propensities, financial changes over at least four previous quarters appear to have additional marginal effects.

JEL Classification: J21, J63, E24

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1 Introduction

Along what time horizons do changing financial conditions trigger employment adjustments at companies? This paper takes a micro approach to the question, using a novel database that links layoff episodes announced by U.S. companies to additional firm-level characteristics. Most of these layoff episodes can be regarded as mass layoffs since they are permanent displacements affecting more than fifty workers. Despite the importance of mass layoffs for the micro and macro literature, this paper is one of the first to analyze the relationship between firm-level financial conditions and layoffs using quarterly microdata that covers a large sample of U.S. companies. Most of the analysis focuses on publicly-listed firms because they report financial measures at regular intervals.

Previous literature has used narrow sources of establishment-level data to look at the timing of employment changes at a micro level. Hamermesh (1989) uses monthly plant-level employment and output measures for seven plants of a single manufacturing firm to analyze the determinants and path of labor adjustments. He shows that establishments in his dataset make discrete, infrequent changes to their workforce in response to changes in expected output. As he explains, it is important to use microdata for these purposes because studies based on aggregated data may fail to detect the true reaction of employment to changes in firms' financial conditions. Davis, Faberman and Haltiwanger (2006) use microdata with broader coverage such as JOLTS and BED to look at establishments' hiring and separations rates. They find that, "although most establishments experience little or no employment change within a quarter, job flows mainly reflect lumpy employment changes at the establishment level". However, these authors do not directly examine the relationship between layoffs and financial conditions because their datasets do not contain establishment-level financial measures. Instead, they use changes in establishment-level employment to proxy for financial and other changes at a micro level.

Both micro and macro research document a complex relationship between employment and other measures of economic activity. In the micro literature, Giroud and Mueller (2017)

find that multi-establishment firms reduce the extent to which local demand shocks impact a single establishment's employment but, in doing so, spread some of the effects across other establishments and locations. While their paper looks at the ways in which local shocks impact a company's employment decisions over a multi-year horizon, my paper looks at the ways in which firm-specific shocks impact a company's propensity to announce mass layoffs on a quarterly basis. In the macro literature, Verbrugge (1997) finds time series differences in U.S. employment measures relative to output measures. Aggregate employment exhibits "steepness", which means that declines are generally faster than increases, whereas output variables such as real GDP and industrial production do not have this property. He emphasizes that, "The next generation of macro models will need to come to grips with the asymmetry in the labor market, and the lack of such asymmetry in production data." This macro finding motivates my investigation into the sluggish nature of companies' mass layoff decisions.

Mass layoffs are a key policy issue because previous research has shown that workers who are laid off en masse experience persistent negative outcomes in both earnings and well-being. For example, two seminal papers compare labor market outcomes for workers who entered unemployment in a mass layoff to similar workers who were not affected by a mass layoff. The first, Couch and Placzek (2010), finds that earnings losses of 12 percent persist for workers even six years after the mass layoff, while the second, Jacobson, LaLonde and Sullivan (1993), finds even larger losses. Davis and von Wachter (2011) provide additional evidence on the negative effects of mass layoffs.

Finally, the exercise of matching layoff announcements to companies' financial performance was undertaken previously by Farber and Hallock (2009). Their dataset covers the 1970–1999 period and is used to investigate the effect of layoff announcements on stock prices of individual companies. Their paper finds a generally non-positive response of stock prices in the days following a layoff announcement; interestingly, the measured response is not significantly different from zero in the later years of their sample (1990–1999). Farber and Hallock do not, however, use their dataset to investigate the financial determinants

of layoff announcements. Relative to their study, this paper builds a more recent dataset and uses it to evaluate the extent to which layoffs are a pent-up (delayed and cumulative) response to changes in financial conditions.

The paper proceeds as follows. Section 2 describes the data, including some summary statistics. Section 3 introduces an empirical framework for testing the relationship between companies' layoff announcements and their previous business conditions. Section 4 presents and discusses the regression results, while Section 5 provides several robustness checks. Section 6 concludes.

2   Data Sources

In this paper, layoff episodes are identified using microdata from the Job Cut Announcement Reports of Challenger, Gray & Christmas, Inc. (2013)— the "Challenger dataset" hereafter. These data compile all publicly available information on announced U.S. layoff episodes, including those announced in the media and those mentioned in companies' financial reports. The data used in this paper cover the time period from Q1 2007–Q4 2012 and list about $12,000$ unique employers and upwards of $17,000$ unique episodes. The entries include company/institution name, date of layoff, location, stated reason for layoff, and number of affected employees. Employers are predominantly for-profit companies, but there are layoffs recorded for approximately $2,000$ government, public sector, and non-profit organizations.

To address the relationship between layoffs and financial conditions, I use additional firm-level economic data from the Bloomberg Professional Service (2014), focusing on companies that are publicly listed on U.S. stock exchanges. Publicly-listed companies account for about half of the layoff data's four million affected (i.e. displaced) employees. Not only are publicly-listed companies larger and more likely to announce layoffs compared to privately-held companies, but publicly-listed companies are also subject to mandatory financial reporting. Thus, metrics such as firm-level revenue (sales, revenue, or turnover)

and profits (EBITDA) are generally available for publicly-listed companies at a quarterly frequency. To construct a complete set of lagged variables, I gather financial data starting in Q1 2005, two years before the layoff data begin.

2.1   Summary Statistics

The approximately three thousand publicly-listed U.S. companies can be divided between those that had layoffs recorded in the Challenger dataset ("matched") and those that did not ("unmatched"). Section 7 of the Appendix has a detailed discussion about data availability and the matching procedure.

Table 1 in the Appendix (Section 9) summarizes the main variables in the dataset for matched and unmatched companies. In particular, it shows that matched companies constitute about a quarter of the dataset. While unmatched companies had no layoffs, even matched companies had infrequent layoffs over the six-year period that included the Great Recession. The table shows that matched companies had at least one quarter with layoffs but an average of only 2.6 quarters with layoffs, with approximately 6% of their employees affected in each layoff quarter.

Comparing average quarterly revenue in the two columns of Table 1 reveals that companies in the matched sample are generally larger than unmatched companies. However, comparing $\Delta ln(Revenue)$ shows that quarterly log revenue changes appear to be less sensitive to differences in average company size. The following sections estimate the regression coefficients from a dataset with both matched and unmatched companies. Most of the regressions use firm fixed effects to control for company size and use $\Delta ln(Revenue)$ as the main explanatory variable, which is comparable across matched and unmatched firms.

