Thy Bust, My Boom: Micro Evidence on Small Firms' Tech Evolution after Dot Com Bubble Burst*

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Abstract

This study investigates the impact of mass tech layoffs on non-tech firms. Using micro-level data from the U.S. Census, we find that non-tech firms in regions affected by tech layoffs experienced significant employment growth, particularly among small firms with fewer than 50 employees. This employment growth drives long-term gains in revenue and productivity for a subset of small firms that successfully hire displaced high-skill workers and navigate the challenges of adopting new technologies. Our findings suggest that mass layoffs in high-tech industries not only reshape the labor market but also generate positive spillover effects for small non-tech firms, primarily through the transfer of technology-related knowledge. These results highlight a crucial, yet often overlooked, externality: tech sector disruptions can serve as a catalyst for technology changes and growth in traditionally less dynamic sectors.

Keywords: Tech layoffs, Spillover, Non-tech firms, Technology adoption, Employment, Revenue.

JEL classification: D2, J23, J24, J63, L25, O33.

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1 Introduction

Over the past two decades, the U.S. technology industry has experienced two notable waves of mass layoffs. The first wave occurred in the early 2000s after the dot-com bubble burst, while the second emerged in 2022 following post-pandemic economic adjustments. Both periods were characterized by rapid expansion followed by sharp contractions within the tech industry, resulting in substantial job losses.[1] However, emerging anecdotal evidence suggests that non-tech firms capitalized on these disruptions by hiring displaced tech workers—individuals who might have previously found non-tech jobs less appealing when the tech sector was thriving.[2] By integrating these skilled workers, non-tech firms have the potential to improve their technological capabilities and, consequently, their long-term financial performance.

Using micro-level datasets from the U.S. Census, we examine how non-tech firms respond to mass tech layoffs. Specifically, we ask: Do these firms hire workers displaced by tech sector contractions? If so, how does this influx of human capital influence their technology adoption and long-term performance? Given that labor and capital adjustments occur over time, it is premature to fully assess the consequences of the most recent wave of layoffs. Therefore, our analysis focuses on the tech layoffs of the early 2000s.

If non-tech firms absorb workers displaced by tech firms, we would expect an increase in their employment levels following nearby tech layoffs. To explore this, we use data from the Longitudinal Business Database (LBD), which provides detailed information on employment, age, payroll, and industry of all U.S. businesses from 1978 to 2021. Following the approach of Jacobson and Sullivan (1993), we identify commuting zones

[1] According to Department of Commerce (2003), the number of workers in the IT producing industries decreased from 2000 to 2002. CBS News reported in September of 2004 that the U.S. information technology sector experienced a loss of 403,300 jobs between March 2001 and April 2004. Based on Layoffs.fyi data up to November 2024, which tracks tech layoffs from 2022 onwards, reported that the tech sector experienced almost 600,000 layoffs.

[2] During an interview with *Computerworld* in 2006, Dan Reynolds, CEO of a staffing service company, The Brokers Group, stated that many IT workers who lost their jobs in the early 2000s left the industry and never returned (Hoffman 2006). Recently, Tsipursky (2023) reported in Forbes that "As the tech industry continues to experience layoffs, companies in non-tech industries have an opportunity to gain top tech talent at below-market rate prices."

that experienced mass tech layoffs—regions containing at least one high-tech firm with over 50 employees that reduced their employment by 30% in a given year—between 2001 and 2004. We focus on non-tech firms within the same commuting zones, as job searches are mainly local (Enrico 2011; Molloy et al. 2014).

To assess the impact of tech layoffs on non-tech firms, we employ a difference-in-differences methodology, comparing employment outcomes of non-tech firms in commuting zones affected by mass tech layoffs (the treatment group) with those in regions that did not experience such layoffs (the control group) during the sample period. To mitigate selection bias stemming from the non-random distribution of firms across locations, we match control firms based on ex-ante characteristics, including industry, employment size, firm age, and the local employment share of high-tech firms.

Our findings indicate that, relative to the control group, non-tech firms experience an average employment increase within three years following tech layoffs. Specifically, after controlling for firm age, firm fixed effects, industry-by-year fixed effects, and state-by-year fixed effects, we document an average 2.5% rise in employment at non-tech firms located in commuting zones affected by mass tech layoffs. A visual inspection of the dynamic coefficient estimates around the layoff years reveals no significant pre-treatment trends, supporting the validity of the parallel trends assumption.

Interestingly, the employment effects are mainly concentrated among small firms with fewer than 50 employees. On average, we document a 2.1% to 3.4% increase in employment of small non-tech firms in the aftermath of tech layoffs. Such change is not only statistically significant but also economically meaningful given the large population of small firms in the economy.[3] In contrast, larger non-tech firms show mixed results: we observe a 3.5% decline in employment among firms with 51 to 100 employees, and a 2.6% increase in firms with more than 100 employees, though these effects are statistically insignificant.

When categorizing firms by age, we document a significant increase of 4% in the

[3]According to the 2021 Statistics of U.S. Business, small businesses with fewer than 50 employees represent 96% of firms and 26% of employment in the U.S. More details can be found at `https://www.census.gov/data/tables/2021/econ/susb/2021-susb-annual.html`. In our sample, firms with fewer than 50 employees account for 95% of observations.

employment of firms under 3 years old, while the effects on more established firms are muted. Moreover, we observe statistically significant increases in the employment of firms in wholesale, retail, service, and construction post-tech layoffs. Taken together, our results indicate a positive spillover effect on employment within a group of non-tech companies, which usually offer less appealing job opportunities during tech boom periods.

Whether the influx of displaced tech workers ultimately benefits non-tech firms is not immediately clear. On the one hand, such hiring may introduce advanced IT skills that facilitate technology adoption at non-tech firms. In this case, we would expect non-tech firms that experience significant employment gains post-tech layoffs to increase their investment in technology. Over time, these firms may experience improvements in their labor productivity. On the other hand, non-tech firms, particularly smaller ones, may have matched with less skilled individuals who lack the ability to implement necessary technological upgrades, and may experience decreased consumer demand following nearby tech layoffs. In such scenarios, we may observe limited or even reduced technology investment in the short term and minimal long-term gains in productivity.

To examine whether they benefit from post-tech layoff hiring, we first track the changes in non-tech firms' revenue and labor productivity over nine years following the events.[4] Using firm-level revenue data collected by the U.S. Census from detailed tax receipts, we replicate our baseline analysis for revenue and revenue per worker, with the latter serving as a measure for labor productivity following Duchin et al. (2010), Barth et al. (2016) and Tate and Yang (2024). In our sample, we observe an average revenue increase of 2.5% and a 2.2% decline in revenue per worker, though these effects are statistically insignificant. These modest changes are not unexpected, as only a subset of firms expanded their workforce in response to the tech layoffs. Furthermore, in larger firms, the new hires' impact on revenue outcomes may be limited. Given these observations, we next turn our attention to small firms to investigate their long-term performance.

Notably, among small firms with an increase in employment post-tech layoffs, we

[4]We adopt a longer post window for firm performance analysis because Brynjolfsson and Hitt (2003) find that productivity and output effects of technology adoption are maximized over 5- to 7-year periods.

observe heterogeneity in long-term revenue performance. Specifically, for firms with 11-50 employees, we observe a 20.5% increase in real revenue and a 15.9% increase in revenue per worker, on average, in nine years after tech layoffs. When scaled to the sample means for firms in this size category, these estimates translate into an average increase of $6.9 million dollars in real revenue and an average increase of $35,171 in revenue per worker. In contrast, firms with fewer than 10 employees ex-ante experience an average decline of 3.6% in revenue and a 10% decline in revenue per worker, despite a statistically significant increase in employment. These findings suggest that hiring after tech layoffs can be a double-edged sword, with the impact varying substantially based on firm size.