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3 Econometric Model

To motivate the econometric model, assume that each firm observes the level of its demand or productivity, z, and chooses the size of its labor force N to maximize expected future profits. In the absence of adjustment costs, a firm would always adjust its labor force to ensure that, in expectation, its marginal revenue product of labor $[MRPL]$ equals wages. However, with employment adjustment costs this condition may not be satisfied in the short run.

With adjustment costs, it may be optimal for the firm to let $MRPL$ fall and make no labor force adjustment in response to a small or non-persistent negative shock. In fact, if firing or rehiring workers is costly, in the case of negative shocks, the firm might be able to make some inframarginal adjustments to forestall layoffs— for example, lowering workers' hours or letting some capital remain idle. If the firm receives additional negative shocks, at that point its optimal policy would be to conduct a layoff to reduce the wedge between $MRPL$ and wages. Such a layoff would be an accumulated reaction to changes in underlying financial or economic conditions. Under fairly standard assumptions, any fall in z should decrease the firm's expected $MRPL$ and increase its propensity to lay off workers, and vice versa for a rise in z.[1] Though not a focus of this paper, firm-level hiring should exhibit similar dynamics.

In the theoretical framework underlying the econometric model, it is assumed that z follows a Markov process. Therefore, past financial performance reveals information about the future. Since the firm's recent financial performance contains the most relevant information about future values of z, recent financial changes should influence layoff propensity more than earlier lags. However, the presence of adjustment costs implies that a firm's earlier financial performance also influences layoff propensity to some extent. The econometric model provides a way of assessing empirically the extent to which earlier

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[1] In particular, I assume that revenue r is increasing in N, increasing in z, and concave in N. I also assume supermodularity between z and N (in other words, $r_z N(z, N) > 0$). These four properties imply that a firm's $MRPL$ is decreasing in N and increasing z.

financial changes affect firms' subsequent layoffs.

Broadly speaking, this paper uses two different estimation approaches to evaluate the dynamic determinants of layoffs. Both approaches have a limited dependent variable governed by the data-generating process of a latent variable. The first approach treats the dependent variable as binary: it takes the value of 1 when a layoff occurs or 0 otherwise. The second approach treats the dependent variable as continuous but censored; it is either the percentage of firm i's workforce affected by a layoff at time t or zero if no layoff occurs. The two approaches are as follows,

Binary: Continuous:

$$L_{i,t} = \begin{cases} 1, & \text{if } L_{i,t}^* > 0 \\ 0, & \text{if } L_{i,t}^* \leq 0 \end{cases} \quad (1) \qquad L_{i,t} = \begin{cases} L_{i,t}^*, & \text{if } L_{i,t}^* > 0 \\ 0, & \text{if } L_{i,t}^* \leq 0 \end{cases} \quad (2)$$

where $L_{i,t}^*$ is the latent variable. The equation for $L_{i,t}^*$ is provided below. It has a distributed lag structure based on companies' quarterly financial changes. A general formulation is:

$$L_{i,t}^* = \sum_{k=0}^{K} \beta_k \Delta X_{i,t-k} + \mu \sigma_{i,t} + \alpha_i + \varphi_t + e_{i,t} \quad (3)$$

where $L_{i,t}^*$ is demand for layoffs (or negative employment adjustments) at firm i in a given quarter t. The explanatory variables are: changes in firm-level financial conditions, $\Delta X_{i,t-k}$ (denoting log changes in revenue from time $t-k-1$ to $t-k$), the standard deviation of financial changes $\sigma_{i,t}$, firm-level effects α_i, and aggregate time effects φ_t. The estimated coefficients on lagged financial changes, $\hat{\beta}_k$, are expected to be negative because positive financial changes should decrease layoff propensity while negative financial changes should increase it.

Since heterogeneous firm-specific factors may play a large role in determining layoffs, the model is estimated using firm-level fixed effects whenever possible (heterogeneity could stem from differences in number of establishments, labor intensity, management strategy, type of workers, international exposure, or a variety of other factors). A specification

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with fixed effects is more robust than one with random effects in that it models these heterogeneous effects as time-independent constants that can be correlated with other regressors.

Another way of interpreting the finite distributed lag model above is to view B_0 as a scaling parameter that indicates the strength of the relationship between $L^*_{i,t}$ and the $\Delta X_{i,t-k}$ variables. Although not used for estimation, the following is equivalent to eq.(3),

$$L^*_{i,t} = B_0 \left[\Delta X_{i,t} + \sum_{k=1}^{K} \frac{B_k}{B_0} \Delta X_{i,t-k} \right] + \mu \sigma_{i,t} + \alpha_i + \varphi_t + e_{i,t} \tag{4}$$

where B_0 is a parameter that applies to all financial changes. Since it is expected that $-1 < B_0 < 0$, the other coefficients on lagged financial changes should all be positive and decreasing in magnitude, with $B_k \geq B_{k+1}$ for all k. In other words, it is expected that each recent financial change (B_k) exerts more influence on layoffs than the previous quarter's financial change (B_{k+1}). While the model predicts that recent financial changes are more relevant than earlier ones, a primary goal of this paper is to estimate the time horizon over which financial conditions have a measurable effect on firms' layoff decisions.

Looking ahead to Section 4, the benchmark analysis uses a binary dependent variable and estimates a linear probability model. Linear regressions have several key advantages when applied to a complex panel dataset: they can include fixed effects and standard errors that are robust to heteroskedasticity and autocorrelation. However, a key drawback of the linear probability model is that the error term is not normally distributed. To verify that the linear regression results are reasonable, I compare them to random-effects linear and probit models that also treat $L_{i,t}$ as binary. At the end of Section 4, I present results from a Tobit model in which $L_{i,t}$ is continuous but censored at zero.

In Section 5, I present a few robustness checks. First, I add several measures of aggregate and industry-level financial conditions to test whether firm-level financial measures are still significant. Next, I alter the baseline regression to focus on possible sources of endogeneity. The regression results are evaluated primarily on the number of significant

lags of the financial change variables. As a result, conclusions about the response of layoffs to financial conditions appear to be similar across the benchmark and alternative models.

4 Layoffs and Previous Financial Changes

Based on the econometric model in the previous section, I use distributed lag panel models to estimate the probability that changes in a company's quarterly revenue lead to an announced layoff. Overall, I find that not only does the recent quarter influence layoff propensity, but at least four prior quarters are also highly significant. This finding is robust across a number of different specifications.

The first regression results from the panel data are given in Table 2. The dependent variable is a binary indicator for whether the company announced a layoff in a given quarter or, with a continuous variable, it is the percentage of workers affected by a company's announced layoff. Regressors represent current and lagged one-quarter changes in firm revenue and its standard deviation over a one-year time horizon (different time horizons had very minimal impacts on the results).