As previously discussed, the ability to attract tech talent and adopt new technology may be a potential explanation for the observed heterogeneity in firms' long-term performance. As the smallest firms confront the highest level of financial obstacle (Beck and Maksimovic 2005), they may be constrained to afford top tech workers while balancing the costs of upgrading technology. To test this explanation, we conduct two sets of tests. First, we utilize a unique dataset, the Annual Capital Expenditure Survey (ACES), administered by the U.S. Census Bureau to examine changes in firms' investments in physical capital, equipment, and software post-tech layoffs. Compared to matched control firms, treated firms with fewer than 10 workers have an average decrease of 15% in capital expenditure on new physical capital and an average decline of 11.4% in capital expenditure on new equipment in three years after experiencing mass tech layoffs. More importantly, we also observed an average decline of 9.2% in the ratio of capital expenditure spending to employment, suggesting a weak balance between employment growth and technology adoption in the smallest firms.

In contrast, firms with 11-50 employees increase capital spending on new physical capital by 18.1% on average after tech layoffs, with the bulk of this increase directed towards new equipment and software. On average, the shares of spending on new equipment and software increase by 3 percentage points and 1.3 percentage points, respectively. Such technology investments may have contributed to a significant increase in long-term revenue growth for firms with 11-50 employees.

In the second test, we examine the heterogeneity in firm performance between those who hired high- versus low-skill workers from high-tech firms. If newly hired talent is a key driver of long-term performance in non-tech firms, we should expect firms, regardless of their sizes, that hire high-skill workers from tech layoffs to outperform their counterparts. To investigate this, we use employer-employee matched data from the Longitudinal Employer-Household Dynamics (LEHD) to identify new hires at non-tech firms by tracing individual employment history. We also use individual-level data from LEHD to estimate worker skills that are portable across firms following Abowd and Margolis (1999) and Card and Kline (2013).

Our findings provide supporting evidence that layoffs in the technology sector facilitate the transfer of talent from tech companies to non-tech companies. Specifically, we find that the smallest firms, those with fewer than 10 employees, that hired relatively higher-skill workers post tech layoffs experience gains in both revenue and productivity after tech layoffs, whereas similarly sized peers that hired lower-skill workers see a decline in performance. For small firms with 11 to 50 employees, we observe an overall increase in both revenue and productivity, with even greater improvements seen in firms that hire higher-skill workers. These findings provide compelling evidence that tech layoffs create positive spillover effects for a subset of small non-tech firms, particularly through knowledge transfer.

Our paper contributes to several strands of literature. The first set of literature focuses on labor outcomes of involuntary separations. Several papers document a long-lasting wage loss of displaced workers across countries (Jacobson and Sullivan 1993; Stevens 1997; Eliason and Storrie 2006; Schmieder and Bender 2016; Graham et al. 2023; Bertheau et al. 2023). The literature also analyses the effects of displacement on a wide variety of additional outcomes, such as divorce (Charles and Melvin Stephens, 2004), mortality (Sullivan and von Wachter, 2009), health condition (Black and Salvanes, 2015). These existing studies focus on the consequences of individuals directly affected by job displacement, whereas we focus on the spillover effects of job displacement on other firms. Specifically, our study is the first to investigate the spillover effects of mass tech layoffs on non-tech firms' employment, technology investment policies, and long-term performance. We find that small non-tech firms capitalize on the opportunity to hire workers after tech layoffs. While this opportunistic hiring does not enhance the smallest firms' financial performance, it does benefit firms with 11 to 50 employees.

We also build on the literature examining the spillover effects of financial distress and mass layoffs. For instance, Bernstein and Iversonn (2019) document the negative spillover effects of bankruptcy on the local employment of nonbankrupt firms, primarily due to a reduction in local consumer traffic and a decline in knowledge spillovers. Our paper focuses on the spillover effect of mass tech layoffs, which may or may not be precipitated by bankruptcy, on the employment of non-tech firms. In contrast to the negative outcomes observed by Bernstein and Iversonn (2019), we document a positive effect on small non-tech firms' employment. We also document a positive effect on technology investment and long-term performance at small firms that hire displaced high-skill workers, supporting the knowledge transfer channel. Additionally, Babina (2019) documents that firms' financial distress motivates talents to become entrepreneurs. While Babina's work focuses on the outcomes for a small set of voluntarily departing talent, our study examines the broader impact of mass tech layoffs on non-tech firms, emphasizing the effects on a larger population of displaced workers.

Our paper is closely related to Gathmann et al. (2020), which documents that mass layoffs involving at least 500 workers per plant in the tradable sector, on average, result in a 1.9% decline in local employment in Germany. Shifting focus to the U.S. tech industry, our study examines layoffs affecting at least 30% of employees in tech firms with a minimum workforce of 50. Interestingly, we observe an average increase of 2.5% in employment of nearby non-tech firms following such tech layoffs. Furthermore, we explore the impact of these layoffs on their long-term revenue performance, highlighting significant variations by firm size due to variations in technology adoption and the quality of new hires. Altogether, our study offers valuable insights into the potential consequences of the recent wave of tech layoffs in the U.S.

Lastly, our paper relates to the literature examining how the availability of external knowledge in the surroundings of economic agents affects their performance. For instance, Peri (1993) demonstrates that an increase in the supply of college graduates leads to higher average wages and land rents in cities. Jaffe et al. (1993) shows that citations to patents often come from patents in the same region, reflecting pre-existing sharing of knowledge and skills among inventors. Peri (2005) and Matray (2021) document the spillover effects of innovation on neighboring firms' innovation through knowledge diffusion. Our study contributes to this literature by documenting a novel channel of knowledge diffusion. Specifically, we show a subset of non-tech firms benefit from the human capital flow induced by mass layoffs in local high-tech firms. This human capital transfer serves as a valuable channel for knowledge transfer, enabling a subset of local non-tech firms to upgrade technology and enhance their long-term revenue and labor productivity.

2 Data

We construct our research samples that track non-tech firms' regional employment, revenue, and technology expenditures by combining micro-level data from the U.S. Census Bureau's Longitudinal Business Database (LBD) with the Annual Capital Expenditures Survey (ACES) and the Longitudinal Employer-Household Dynamics (LEHD). We describe each data source and the merging process in detail below.

2.1 Longitudinal Business Database

Our analysis requires us to reliably measure firms' employment in a given region over time. To this end, we use establishment-level data from the Longitudinal Business Database (LBD) administered by the U.S. Census Bureau. The LBD tracks the universe of U.S. business establishments with at least one paid employee annually (Jarmin and Miranda 2002; Melissa et al. 2021). The LBD contains unique establishment identifiers that allow us to track establishment-level employment, payroll, county, state, industry, and parent firm over time. We also obtain firm-level revenue data from the revenue-augmented LBD, which collects revenue data from the detailed tax receipts variables contained in the Standard Statistical Establishment List (SSEL) and the Business Register (BR) (Haltiwanger et al. 2019).

Because job searches are largely local (Enrico 2011; Molloy et al. 2014), we expect the spillover effect of tech layoffs to be concentrated within the same local labor markets. Following the previous literature, we define local labor markets by commuting zones (CZ), which reflect the local economy where people live and work.[5,6] We aggregate establishment-level employment to firm-CZ level by summing up employment of a firm's establishments in a given commuting zone. Following Haltiwanger and Miranda (2013) and Babina et al. (2021), we define a firm's age in a given commuting zone as the age of the oldest establishment with the first positive employment in the commuting zone.

Following the Statistics of U.S. Businesses program, we classify firms into four-digit SIC industries that paid the largest share of their payroll based on their establishment-level payroll data in a given commuting zone. We then identify high-tech companies using SIC codes based on Ljungqvist and Wilhelm (2003), which include industries in computer hardware, communication equipment and services, electronics, navigation equipment, measuring and controlling devices, and software. Appendix B reports the 4-digit SIC codes and titles of high-tech sectors. Firms that are not in the high-tech industries are defined as non-tech firms.

Following Jacobson and Sullivan (1993), we define mass tech layoff events as instances where high-tech firms with over 50 employees reduce their workforce by 30% in a given year between 2001 and 2004. Non-tech firms in commuting zones with at least one such event are considered treated, with the year of the earliest event designated as the treatment year. We track non-tech firms five years before and three years after the mass tech layoff year. To avoid capturing the labor market effects of the 2008 financial crisis, we adopt a shorter post-treatment window in the baseline sample, and our baseline sample

[5]Studies use commuting zones to proxy for local labor markets, including Autor and Hanson (2013), Chetty and Saez (2014), Acemoglu and Restrepo (2020), Autor and Hanson (2020) and Matray (2021).

[6]We link establishment county codes (FIPS) from the LBD to commuting zones using the bridge provided by the USDA at `https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/`.

period spans from 1996 to 2007.

Control firms are carefully sampled from non-tech firms in commuting zones that did not experience mass tech layoffs during our sample period. For each treated firm, we first require its control firms to be in the same four-digit SIC industry code and decile of firm-CZ employment within the year before the event. Second, we keep up to four matches with the nearest propensity score constructed using a linear probability model based on the logarithm of firm employment, firm age, and the employment share of high-tech firms in a given commuting zone.[7]

Table 1 presents summary statistics of our firm-commuting zone-year level sample in Panel A.[8] Columns 1-3 report observation counts, sample means, and standard deviations of key variables used in our analysis. In columns 4-6, we report statistics for variables in the pre-treatment period. In columns 7-9, we report the same statistics but for variables in the post-treatment period. On average, the firms in a given commuting zone are 12 years old, with 16 employees. As compared to studies that use LBD data (e.g., Babina et al. (2021)), firms in our sample have similar ages but lower employment because we define firm boundaries based on commuting zones they are located in and employment is aggregated across a firm's establishments in a given commuting zone. Importantly, columns 5 and 8 show that the average employment of non-tech firms increases from 15.5 in pre-layoff periods to 17 in post-layoff periods.

To examine the effect on non-tech firms' financial performance, we restrict our sample to a subset of firm-CZ-years from our baseline that includes firm-year-level revenue data reported in the revenue-augmented LBD.[9] Revenue data are adjusted for inflation using the 2018 GDP deflator. Following Haltiwanger et al. (1999), Barth et al. (2016) and Tate and Yang (2024), we define labor productivity as the ratio of revenue to employment, with employment aggregated across all domestic establishments of a given firm to ensure

[7] Similar matching approaches have been used in the literature, such as Ma et al. (2016), Graham et al. (2023), and Lagaras (2024).

[8] All observation counts and estimates are rounded according to the US Census Bureau's disclosure policies.

[9] Although revenue data is available for private and publicly listed firms, it is not as comprehensive as employment data and is only available for a subset of domestic firms. Further details can be found in Haltiwanger et al. (2019).

consistency with how revenue is calculated.[10] In this sample, we extend the post-event window from three years to nine years because Brynjolfsson and Hitt (2003) finds that productivity and output effects of technology adoption are maximized over a long period (5 to 7 years). The revenue sample spans from 1996 to 2013. Panel B of Table 1 reports summary statistics of firm revenue and productivity. On average, firms in our sample have an average revenue of $18.1 million and productivity of $0.64 million.

2.2 Annual Capital Expenditures Survey

We obtain data on business capital expenditures in new and used structures, equipment, and capitalized computer software from the Annual Capital Expenditures Survey (ACES). ACES is an annual mandatory survey conducted by the Census Bureau, starting from 1994, and provides the only comprehensive estimates of annual U.S. capital expenditure data that covers all domestic, private, and non-farm businesses. The ACES has been used by several agencies, such as the Bureau of Economic Analysis, the Federal Reserve Board, the Department of the Treasury, the Bureau of Labor Statistics, to refine estimates of investment and stock in structures and equipments.[11]

We link ACES data to our baseline sample through an internal firm identifier to construct the technology investment sample spanning from 1996 to 2007. Table 1, Panel C, reports summary statistics for the LBD-ACES linked sample.[12] On average, firms in our sample spend $85 million on new structure and equipment, with $70 million (83%) allocated specifically to new equipment. Investment in new equipment shows a significant increase of approximately 40% (=(83,590-59,860)/59,860) in the post-tech-layoff period, reflecting a notable rise in information technology (IT) investments that is consistent with the trend reported by Department of Commerce (2003).

[10] As mentioned in Tate and Yang (2024), which also utilizes LBD in their analysis, there is a lack of sufficient variables for computing total factor productivity (TFP) since our sample comprises both manufacturing and non-manufacturing firms. However, among the manufacturing firms, Foster et al. (2001) demonstrates a strong correlation between labor productivity and TFP.

[11] More details about the ACES can be found at `https://www.census.gov/programs-surveys/aces/about.html`.

[12] Our sample size is reduced due to the survey's frequency on granular spending categories and variations in response rates. ACES publishes estimates of capital spending by granular categories approximately every five years. Additionally, many firms do not capitalize software in their accounting records.

2.3 Longitudinal Employer-Household Dynamics

To identify worker flows from high-tech firms to non-tech firms post-tech layoffs, we use quarterly employer-employee matched data from the Longitudinal Employer-Household Dynamics (LEHD) maintained by the U.S. Census. We have access to LEHD for 27 participating U.S. states. About 95% of all U.S. private sector jobs are contained in the LEHD dataset. Within the covered states, the Employment History Files (EHF) of the LEHD program track workers' quarterly earnings, locations, and industries across employers.[13,14] The National Individual Characteristics File (ICF) provides detailed information on various demographic characteristics such as education, age, gender, and race. We link workers from LEHD with firms in our sample through the Business Register Bridge (BRB) following Babina et al. (2021) and Ma (2024).

We identify displaced tech workers as those who exit a high-tech firm within four quarters following the firm's layoff and do not return to the same firm for at least two years. Workers who remain in the same high-tech firms for at least four quarters following the firm's layoff are defined as stayers. Displaced tech workers who joined non-tech firms in our baseline sample in the year of or one year after the mass tech layoff are defined as new hires. To limit the effect of temporary workers on our analysis, we exclude tech workers with less than 2 quarters of tenure in the year before the layoff. We also restrict our sample to workers aged 16 to 64 in the year preceding the layoffs to account for potential retirements.

Table 2 reports summary statistics separately for displaced tech workers who joined non-tech firms in our sample after tech layoffs in column 1 and tech workers who stay employed at the same tech firms in column 2. These statistics are informative of the observable characteristics of workers who are more likely to leave tech firms and join non-tech firms during mass tech layoffs. Within our sample, compared to stayers, displaced tech workers tend to be female, younger, less educated, have shorter tenure, and receive

[13] Workers' earnings include all forms of immediately taxable compensation, including gross wages and salaries, bonuses, exercised stock options, tips, and other gratuities. See Vilhuber et al. (2018) for more detailed descriptions of the LEHD program and the underlying datasets that it generates.