The results in Table 2 show that the estimated coefficients on lagged revenue changes are generally significant, indicating— as expected— a strong negative relationship between layoff propensity and previous financial conditions. As an aside, perfect multicollinearity is not a concern in this context because one-quarter changes in revenue do not exhibit high serial correlation. The discussion below summarizes the findings from different model specifications.

Linear models– Column (1) of Table 2 shows estimates from a linear probability model that regresses layoffs on log revenue changes, controlling for firm and time fixed effects. The estimated coefficients show that a 10 basis point decrease [increase] in current-quarter log revenue growth, which is roughly one standard deviation, raises [lowers] a company's current layoff probability by around 0.5%. Furthermore, a change in revenue at time t has additional marginal effects on the company's layoff probability in each of

the following four quarters. Relative to Column (1), Column (2) shows that an additional (sixth) lag of the explanatory variable does not appear to have a significant marginal effect, suggesting that the distributed lag model is dynamically complete with five quarters of revenue changes.

Based on the five-lag structure of the baseline model, Column (3) uses a linear regression with random effects and industry-by-year fixed effects. Although this is not the preferred specification, it bridges the gap between the linear fixed-effect models and the non-linear models that are estimated with industry-by-year fixed effects. The results in Column (3) appear to be relatively consistent with Column (1), although the magnitude of estimated coefficients are a bit larger in the random effects specification. Considering the noisy nature of firm-level microdata, the R-squared values in Columns (1) and (2) indicate a reasonably good fit. Column (3) presents the coefficient estimates from a random effects model but a Hausman test shows that a linear model with fixed effects is preferable to one with random effects in this context.

Non-linear models– Column (4) shows the results from the probit model. Due to the incidental parameters problem, the probit model cannot be estimated with fixed effects; instead I include a year-by-industry fixed effect to control for some of the heterogeneity across firms and over time. The probit results show patterns similar to the linear models except that the magnitude of marginal effects are a bit larger with probit especially compared to the baseline linear model in Column (1).

Column (5) in Table 2 shows results from a Tobit model, which finds that all five lags of changes in revenue are negatively related to the probability and size of a subsequent layoff. The table reports marginal effects of revenue changes on layoff probability (based on the mean values of the explanatory variables), allowing for an ad-hoc comparison with the linear probability model. Interestingly, the Tobit model results are somewhat stronger than the baseline results in Column (1). Consequently, this suggests that the baseline linear estimates do not overstate the relationship between firm-level layoffs and changes in previous financial conditions.

Summary– In general, the linear, probit, and Tobit results shown in Table 2 appear to be consistent with one another. In all specifications, the estimated coefficients on revenue changes are all negative (as expected) and they tend to decrease in magnitude with more recent quarters receiving larger weight than earlier lags. There is a dimension along which the models disagree: the sign and significance of the standard deviation measure. Its relationship with layoffs should be negative in the face of adjustments costs but its estimated coefficient is positive in Column (2), negative in Column (4), and indistinguishable from zero in all other models. The sensitivity of this coefficient to model specification suggests that the standard deviation of revenue has an unclear relationship with layoff propensity in this regression.

Interpretation– To interpret the results from Table 2, consider several possible timing hypotheses: (A) if layoffs at companies respond quickly to financial conditions, the coefficient on the most recent financial change, t, would be negative while the coefficients on other lags would be indistinguishable from zero; (B) instead, if layoffs at companies respond with a delay of k quarters, the coefficient on t would be indistinguishable from zero while the coefficient on $t - k$ would be negative; (C) finally, if layoffs at companies respond in a pent-up manner to financial conditions, then coefficients on multiple lags would be negative and significant.

Interestingly, none of the models appear to confirm Hypothesis (A) that layoffs are immediate nor Hypothesis (B) that layoffs purely delayed responses to firm-level financial conditions. Instead, they appear to support Hypothesis (C) that layoffs are a pent-up reaction to declining financial conditions: the analysis shows that negative labor adjustments are more likely to happen at a company after revenue declines in some or all of five previous quarters.

Alternative models– At first glance, a proportional hazard model seems suitable for addressing companies' differential propensities to conduct layoffs over time; however, upon further consideration, there are several reasons that a duration-dependent hazard model would require strong parametric assumptions. First, controlling for unobserved

heterogeneity is not trivial in such models. This is particularly the case when attempting to include time-varying covariates and aggregate time effects. Second, the model would require additional structural assumptions to accommodate the left- and right-censoring and multiple quarters of layoffs per company in my dataset. Since the primary focus of this paper is the relationship between companies' layoffs and their time-varying financial conditions, the distributed lag framework of this paper was chosen as a way to minimize the impact of modeling assumptions. A further reason to prefer panel regressions to hazard models is that while duration-dependent models are particularly well-suited to controlling for sample selection issues, the vast majority of publicly-listed companies survive after a layoff episode (i.e. they continue to be viable and remain in the sample in subsequent quarters) and thus selection is not a major concern in this context.

Endogeneity, however, is a more central concern. A common way of addressing endogeneity in distributed lag models is through an Arellano-Bond style IV model that uses previous levels of revenue as instruments. Unfortunately, such instruments are unlikely to be exogenous in this context. A panel VAR model would be more appropriate in that it allows for feedback effects from revenue changes to layoffs at different lags, however, panel VAR models in their current form cannot accommodate limited dependent variables. Although I do not employ IV or VAR models, a few robustness checks related to endogeneity are presented in Section 5.2, where I also highlight reasons that endogeneity may not be severe in the baseline model.

5 Robustness

Several robustness checks are performed to examine the validity of the results presented in the previous section. The first set of robustness checks investigates the significance of the coefficients in the baseline regression when controlling for industry-level conditions. The second set of robustness checks investigates the sensitivity of the baseline regression to possible sources of endogeneity. Section 8 of the Appendix discusses two additional

specifications: one confirms that positive and negative revenue changes appear to have symmetric effects and the other substitutes profits for revenue in the main regressions.

5.1 Industry versus Firm-level Changes

The first robustness check addresses the hypothesis raised by Bordeman, Kannan and Pinheiro (2016) that firms' layoff announcements contain mostly industry-wide news. Specifically, Table 3 looks at whether firm-level financial changes have a significant impact on layoffs when industry-level and aggregate financial measures are also included in the regression. The measure of industry-level financial conditions uses total returns instead of GDP because, with the exception of some recent quarterly data by sector, detailed industry-level GDP is generally only available from the BEA on an annual basis.