[14] LEHD does not provide occupation information, which limit our ability in assessing job specific impact.

lower earnings. Furthermore, the earning growth is also lower for displaced workers at 1.8%, compared to 5.3% for those who stay, which is consistent with findings in Bartel and Borjas (1981).

After layoffs in the tech sector, where do tech workers go? Figure 1 plots the distribution of displaced workers who left tech firms during mass layoffs and joined non-tech firms in our sample by SIC industry sectors of their new employers. The figure shows that the majority of displaced tech workers joined the services sector, which include both low-skill (e.g., hotel and other lodging, and personal services) and high-skill services (e.g., legal services, motion pictures, and business services). Retail trade, manufacturing, finance, insurance and real estate, transportation and public utilities sectors also absorbed a significant number of displaced tech workers, while sectors like wholesale trade and construction experienced a moderate influx.

3 Non-tech firm employment

To test whether non-tech firms respond to mass tech layoffs by hiring displaced workers, we examine employment changes at non-tech firms by estimating the following equation:

$$log(y_{i,c,t}) = \gamma_1 \times Post_{c,t} \times Layoff_c + \gamma_2 \times Post_{c,t} + \alpha_{i,c} + \alpha_t + \beta X_{i,c,t} + \epsilon_{i,t} \qquad (1)$$

where $y_{i,c,t}$ represents the employment of firm i located in commuting zone c and year t; $Post_{c,t}$ equals one for the year at and after the earliest mass tech layoffs in commuting zone c, zero otherwise; $Layoff_c$ equals one for commuting zone experiencing at least one mass tech layoff from 2001 through 2004, zero otherwise. $\alpha_{i,c}$ represents firm at the commuting zone level fixed effects, and α_t represents year fixed effects; $X_{i,c,t}$ presents firm age in a given commuting zone-year. In more restrictive specifications, we further control for interacted 4-digit SIC industry and year fixed effects $\alpha_{j,t}$ to absorb time-varying industry shocks and for interacted state and year fixed effects $\alpha_{s,t}$ to absorb time-varying local shocks. In all specifications, we cluster standard errors at the firm level.

Table 3 presents the results. Column 1 shows that mass tech layoffs are associated with an average employment increase of 1.8% at non-tech firms within treated commuting zones, compared to the matched control sample, in a specification with firm at the commuting zone level and year fixed effects. The estimated effect is statistically significant at the 1% level. We next repeat the estimation, additionally controlling for (4-digit SIC) industry-year fixed effects (column 2), state-year fixed effects (column 3), and both industry-year and state-year fixed effects (column 4) to control for industry and local economic shocks, respectively, that might be contemporaneous with the timing of the mass tech layoffs and non-tech firm expansion. The estimated effects remain robust through all specifications. In the most stringent specification (column 4), we document a 2.5% increase in non-tech firms' employment after mass tech layoffs. These results indicate the reallocation of human capital from high-tech firms to nearby non-tech firms.

One may posit that the burst of tech bubbles may not be an exogenous shock. Also, the choice of non-tech firms may not be random, which may explain their employment growth after post-tech layoffs. Besides carefully matching treated firms with control firms in the various characteristics as described in Section 2.1, we also demonstrate that both treated and control firms exhibit parallel trends before the mass tech layoff event.

Specifically, we create separate dummy variables for each observation before and after the mass tech layoff event. Pre_n is an indicator set to one for the n^{th} year before the mass tech layoff event, zero otherwise. $Post_n$ is an indicator set to one for the n^{th} year after the mass tech layoff event, zero otherwise. The first year before the year of the mass tech layoff event is set as the omitted coefficient. We augment our baseline specification by interacting these variables with $Layoff_c$ and plot the dynamic coefficient estimates in Figure 2. The plot shows statistically and economically insignificant changes in employment of treated firms before tech layoffs, which supports the parallel trends assumption of the difference in differences and a casual interpretation of our findings. In contrast, we observe a significant and persistent increase in employment of treated tech firms after the mass tech layoff.

What types of non-tech firms hire displaced tech workers? Small and less established non-tech firms might have been in a disadvantageous position in attracting high-skill workers before the tech bubble burst, so they may seize the opportunity to hire more displaced workers. To test this hypothesis, we first categorize firms into four groups based on employment size in a given commuting zone one year before the mass tech layoffs: fewer than 10 employees, 11-50 employees, 51-100 employees, and over 100 employees.[15,16] We estimate Equation 1 for each group with industry-by-year fixed effect and state-by-year fixed effect controlled.

Table 4 reports the employment changes at non-tech firms around the time of mass tech layoffs by firm size. Columns 1 and 2 present the results for the smallest firms with fewer than 10 employees and small firms with 11-50 employees, respectively. Columns 3 and 4 present the results for medium and large firms, with 51-100 employees and over 100 employees, respectively. The interaction coefficients $Post_{c,t} \cdot Layoff_c$ for firms with fewer than 10 employees and firms with 11-50 employees indicate a 2.1% and 3.4% increase in employment for these small firms, respectively. These changes are statistically significant at the 1% level. The average hiring of approximately one person per small firm following mass tech layoffs is economically meaningful, particularly considering the large number of small firms in the economy. In contrast, the interaction coefficient $Post_{c,t} \cdot Layoff_c$ for firms with 51-100 employees is statistically insignificant and negative, suggesting no notable employment growth for local medium-size non-tech firms following mass tech layoffs. For large firms with over 100 employees, we observe an average employment increase of 2.55%. This change is not only statistically insignificant but may have little impact on large firms' investment policies and performance.

In the next test, we repeat our analysis in Table 5 but categorize firms by age into four groups: under 3 years, 4-9 years, 10-16 years, and older than 16 years.[17] Table 5 presents employment changes at local non-tech firms around the time of mass tech layoffs by firm age. We find that young local non-tech firms experience a significant 3.97% (Column 1)

[15]This classification is a condensed version of the one used in the Business Employment Dynamics reported by the Bureau of Labor Statistics, which classifies firms into 9 groups. More details can be found at urlhttps://www.bls.gov/bdm/bdmfirmsize.htm.

[16]Internet Appendix Table C1 reports summary statistics of key variables by firm size.

[17]The age group cutoffs are picked based on age quantiles within our sample.

employment growth post-layoffs. In contrast, the effects are muted at more established firms, as evidenced by the insignificant interaction coefficients in Columns 2 to 4. Taken together, employment in the treated non-tech firms increases overall, but this growth is primarily driven by an increase in employment at small and young firms that pay less attractive wages(Oi and Idson 1999; Brown and Medoff 2003; Babina et al. 2021).

Lastly, we examine heterogeneity in employment changes across industries to better understand where tech workers go after the tech bubble burst. Figure 3 displays the coefficient estimates (i.e., γ_1) from estimating Equation 1 with the logarithm of employment as the dependent variable, conducted separately for each 2-digit SIC sector.[18] Our results indicate employment growth for local firms in the non-farm agriculture, construction, transportation, wholesale, retail, and service sectors, although the changes are not statistically significant for the agriculture and transportation sectors. [19] Overall, we observe that mass tech layoffs are associated with economically significant increases in local non-tech small and young firms' employment, and these effects are meaningful across key economic sectors.

4 Non-tech firm long-term performance

Our baseline results indicate that local non-tech firms, especially small firms with fewer than 10 employees and 11-50 employees, experience employment growth following mass tech layoffs within commuting zones, compared to observably similar firms. The next key question is whether hiring post-tech layoffs benefits non-tech firms. On the one hand, such hiring can benefit by introducing advanced IT skills that facilitate technology adoption and enhance overall productivity. In this case, we should expect non-tech firms with a significant increase in employment to increase investment in technology post-tech layoffs. Over time, these firms may have an increase in their financial performance. On

[18]For sectors that include high-tech subsectors, we exclude those specific subsectors.