The results in Table 3 show that changes in industry-level total returns and changes in S&P 500 total returns generally have a negative relationship with firm-level layoffs, as expected (since lower total returns in an industry or in aggregate should raise companies' layoff propensities). Column (1) shows the results when industry-level total returns are added to the baseline regression model. While the coefficients on the $\Delta Revenue$ variables resemble those in the baseline model of Table 2, the coefficients on the $\Delta IndustryTR$ variables are not significant. This latter finding changes in Column (2) when the same specification is run without time fixed effects. In this case, industry total returns become significant, likely because they help control for common aggregate layoff patterns. In Column (3), instead of industry total returns, changes in the S&P 500 index are used as explanatory variables whereas time effects are omitted. Finally, Column (4) combines the specifications in Columns (2) and (3) to include both industry-level and aggregate variables. The estimated coefficients on the $\Delta Revenue$ variables look very similar to the baseline linear model from Table 2.

The key takeaway from this robustness check is that the inclusion of industry-level financial variables in the regression does not substantially weaken the estimated relationship between firm-level financial conditions and layoffs.

5.2 Endogeneity

Layoff announcements may occur days or weeks before layoff actions, in some cases for statutory reasons, which is helpful in that it reduces the simultaneity of changes in employment and changes in business conditions. In other words, revenue changes in the current period are less likely to be impacted by a layoff announcement when the layoff action takes place after the announcement. This suggests that, for an analysis of layoff timing, preemptive announcement data may actually be preferable to other measures. Nevertheless, endogeneity is still a concern in this analysis. This section tries to reduce sources of potential endogeneity in the baseline regressions to test whether the baseline model results can be interpreted as causal effects of firm-level financial changes on layoffs.

In the benchmark model of Table 2, for example, identification depends on the assumption of a fully specified distributed lag structure with neither simultaneity nor feedback effects. With regard to simultaneity, while it is easy to argue that lagged financial changes are not affected by current layoff announcements, it is possible that the most recent financial change from time $t-1$ to time t is affected by a layoff announcement (or lack thereof) at time t. To test this, in the first two columns of Table 4 I drop the first explanatory variable ($\Delta Revenue_t$) from the regression equation and re-run the linear and Tobit model estimates. Column (1) of Table 4 shows that, when excluding revenue in the most recent quarter, the remaining four quarters of previous revenue changes continue to have significant impacts on layoff propensity. Column (2) shows that the Tobit model yields slightly higher estimates than the linear model (similar to the findings from using the original dataset in Table 2).

With regard to feedback from previous layoffs to current or previous revenue changes, in Columns (3) and (4) of Table 4 I use a subsample of observations in which feedback effects are less likely. Specifically, I exclude any observation in which a layoff occurred at a given company in the $t-1$ through $t-4$ time horizons. The subsample thus consists of companies and time horizons that did not have a "recent layoff". This sample restriction should limit the extent to which previous layoffs affect revenue changes over $t-1$ through $t-4$. Column (3) applies the baseline linear model to the subsample and its results show that, consistent

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with earlier findings, changes in revenue for all five lags affect layoff propensity in the subsample. In Column (4), applying a Tobit model to the subsample shows significant effects for the first four quarters of revenue changes (compared to significant effects for five quarters in the Tobit model of Table 2).

Although the estimated coefficients in Table 4 are generally smaller in magnitude than the baseline, the coefficients are still highly significant. In both cases, lagged financial changes through at least $t - 3$ have negative marginal effects. Consequently, this suggests that feedback from layoffs to financial conditions do not alter the results substantially; in fact, the robustness checks support the paper's main conclusions about the pent-up nature of firms' layoff decisions.

6 Conclusion

Mass layoffs affect hundreds of thousands of U.S. workers each year and can seriously harm workers' careers and well-being. This paper builds a new quarterly dataset for publicly-listed companies and uses it to evaluate the extent to which mass layoff episodes are foreshadowed by firm-level financial changes. The results show that companies' layoffs are neither immediate nor delayed, but are "pent-up" in that they are influenced by the company's financial conditions over at least four previous quarters. Interestingly, I find that positive and negative financial changes have fairly symmetric effects: positive financial changes lower companies' layoff propensities in roughly the same manner that negative financial changes raise them.

This paper contributes to a vast literature on the dynamics of labor adjustment by estimating the temporal relationship between downsizing and financial conditions for the universe of publicly-listed U.S. companies. In a structural context, recent work by Cooper, Haltiwanger and Willis (2007) finds that U.S. employers face sizable non-convex costs of employment adjustments; my econometric results based on microdata accord with their findings.

My results also shed light on the usefulness or necessity of obtaining high-frequency data to study the relationship between economic activity and employment adjustments. The results are mixed. On the one hand, quarterly or semi-annual data can be useful for circumventing time aggregation issues, since I find that firms' layoff propensities are affected more by their financial changes in recent quarters than by their financial changes several quarters ago. On the other hand, I find that firms' layoff propensities generally evolve over a one-year time horizon, which suggests that annual data on employment and financial conditions may be sufficient in many settings.

As highlighted in Hamermesh and Pfann (1996), labor adjustment patterns have both micro and macro policy implications. In a micro setting, a better understanding of mass layoffs— the frequency with which they happen and the conditions that trigger them— can help policy-makers design programs to mitigate the adverse effects of such layoffs. In a macro context, the timing of labor adjustments and their relationship to other measures of economic activity can be useful inputs into research on the dynamics of aggregate employment fluctuations or the business cycle properties of labor productivity.

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7 Appendix: Data Discussion

Matching

To create the matched database, the company name in the Challenger dataset was standardized to match a comprehensive database of Bloomberg tickers containing all companies listed on U.S. stock exchanges.[2] This comprehensive database contains approximately 4,000 listed companies; more than 800 companies in the Challenger dataset were identified as matches. These matched companies (those with at least one reported mass layoff) had approximately 24.1 million employees, roughly 20% of total U.S. private employment during that time period. In other words, the Challenger dataset appears to capture many of the largest U.S. corporate employers.

Regarding the financial variables, the dataset looks fairly complete; although 25% of companies do not report revenue measures (these companies were subsequently dropped from the dataset), more than 50% of reporting companies have quarterly revenue measures for at least four years. In fact, 30% of reporting companies provide revenue data for every quarter in the sample period. The companies with some missing data generally fall into two categories: (1) those that were initially private but were then listed on the stock market during the sample period, and, (2) companies that were delisted during the sample period. Companies were delisted for various reasons. Some were acquired by other companies or by private equity firms; others failed to meet the stock exchange listing requirements (which often foreshadowed bankruptcy filing). In most cases, historical information was available for the time in which these companies were operational, but the entry and exit of firms leads to an unbalanced dataset. In all of the regression analysis, layoff episodes where the announced reason was bankruptcy or closing were dropped from the dataset, but previous layoff episodes by firms that later declared bankruptcy were included. As a robustness check, layoffs related to mergers or acquisitions were excluded— this sample restriction had a negligible impact on the results.