[19]Examples of tech jobs in construction include building information modeling specialists, who design and manages 3D digital models of buildings, and construction technology managers, who implement and oversee technologies like software or equipment for project management. Wholesale and retail sectors hire E-commerce platform managers to manages online operations, including website maintenance and order processing. They also need tech professions to develop and use software tools to improve inventory and distribution efficiency.

the other hand, small firms may be financially constrained to attract skilled tech workers while managing the costs of new technology. They may also have hired less qualified individuals who cannot effectively implement necessary upgrades. In these cases, there may be a lack of investment in technology and no improvement in revenue performance.

To answer this question, we examine changes in firms' revenue performance during mass tech layoffs. To this end, we restrict our sample to firms with reported revenues in LBD and extend the analysis period to nine years following mass tech layoffs. The extension is based on the well-documented fact that technology advancement, which is fueled by investments in human capital, takes a long period to maximize productivity (Romer 1990; Brynjolfsson and Hitt 2003). Within a sample of firms with revenue data, we estimate the firm performance changes following mass tech layoffs using difference-in-differences regression analyses with Equation 1. The dependent variables are the logarithm of revenue and the logarithm of revenue per worker, a proxy for productivity.

Columns 1 and 2 of Table 6 present the results. Columns 1 and 2 show that across all firms in our sample, there is an average revenue increase of 2.5% and a 2.2% decline in productivity, though these effects are statistically insignificant. These modest changes are not unexpected; as discussed in Section 3, only a subset of firms increased employment in response to the tech layoffs. Additionally, in large firms, newly hired workers may play a negligible role, thereby having minimal impact on overall performance. Given these factors, we next focus on small firms to examine their long-term performance.

Following mass tech layoffs, we observe significant increases in revenue and productivity for small firms with 11-50 employees, but negative effects on the performance of firms with fewer than 10 employees (i.e., the smallest firms). Specifically, columns 3-4 of Table 6 show an average revenue decline of 3.6% and an average productivity decline of 9.9% at the smallest firms. The deterioration in performance following the employment growth after the tech layoffs may be attributed to two factors: these firms may have hired less qualified individuals who are unable to effectively implement necessary upgrades, or they may be constrained to advance their technology. In contrast, columns 5-6 show that the revenue and productivity of small non-tech firms with 11-50 employees, on average, increase by 20.5% and 15.91%, compared to control firms. Overall, firms with 11-50 employees exhibit growth in employment and performance following layoff events. This finding suggests that these small non-tech firms may have seized the opportunity to attract talent, enabling them to facilitate technology adoption and improve overall productivity. We will further test these hypotheses in Section 5.

As discussed in Section 2.1, unlike employment data that can be measured at the firm-commuting zone level, revenue is reported at the firm level in LBD. Measuring revenue at the firm level may create a bias in our estimation for firms with multiple establishments in both treated and non-treated commuting zones. To address this concern, we repeat our analysis with revenue and productivity adjusted by firm employment share in a given commuting zone as dependent variables. This adjustment assumes there is a positive correlation between a firm's employment in a given commuting zone and its regional revenue are positively correlated. Internet Appendix Table C3 presents these results. We find that our coefficient estimates remain robust, alleviating this concern.

To further enhance our understanding of the short-term and long-run impact on small firms' revenue performance, we divide the post-layoff periods into three stages. The first stage $Post_{1,c}$ equals one for the year and next three years after mass tech layoffs, and zero otherwise; the second stage $Post_{2,c}$ equals one for the fourth to the sixth years after mass tech layoffs, and zero otherwise; the last stage $Post_{3,c}$ equals one for the seventh to the ninth years after mass tech layoffs, zero otherwise. We estimate the following equation:

$$y_{i,c,t} = \sum_{n=1}^{3} \theta_n \times Post_{n,c} \times Layoff_c + \sum_{n=1}^{3} \gamma_n \times Post_{n,c} + \alpha_{i,c} + \alpha_{j,t} + \alpha_{s,t} + \beta X_{i,c,t} + \epsilon_{i,t} \quad (2)$$

where i represents a firm, t represents a year, and c represents a commuting zone. $y_{i,c,t}$ is the logarithm of one plus revenue and productivity. $Layoff_c$ equals one for a commuting zone experiencing at least one mass tech layoff, zero otherwise. Control variables are the same as the ones described in Equation 1. Standard errors are clustered at the firm level.

In Figure 4, we observe that the mass tech layoffs have economically meaningful and long-lasting impacts on local non-tech small firms with 11-50 employees. Specifically, these firms experience a 16.84% increase in revenue within the first three years following local tech layoff events, a 22.78% increase from the third year to sixth year post-events, and a 34.79% increase from the sixth to ninth year, compared to non-tech firms located in commuting zones without mass tech layoffs (i.e., light grey bars in 4(a)). Moreover, the productivity of small firms in this size category exhibits a markable upward trend (i.e., light grey bars in 4(b)). Conversely, Figure 4 (dark grey bars) shows that small firms with fewer than 10 employees do not realize substantial productivity and revenue gains over the short- or long-term despite an observed employment increase following local mass tech layoffs. These findings suggest that small firms with 11-50 employees may be more adept at leveraging the skills and knowledge brought by high-tech human capital, resulting in enhanced performance. In contrast, firms with fewer than 10 employees may face challenges in converting the costs of hiring high-tech human capital into significant performance improvements.

5 Mechanism

In Section 3, we document employment increases at small non-tech firms after mass tech layoffs. However, in Section 4, we observe varied revenue performances among small firms after tech layoffs, suggesting heterogeneous effects of hiring displaced tech workers. In this section, we explore the potential reasons that explain this heterogeneity.

5.1 Investment in Technology

A possible reason could be that non-technology companies with 11 to 50 employees seized the opportunity to hire high-skill tech workers, which enabled them to adopt new technologies and enhance their overall productivity (Cohen and Levinthalz 1989; Autor and Murnane 2003; Kogan and Stoffman 2017). However, the smallest firms might have employed displaced workers who are less proficient in advancing technology, or they may lack the financial resources, potentially due to a decline in consumer demand, to increase technology spending after growing their workforce. If this is the case, we would expect small non-tech firms with 11 to 50 employees to increase their investment in technology, while the smallest firms might not increase or even cut such investments.

In this section, we examine the change in capital expenditures following mass tech layoffs by integrating data on capital expenditure on new structures, equipment, and software from the Annual Capital Expenditures Survey (ACES). We estimate changes in firm technology investment following mass tech layoffs using Equation 1 for small firms, using various capital expenditure metrics as our dependent variables.

The results of these regressions are presented in Table 7. Columns 1 and 2 of Panel A show that firms with fewer than 10 employees experience declines of 14.96% in total new capital expenditures and 11.41% in new equipment spending, respectively. Column 3 in Panel A, which examines the intensity of new capital spending on new equipment, yields similar results. In contrast, columns 1 to 3 in Panel B show that non-tech firms with 11-50 employees report an 18.13% increase in total new capital expenditures, a 28.32% increase in spending on new equipment, and an 8.14% increase in the intensity of new equipment, on average, relative to the control group.

In Table 7, columns 4-5 of each panel, we use alternative measures to capture the relative importance of capital spending on new equipment and software. Consistent with our hypothesis, we find that non-tech firms in affected commuting zones, which benefit from local mass tech layoffs, exhibit relatively higher IT investment post-layoff. In particular, for small firms with fewer than 10 employees located in affected commuting zones, there is a 3.8 percentage point increase in the share of new equipment spending (Panel A, column 4) and a 1 percentage point rise in the share of software spending (Panel A, column 5). However, these increases could be attributed to a decrease in total new capital expenditure, as indicated in column 1 of Panel A. For firms with 11-50 employees, columns 4 and 5 of Panel B reveal a rise in the percentage of expenditure on new equipment and capitalized software by 2.9 percentage points and 1.3 percentage points at treated firms, respectively, compared to the control group. Together, these results suggest that small firms that effectively balance the hiring cost of high-tech human capital and technology investment gain in terms of revenue and productivity from local mass tech layoffs.

5.2 Talent Acquisition

Given the complementary nature of skills and technology (Goldin and Katz 1998, 2008; Autor and Murnane 2003; Goos and Manning 2007; Autor and Hanson 2013), non-tech firms that hire skilled workers may be better equipped to enhance their technology and long-term performance. In this section, we investigate whether the performance enhancements of non-tech firms depend on the selection of displaced workers. If newly hired talent is a key driver of long-term performance in non-tech firms, we should expect non-tech firms with high-skill new hires to outperform their counterparts.

To this end, we first use employer-employee matched dataset created using LEHD-LBD and estimate worker skill levels following Abowd and Margolis (1999) and Card and Kline (2013) by:

$$y_{k,t} = \alpha_k + \psi_i + \eta_t + X_{k,t}\beta + \epsilon_{k,t} \tag{3}$$

where $y_{k,t}$ denotes the logarithm of worker k's earnings (in 2018 dollar) in year t. α_k represent worker fixed effects and reflect time-invariant worker skill (e.g., talent) that are portable across firms. ψ_i represent firm i's fixed effects and capture time-invariant firm characteristics that may affect firm wage-setting policies. η_t are year fixed effects that absorb time-varying macro trends. $X_{k,t}$ is a vector of time-varying controls, including year dummies interacted with education dummies and function of worker age interacted with education dummies.

Next, we identify new hires at non-tech companies. Specifically, we start by identifying displaced tech workers as those who leave a high-tech company within a year after the company's layoff and do not return to the same employer for at least two years. Displaced tech workers who joined non-tech firms within our baseline sample either in the year of or the year following the mass tech layoff are considered new hires.

We take the average worker fixed effects of new hires estimated using Equation 3 as a proxy for the skill level of new hires in a given firm. For firms that hired displaced tech workers, we rank them based on the quality of the newly recruited workers and set $HighQuality_i$ to one if the new workforce quality at firm i is above the sample median, and zero otherwise. If there are no new hires, $HighQuality_i$ is set to zero. We then test whether the performance improvements of non-tech firms are influenced by the selection of displaced workers by estimating the following regression:

$$\begin{aligned} y_{i,c,t} =& \gamma_3 \times Post_{c,t} \times Layoff_c \times HighQuality_i + \gamma_2 \times Post_{c,t} \times Layoff_c + \\ & \gamma_1 \times Post_{c,t} + \alpha_{i,c} + \alpha_{j,t} + \alpha_{s,t} + \beta X_{i,c,t} + \epsilon_{i,t} \end{aligned} \tag{4}$$

where i represents a firm, t represents a year, and c represents a commuting zone. $y_{i,c,t}$ is the logarithm of one plus revenue or productivity of firm i located in commuting zone c in year t. $Post_{c,t}$ equals one for years at and after the first mass tech layoff event in commuting zone c, zero otherwise; $Layoff_c$ equals one for commuting zone experiencing at least one mass tech layoff, zero otherwise. $X_{i,c,t}$ presents firm age in a given commuting zone-year. We further control for time-invariant firm characteristics by including firm at the commuting zone level fixed effects $\alpha_{i,c}$, interacted 4-digit SIC industry and year fixed effects $\alpha_{j,t}$ to absorb time-varying industry shocks and for interacted state and year fixed effects $\alpha_{s,t}$ to absorb time-varying local shocks. Standard errors are clustered at the firm level.

We present these results in Table 8. In columns 1-2, we estimate Equation 4 for all firms within our sample using (log-transformed) revenue and productivity, respectively, as our dependent variables. Our findings indicate that non-tech firms experience significant revenue increases when they hire high-skill workers displaced during mass tech layoffs, in contrast to firms that either hire lower-skill workers or restrain from hiring. Specifically, local non-tech firms that recruit high-quality tech workers during mass tech layoffs experience an additional 36.38% increase in revenue and a further 56.2% increase in revenue per worker compared to other treated firms.

As presented in Section 4, although small non-tech companies generally see a rise in employment following large-scale tech layoffs, there is a noticeable variation in their long-term outcomes: the smallest companies with fewer than 10 employees face notable declines in revenue and productivity, whereas businesses with 11 to 50 employees show substantial gains in both revenue and productivity. A possible explanation for this disparity is that the smallest firms might have hired lower-quality employees who are less capable of advancing technology. If this is the reason, we would expect that the smallest firms that see poorer long-term performance are those that have hired lower-skill workers, whereas those that employ higher-skill workers would see long-term revenue and productivity growth. To test this, we repeat our analysis in columns 1 and 2 of Table 8 for the smallest firms and report results in columns 3 and 4 of the same table. The findings indicate that the smallest firms that recruit higher-quality workers, on average, outperform their counterparts.

Overall, the results in this section reinforce the notion that the quality of new human capital contributes to firm performance. These findings highlight the importance of worker selection, especially for small firms that hire displaced workers during mass tech layoffs.

6 Conclusion

This paper use comprehensive micro-level datasets that combine administrative data from the Census Bureau on employment, technology investment, and revenue to investigate the impact of mass tech layoffs on local non-tech firms. We find that mass tech layoffs are followed by increases in employment in local non-tech firms. We show that small and young firms mainly drive this growth. Furthermore, small firms with 11-50 employees exhibit performance improvement with employment growth post-layoffs. On the other hand, the smallest firms with less than 10 employees experience increases in employment yet do not achieve notable short-term revenue growth and encounter reduction in long-term revenue and productivity.

To understand the underlying reason for the mixed impact of mass tech layoffs on revenue performance, we test the hypothesis that production is intricately tied to both human capital and technology investment. Our findings indicate that small firms that experience employment growth and performance improvement increase total capital expenditure, especially on new equipment and software. We also provide evidence that the quality of human capital hired during mass tech layoffs plays a pivotal role in long-term performance.

A key implication of our findings is that the impact of mass tech layoffs on local non-tech firms is heterogeneous. Our evidence suggests small firms increase their employment after local mass tech layoffs. However, only firms that select relatively high-quality workers and invest in technology show long-term growth in revenue and productivity. Our study offers valuable insights into the potential consequences of the recent wave of tech layoffs in the U.S. Lastly, it's important to highlight a caveat of our analysis: Our results are specific to a sample of non-tech firms that survived for at least one year (i.e., have at least one employee) following a mass tech layoff event, and do not extend to firms that cease operations prior to such event.

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Figure 1. Distribution of Tech Workers' Next Employers
This figure shows the distribution of workers who left tech firms during mass layoffs and joined non-tech firms by the industry sectors of their new employers. New employers are divided into nine industry groups by two-digit SIC industry.