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[2]Previously available at http://www.bloomberg.com/markets/companies/country/usa/.

Measures of annual company-level employment are less consistent than the financial measures discussed above, both in terms of data availability and definitions. Although the Bloomberg data has many missing values for employment, when possible, I supplemented it with the employment values reported in each company's 10-K filings with the U.S. Securities and Exchange Commission. In this manner (which was very labor-intensive), I recovered most missing values of the employment variable for matched companies. To limit the simultaneity of their employment and layoff information, in a given quarter I use the total employment measure that was reported for the previous quarter-end. In addition to the problem of missing data for unmatched companies, there are two additional shortcomings with the employment variable: (1) some companies count part-time employees while others do not, and (2) multinational corporations sometimes report only an aggregate of employment at U.S. and non-U.S. locations. For all of these reasons, the total employment variable is used sparingly in the empirical analysis.

Advantages and disadvantages

Using layoff announcements involves both advantages and disadvantages. One advantage of layoff announcements is that the announcement date is likely closer to the company's decision date, which is presumably a more accurate indicator of the response of employment to information about financial conditions. The Challenger dataset also contains the announced reason and size of the layoff, which makes it easy to identify unique layoff episodes. Another advantage of measuring layoffs instead of changes in employment at firms is that layoffs reflect firm-initiated employment changes and not worker quits. Although quits may lead to lower employment at the firm in the short run, quits are fundamentally different from layoffs— see, for example, McLaughlin (1991).

However, using announced layoffs to define the sample has several disadvantages. The first is that the resulting data might disproportionately reflect large layoffs by large companies. For example, the WARN notification requirement pertains only to employers with 100 or more employees. This regulation ensures that workers are informed about mass

layoffs at least 60 days before the layoff episode if more than a third of the establishment's workforce or at least 500 workers will be affected.[3] This requirement makes it difficult for larger companies to conceal large layoff episodes, which suggests that these types of layoff episodes are more likely to appear in news articles and companies' financial reports. In fact, Table 1 appears to confirm this size discrepancy. Fixed effects, which I include in nearly all specifications, should help control for the impact of firm size on the probability of announcing a layoff. A second disadvantage is that layoff announcement data may not always reflect the true number of workers affected by the later layoff action; in certain cases an announced layoff may not happen at all. These two shortcomings are less of a concern with this analysis, because the main measure is layoffs by publicly-listed companies (which are more likely to be consistently captured by the Challenger dataset), and also because the primary focus of this paper is the decision process determining layoff actions. When looking at the timing of layoff decisions, layoff announcements may contain more relevant information about intended layoffs than the later layoff actions.

8 Appendix: Additional Robustness Checks

To complement the analysis in Sections 4 and 5, here I look at two alternative types of explanatory variables. First, I test whether revenue changes might take a non-linear form in the baseline regression equation. Second, I use lagged changes in quarterly firm-level profits instead of revenue as the explanatory variables.

Impact of negative revenue changes

The first set of robustness checks investigates whether negative financial changes have a larger impact on layoffs than positive changes. In this specification, additional terms are added to the baseline regression model to allow negative financial changes to have a larger

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[3]Source: http://www.dol.gov/compliance/guide/layoffs.htm

impact than positive financial changes. A general formulation of this model is,

$$L_{i,t}^* = \sum_{k=0}^{K} \beta_k \Delta X_{i,t-k} + \theta_k \Delta X_{i,t-k}^- + \mu \sigma_{i,t} + \alpha_i + \varphi_t + u_{i,t} \qquad (5)$$

In the first set of results displayed in Table 5, the additional terms for negative changes are defined as, $\Delta X_{i,t-k}^- = \Delta X_{i,t-k} \cdot I[\Delta X_{i,t-k} < 0]$, allowing for a different slope coefficients when a financial change was negative. In the second set of results displayed in Table 5, the additional terms are defined as indicator variables, $I[\Delta X_{i,t-k} < 0]$, allowing negative financial changes to shift the intercept of layoff propensity without regard to the size of the financial change.

The hypothesis being tested in these robustness checks is that decreases in revenue–especially large decreases– should affect layoff propensity more than increases in revenue. In the first regression, this hypothesis would be confirmed if the coefficients on the new ΔX^- terms in the first regression were negative and significant at all lags (i.e. if larger negative financial changes have marginally positive effects on layoff propensity). Instead, the estimates of coefficient on the ΔX^- terms shown in Column (1) of Table 5 tend to be either positive or insignificant from zero; this suggests that the first regression is misspecified. In the second regression, this hypothesis would be confirmed if the coefficients on the indicator variables were be positive and significant at all lags (i.e. if any negative financial change makes layoffs more likely). However, the results displayed in Column (2) show a significant negative coefficient on just one of the new indicator variables— all the other estimated coefficients are insignificant.

Looking across the two regression models in Table 5, not only are the coefficient estimates generally not significant but, when they are significant, they often do not have the expected signs. Since neither model yields a meaningful interpretation, there is no evidence that negative financial changes disproportionately increase a firm's layoff propensity relative to positive financial changes. That is to say that the effect appears symmetric: positive financial changes appear lead to lower layoff propensity as much as similarly-sized negative

changes lead to higher layoff propensity.

Profits as an explanatory variable

In previous analysis, revenue is the preferred explanatory variable for two reasons. First, there are many more missing values in companies' quarterly profits than in their revenues (using profits cuts the sample size in half). Furthermore, while lagged revenue has a straightforward interpretation in the theoretical framework of Section 3, a model with profits is less clear-cut. Nonetheless, when looking for proxies of firms' idiosyncratic financial changes, profits are a reasonable alternative to revenues.

Table 6 shows results when lagged changes in profits are used as explanatory variables, based on linear panel models with five lags (Column 1) and six lags (Column 2), and a Tobit model (Column 3). As in Table 2, layoffs appear to be pent-up reactions to underlying changes in companies' individual business conditions. Specifically, the results confirm the significance of five lags of quarterly changes in company profit. Interestingly, and unlike revenue, the standard deviation of profits has a significant positive relationship with layoff propensity in all three columns of Table 6.