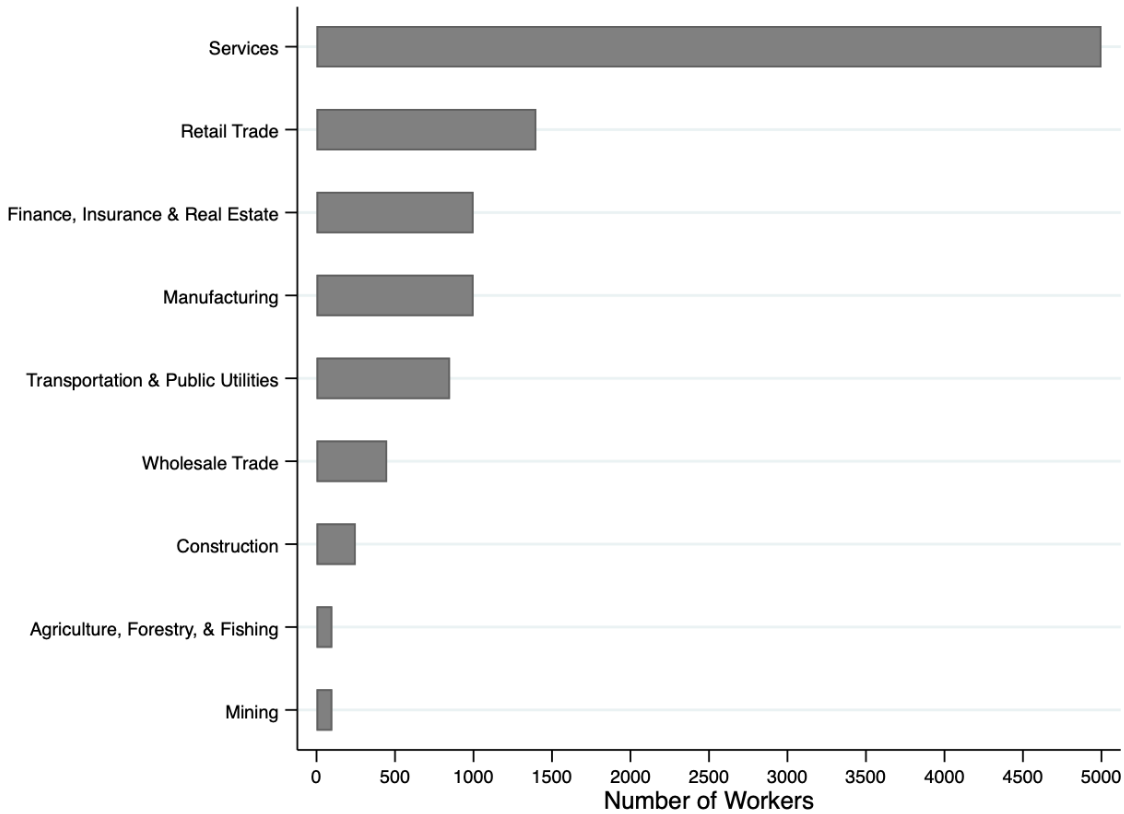


Figure 2. Dynamic Effects of Mass Tech Layoffs on Changes of Employment
This figure plots the dynamic effects of mass tech layoff on the employment at local non-tech firms estimated by the follow equation:

$$
\begin{aligned}
log(y_{i,c,t}) = & \sum_{n=2}^{3+} \theta_{Pre_n} 1_{Pre_n} \times Layoff_c + \sum_{n=0}^{3} \theta_{Post_n} 1_{Post_n} \times Layoff_c + \\
& \sum_{n=2}^{3+} \theta_{Pre_n} 1_{Pre_n} + \sum_{n=0}^{3} \theta_{Post_n} 1_{Post_n} + \alpha_{i,c} + \alpha_{j,t} + \alpha_{s,t} + \beta X_{i,c,t} + \epsilon_{i,t}
\end{aligned}
$$

where $y_{i,c,t}$ represents the employment of firm i located in commuting zone c and year t; $Layoff_c$ equals one for commuting zone experiencing at least one mass tech layoff from 2001 through 2004, zero otherwise. 1_{Pre_n} equals one for the year of the n^{th} observation observed before the year of mass tech layoff, zero otherwise. 1_{Post_n} equals one for the year of the n^{th} observation observed after the year of mass tech layoff, zero otherwise. The first observation prior to the mass tech layoff (1_{Pre_n}) is the omitted coefficient. $\alpha_{i,c}$ represents firm at the commuting zone level fixed effects, $\alpha_{j,t}$ represents 4-digit SIC-by-year fixed effects, and $\alpha_{s,t}$ represents state-by-year fixed effects. $X_{i,c,t}$ controls for firm age. The figure plots estimates of θ_{Pre_n} and θ_{Post_n}, along with 95% confidence intervals. Standard errors are clustered at the firm level.

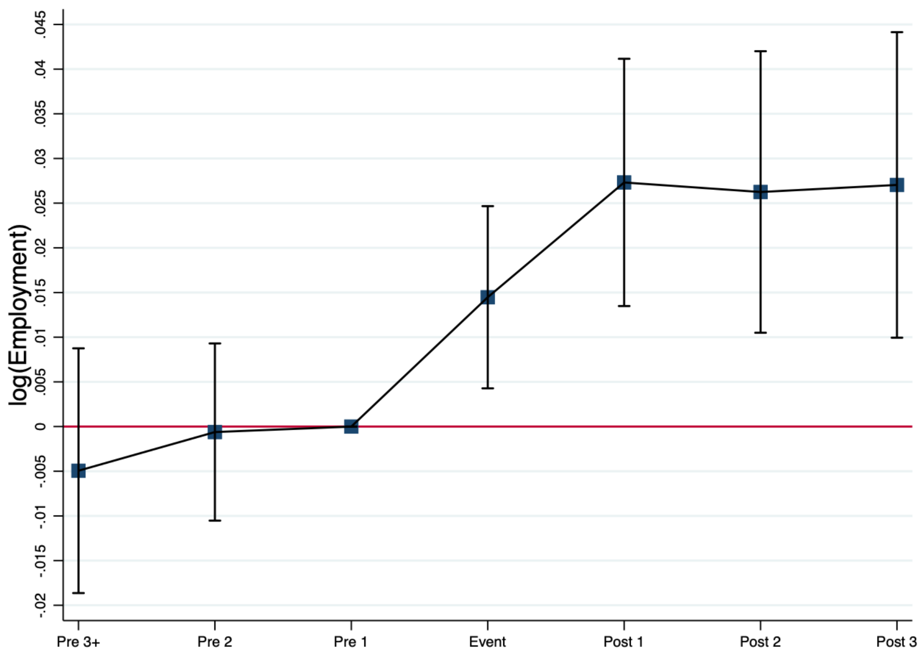


Figure 3. Mass Tech Layoff and Employment of Non-tech Firms by Industry
This figure plots the effects of mass tech layoffs on the employment of non-tech firms by two-digit SIC industry. For each industry group, the effects on employment are estimated using the following equation:

$$log(y_{i,c,t}) = \gamma_1 \times Post_{c,t} \times Layoff_c + \gamma_2 \times Post_{c,t} + \alpha_{i,c} + \alpha_{j,t} + \alpha_{s,t} + \beta X_{i,c,t} + \epsilon_{i,t}$$

where $y_{i,c,t}$ represents the employment of firm i located in commuting zone c and year t; $Post_{c,t}$ equals one for the year at and after the earliest mass tech layoffs in commuting zone c, zero otherwise; $Layoff_c$ equals one for commuting zone experiencing at least one mass tech layoff from 2001 through 2004, zero otherwise. $\alpha_{i,c}$ represents firm at the commuting zone level fixed effects, $\alpha_{j,t}$ represents 4-digit SIC-by-year fixed effects, and $\alpha_{s,t}$ represents state-by-year fixed effects. $X_{i,c,t}$ controls for firm age. The figure plots estimates of γ_1 along with 95% confidence intervals by industry. Standard errors are clustered at the firm level.