9 Appendix: Tables and Graphs

Table 1: Summary Statistics, 2007–2012

		Matched	Unmatched
Quarterly Revenue	Average	3,012	432
(millions of $s)	Median	566	75
	St. dev.	8,215	1,664
$\Delta ln(Revenue)$	Average	0.01	0.02
	Median	0.00	0.00
	St. dev.	0.11	0.11
Total employees*	Average	31,834	–
	Median	7,398	–
	St. dev.	97,282	–
Layoff episodes	Average	2.6	0
(number)	Median	2.0	0
Number of workers	Average	845	0
per episode:	Median	175	–
Fraction of workers	Average	0.06	–
per episode:	Median	0.01	–
Observations	Companies	813	2,347
	Quarters	21,021	59,554

*Source: Matched Challenger database. *The measure of total employees was predominantly missing for unmatched companies in the dataset.*

Table 2: Layoff Propensity from Lagged Changes in Company-level Revenue

	(1)	(2)	(3)	(4)	(5)
Model:	Linear	Linear	Linear	Probit	Tobit
	(FE)	(FE)	(RE)	(mfx)	(mfx)
Dep. var:	$L_{i,t}$ binary				$L_{i,t}$ continuous
$\Delta Revenue_t$	-0.052***	-0.072***	-0.064***	-0.070***	-0.062***
	(0.012)	(0.020)	(0.007)	(0.006)	(0.006)
$\Delta Revenue_{t-1}$	-0.049***	-0.067***	-0.053***	-0.063***	-0.057***
	(0.010)	(0.017)	(0.007)	(0.006)	(0.006)
$\Delta Revenue_{t-2}$	-0.039***	-0.045***	-0.035***	-0.047***	-0.042***
	(0.011)	(0.015)	(0.007)	(0.006)	(0.006)
$\Delta Revenue_{t-3}$	-0.039***	-0.039***	-0.030***	-0.044***	-0.039***
	(0.009)	(0.012)	(0.005)	(0.006)	(0.006)
$\Delta Revenue_{t-4}$	-0.021***	-0.011	-0.011**	-0.021***	-0.016***
	(0.006)	(0.010)	(0.005)	(0.006)	(0.006)
$\Delta Revenue_{t-5}$		0.010			
		(0.009)			
StDev($\Delta Revenue$)	0.008	0.012*	0.001	-0.009***	0.001
	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)
Observations	69,101	68,460	68,329	67,686	70,494
R^2/LogL	R^2=0.19	R^2=0.19	R^2=0.02	LL= -8089	LL= -4534
Firm FEs	Yes	Yes	No	No	No
Time FEs	Yes	Yes	No	No	No
Industry×Year FEs	No	No	Yes	Yes	Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ *Two-way clustered (or bootstrapped) standard errors in parentheses.[4] Mfx denotes marginal effects. Revenue variables are winsorized at the 10% and 90% levels.*

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[4]Standard errors in the linear regressions are clustered on both the firm and time dimensions. For details, see Correia, S. (2015). Reghdfe: Stata Module for Linear and Instrumental-variable/GMM Regression Absorbing Multiple Levels of Fixed Effects.

Table 3: Layoff Propensity: Industry & Aggregate Variables

	(1)	(2)	(3)	(4)
Model:	Linear	Linear	Linear	Linear
Dep. var:	$L_{i,t}$ binary			
$\Delta Revenue_t$	-0.047***	-0.047***	-0.061***	-0.052***
	(0.011)	(0.007)	(0.007)	(0.007)
$\Delta Revenue_{t-1}$	-0.045***	-0.044***	-0.054***	-0.047***
	(0.011)	(0.007)	(0.007)	(0.007)
$\Delta Revenue_{t-2}$	-0.037***	-0.033***	-0.045***	-0.037***
	(0.011)	(0.007)	(0.007)	(0.007)
$\Delta Revenue_{t-3}$	-0.038***	-0.034***	-0.043***	-0.038***
	(0.010)	(0.006)	(0.006)	(0.006)
$\Delta Revenue_{t-4}$	-0.021***	-0.020***	-0.021***	-0.021***
	(0.006)	(0.006)	(0.006)	(0.007)
StDev($\Delta Revenue$)	0.007	0.007	0.007	0.005
	(0.005)	(0.005)	(0.005)	(0.005)
$\Delta IndustryTR_t$	0.002	-0.031***		-0.006
	(0.018)	(0.005)		(0.008)
$\Delta IndustryTR_{t-1}$	-0.017	-0.041***		-0.017*
	(0.017)	(0.005)		(0.009)
$\Delta IndustryTR_{t-2}$	-0.003	-0.040***		-0.010
	(0.012)	(0.005)		(0.009)
$\Delta IndustryTR_{t-3}$	-0.011	-0.035***		-0.012
	(0.010)	(0.004)		(0.008)
$\Delta IndustryTR_{t-4}$	0.006	-0.009**		-0.011**
	(0.013)	(0.004)		(0.005)
$\Delta S\&P_t$			-0.020***	-0.011
			(0.006)	(0.007)
$\Delta S\&P_{t-1}$			-0.025***	-0.034***
			(0.007)	(0.011)
$\Delta S\&P_{t-2}$			-0.067***	-0.038***
			(0.008)	(0.012)

	(1)	(2)	(3)	(4)
$\Delta S\&P_{t-3}$			-0.022***	-0.032***
			(0.006)	(0.011)
$\Delta S\&P_{t-4}$			-0.037***	-0.029**
			(0.006)	(0.012)
Observations	64,398	64,398	63,333	58,989
R^2	0.19	0.19	0.20	0.20
Firm FEs	Yes	Yes	Yes	Yes
Time FEs	Yes	No	No	No

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Two-way clustered standard errors in parentheses.

Table 4: Layoff Propensity Specification Tests

	(1)	(2)	(3)	(4)
	No lag t	No lag t	Subsample	Subsample
	Linear, FE	Tobit, mfx	Linear, FE	Tobit, mfx
Dep. var:	$L_{i,t}$ binary	$L_{i,t}$ contin.	$L_{i,t}$ binary	$L_{i,t}$ contin.
$\Delta Revenue_t$			-0.027***	-0.035***
			(0.007)	(0.006)
$\Delta Revenue_{t-1}$	-0.037***	-0.048***	-0.033***	-0.029***
	(0.009)	(0.005)	(0.009)	(0.005)
$\Delta Revenue_{t-2}$	-0.029***	-0.034***	-0.022**	-0.018***
	(0.010)	(0.006)	(0.008)	(0.005)
$\Delta Revenue_{t-3}$	-0.030***	-0.030***	-0.032***	-0.021***
	(0.009)	(0.006)	(0.009)	(0.004)
$\Delta Revenue_{t-4}$	-0.035***	-0.037***	-0.020***	-0.003
	(0.007)	(0.005)	(0.005)	(0.005)
StDev($\Delta Revenue$)	0.007	0.000	0.000	0.001
	(0.005)	(0.004)	(0.004)	(0.002)
Observations	69,101	70,494	52,411	51,865
R^2/LogL	R^2=0.19	LL=-4591	R^2=0.15	LL= -2315
Firm FEs	Yes	No	Yes	No
Time FEs	Yes	No	Yes	No
Industry×Year	No	Yes	No	Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ *Two-way clustered (or bootstrapped) standard errors in parentheses.*

Table 5: Response of Layoffs to Negative Changes in Revenue

	(1)		(2)
Model:	Linear (FE)		Linear (FE)
Dep. var:	$L_{i,t}$ binary	$L_{i,t}$	binary
ΔX_t	-0.042***	ΔX_t	-0.016
	(0.013)		(0.010)
ΔX_{t-1}	-0.035**	ΔX_{t-1}	-0.040***
	(0.014)		(0.013)
ΔX_{t-2}	-0.013	ΔX_{t-2}	-0.026**
	(0.010)		(0.012)
ΔX_{t-3}	-0.038***	ΔX_{t-3}	-0.028**
	(0.011)		(0.012)
ΔX_{t-4}	-0.016*	ΔX_{t-4}	-0.018**
	(0.008)		(0.008)
$StDev(\Delta X)$	0.009*	$StDev(\Delta X)$	-0.001
	(0.005)		(0.006)
ΔX_t^-	0.003	$I[\Delta X_t < 0]$	-0.086**
	(0.002)		(0.033)
ΔX_{t-1}^-	0.004	$I[\Delta X_{t-1} < 0]$	-0.024
	(0.003)		(0.024)
ΔX_{t-2}^-	0.007***	$I[\Delta X_{t-2} < 0]$	-0.031
	(0.002)		(0.022)
ΔX_{t-3}^-	-0.000	$I[\Delta X_{t-3} < 0]$	-0.026
	(0.003)		(0.024)
ΔX_{t-4}^-	0.001	$I[\Delta X_{t-4} < 0]$	0.001
	(0.002)		(0.002)
Observations	69,752		69,101
R^2	0.19		0.19
Firm & Time FEs	Yes		Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ *Two-way clustered standard errors in parentheses.*

Table 6: Layoff Propensity from Company-level Profits

	(1)	(2)	(3)
	Linear, FE	Linear, FE	Tobit, mfx
Dep. var:	$L_{i,t}$ binary		$L_{i,t}$ continuous
$\Delta Profit_t$	-0.030***	-0.030***	-0.028***
	(0.007)	(0.007)	(0.003)
$\Delta Profit_{t-1}$	-0.027***	-0.025***	-0.028***
	(0.007)	(0.007)	(0.004)
$\Delta Profit_{t-2}$	-0.029***	-0.031***	-0.028***
	(0.007)	(0.007)	(0.003)
$\Delta Profit_{t-3}$	-0.022***	-0.023***	-0.020***
	(0.006)	(0.006)	(0.003)
$\Delta Profit_{t-4}$	-0.010**	-0.012**	-0.010**
	(0.005)	(0.005)	(0.004)
$\Delta Profit_{t-4}$		-0.006	
		(0.004)	
StDev$(\Delta Profit)$	0.017***	0.019***	0.005**
	(0.006)	(0.006)	(0.002)
Observations	38,661	37,510	39,695
R^2/LogL	R^2=0.20	R^2=0.21	LL= -2366
Firm FEs	Yes	Yes	No
Time FEs	Yes	Yes	No
Industry×Year	No	No	Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ *Two-way clustered (or bootstrapped) standard errors in parentheses. Profits variables are winsorized at the 10% and 90% levels. Mfx denotes marginal effects.*

Additional tables and graphs from the Challenger dataset explore layoff patterns in the U.S. over the 2007–2012 period. Specifically,

- Figure 1 shows a negative relationship between aggregate real GDP and the number of layoff episodes announced by all U.S. companies. In particular, the number of layoff episodes announced by for-profit firms was already elevated in 2007, continued rising in 2008, and peaked in the first quarter of 2009 (about five quarters after the beginning of the Great Recession).

- Table 7 shows that governments, schools, and non-profit employers conducted most of their mass layoffs in 2009–2011, whereas for-profit companies conducted more layoffs in 2008–2009.

- Figure 2 disaggregates layoff announcements by company ownership, distinguishing between for-profit firms that are publicly listed and those that are privately held. It shows that in the Great Recession, layoffs at publicly-listed companies peaked several months before layoffs at privately-held companies.

- Table 8 shows the industry composition of corporate layoff announcements. Notably, in 2007–2008 more than a third of announced worker layoffs came from just three sectors: Automotive, Financial, and Construction. This finding is unsurprising since all three of these sectors experienced major financial difficulties at the beginning of the recession.

- Figure 3 shows a detailed breakdown of layoffs in the non-corporate sector by year and type of employer. It indicates that state and local governments started large-scale layoffs in 2008, whereas school districts and universities conducted more layoffs in the 2009–2011 period than in other years. The federal government had the most layoffs in 2011 (especially in the military, postal service, IRS, and Census Bureau), making it the highest year for layoffs by public employers.

Figure 1: Layoffs at U.S. Companies versus Quarterly Real GDP
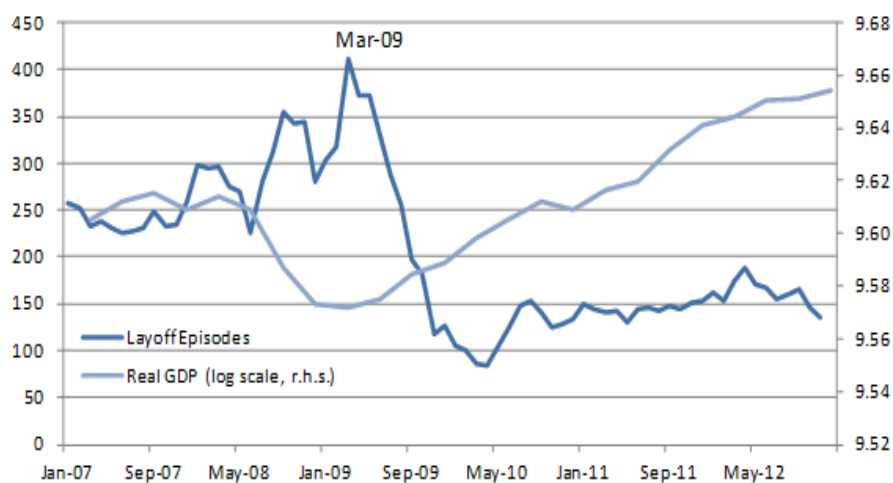
Sources: Layoff episodes per month from Challenger dataset (3-month centered moving averages), Quarterly Real GDP from FRED (2014)

Table 7: Worker Layoffs by Employer Type (percent of column)

| Employer type | Employer composition by year (%) | | | | | | All |
	2007	2008	2009	2010	2011	2012	Years
Federal gvt	0.5	0.0	3.8	5.7	16.3	0.2	3.7
State and local gvt	1.8	4.7	6.1	11.5	7.6	3.1	5.6
Local schools	1.5	0.8	3.1	6.6	5.9	5.0	3.2
Universities	0.2	0.3	1.3	2.0	1.9	0.5	0.9
Non-profits	0.5	0.5	0.3	0.9	0.6	0.3	0.5
Subtotal– Public	4.4	6.3	14.6	26.8	32.4	9.1	13.9
Listed companies	51.3	55.3	55.1	33.8	33.1	49.6	49.0
Private companies	44.3	38.4	30.3	39.4	34.5	41.3	37.1
Total workers (thousands)	771	1,217	1,273	530	606	485	4,882

Source: Challenger dataset

Figure 2: Layoffs by Company Type: Episodes per Month
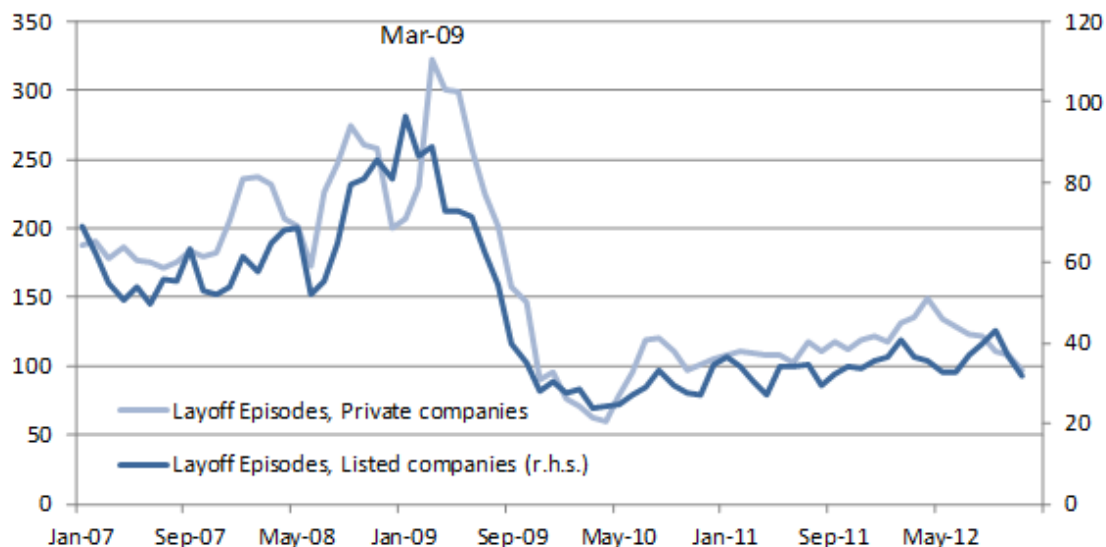
Source: Challenger dataset (3-month centered moving averages)

Table 8: Distribution of Layoffs by Industry (percent of column)

Industry	Industry composition by year (%)						All Years
	2007	2008	2009	2010	2011	2012	
Automotive	10.7	11.2	16.0	4.1	2.6	5.4	10.3
Construction	4.9	2.5	2.3	1.3	3.1	0.8	2.6
Financial	20.9	22.7	4.7	6.2	15.6	9.1	14.1
Subtotal	36.6	36.3	23.1	11.6	21.3	15.3	27.0
Aerospace/Defense	1.3	2.2	4.8	4.9	7.8	4.1	3.7
Computer	5.5	5.7	6.0	5.7	3.6	9.4	5.9
Consumer Products	5.5	4.4	3.4	4.8	4.9	7.4	4.7
Health Care/Products	4.0	3.9	3.5	7.2	6.7	6.6	4.7
Industrial Goods	6.1	5.1	11.5	6.8	6.5	5.3	7.3
Pharmaceuticals	4.3	3.3	4.2	13.8	5.4	3.1	4.8
Retail	7.2	7.0	9.1	10.0	12.5	7.3	8.4
Transportation	2.9	7.3	5.2	6.7	3.6	9.0	5.7
Total workers (thousands)	736	1,140	1,087	388	408	440	4,198

Source: Challenger dataset

Figure 3: Layoffs at U.S. Non-Corporate Employers, Number of Workers
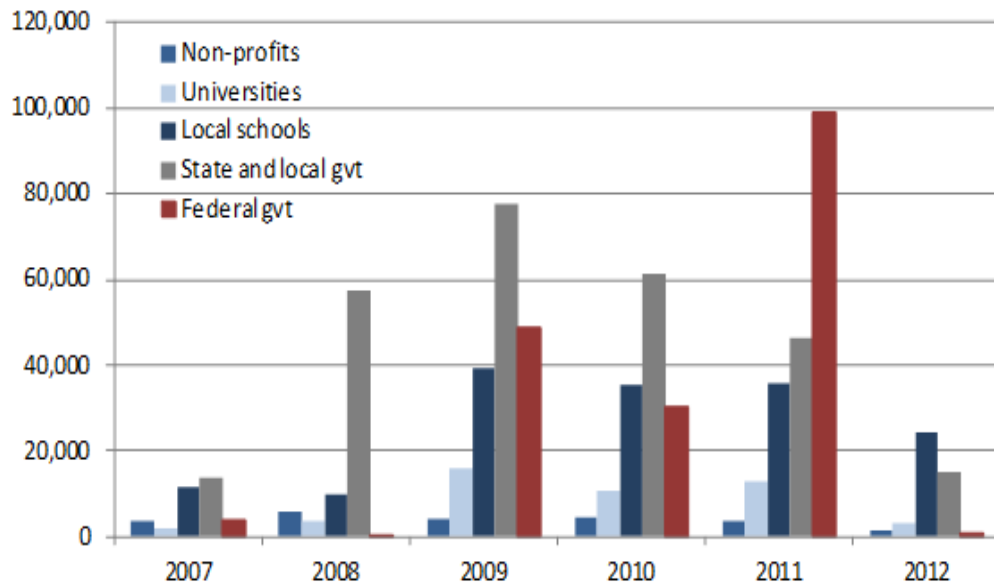
Source: Challenger dataset. Total public employer layoffs: 34 thousand workers in 2007; 76 thousand in 2008; 186 thousand in 2009; 142 thousand in 2010; 197 thousand in 2011; and 45 thousand in 2012.