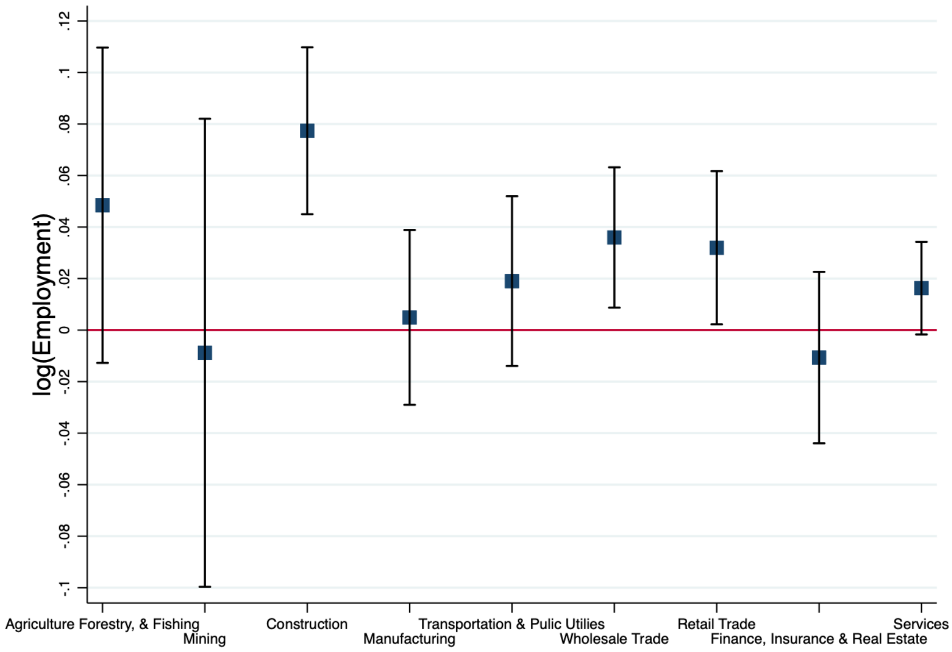
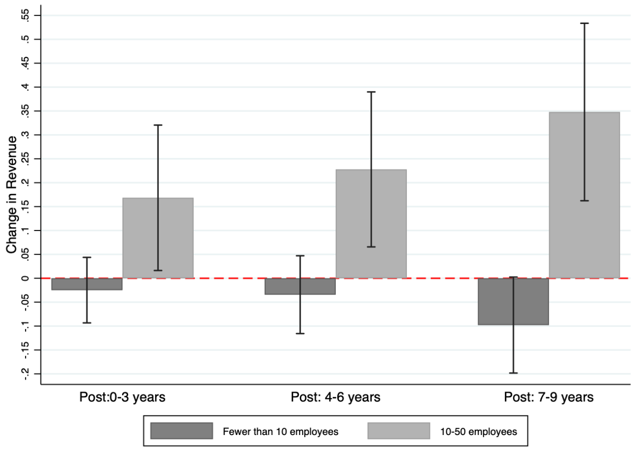


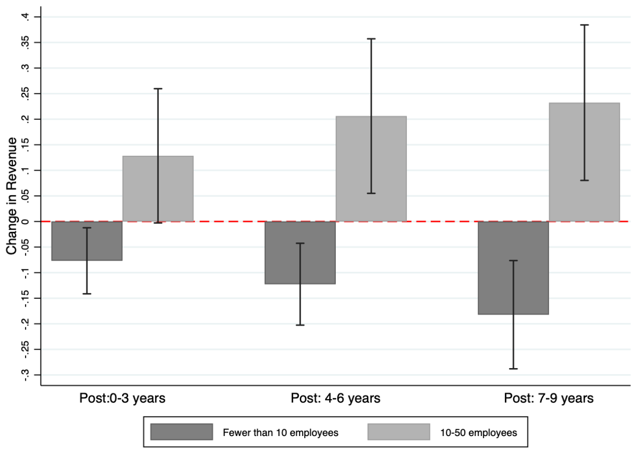
Figure 4. Mass Tech Layoff and Revenue of Non-tech Small Firms by Periods
This figure plots the effects of mass tech layoffs on non-tech small firms' revenue by post-periods. Small firms are categorized into two groups based on their employment in a given commuting zone: fewer than 10 employees and 11-50 employees. The post-layoff periods are divided into three periods. The first period $Post_{1,c}$ equals one for the year and next three years after the earliest mass tech layoffs in commuting zone c, zero otherwise; the second period $Post_{2,c}$ equals one for the fourth to the sixth years after the earliest mass tech layoffs in commuting zone c, zero otherwise; the last period $Post_{3,c}$ equals one for the seventh to the ninth years after the earliest mass tech layoffs in commuting zone c, zero otherwise. The effects are estimated by the following equation:

$$y_{i,t} = \sum_{n=1}^{3} \theta_n \times Post_{n,c} \times Layoff_c + \sum_{n=1}^{3} \gamma_n \times Post_{n,c} + \alpha_{i,c} + \alpha_{j,t} + \alpha_{s,t} + \beta X_{i,c,t} + \epsilon_{i,t} \tag{6}$$

where $y_{i,t}$ represents the logarithm of one plus revenue (a) and productivity (b) of firm i in year t; $Layoff_c$ equals one for commuting zone experiencing at least one mass tech layoff from 2001 through 2004, zero otherwise. $\alpha_{i,c}$ represents firm at the commuting zone level fixed effects, $\alpha_{j,t}$ represents 4-digit SIC-by-year fixed effects, and $\alpha_{s,t}$ represents state-by-year fixed effects. $X_{i,c,t}$ controls for firm age. The figure plots estimates of θ_n, along with 95% confidence intervals. Standard errors are clustered at the firm level.



(a) Revenue



(b) Productivity

Table 1
Summary Statistics for Non-tech Firms

This table reports the mean and standard deviation of key variables from the Longitudinal Business Database (LBD) administered by the U.S. Census Bureau. Employment is the number of employees of a firm in a given commuting zone. Firm Age is the number of years since a firm has positive employment in a given commuting zone. Revenue is the total revenue made by all domestic establishments of a given firm in thousand and adjusted to 2018 constant dollars. Productivity is calculated as the ratio of revenue and employment at the firm level. New Capex is the business expenditures for new plant and equipment of a given firm in thousand and adjusted to 2018 constant dollars. New Capex on Equipment is the spending on new equipment of a given firm in thousand and adjusted to 2018 constant dollars. Capitalized software is the capital expenditure for computer software developed or obtained for internal use by a given firm in thousand and adjusted to 2018 constant dollars. Columns 1-3 present summary statistics for all firms. Columns 4-6 and 7-9 present summary statistics for firms before and after mass tech layoffs, respectively. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	All Firms			Firms before Layoffs			Firms after Layoffs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.
				Panel A					
Employment	114,200,000	16.08	103.1	64,710,000	15.52	98.68	49,490,000	16.82	108.5
Firm Age	114,200,000	12.82	8.299	64,710,000	11.55	7.851	49,490,000	14.49	8.57
				Panel B					
Revenue (thousand \$)	27,160,000	18,170	723,300	12,620,000	13,100	372,700	14,540,000	22,570	925,400
Productivity (thousand \$)	27,160,000	639.3	16,940	12,620,000	617.9	10,070	14,540,000	657.9	21,160
				Panel C					
New Capex (thousand \$)	380,000	84,890	696,700	212,000	73,800	592,300	168,000	98,800	808,700
New Capex on Equip (thousand \$)	380,000	70,380	665,400	212,000	59,860	573,800	168,000	83,590	764,700
Capitalized Software (thousand \$)	371,000	2,142	22,820	7,900	386.4	6,667	363,100	2,225	23,300

Table 2
Summary Statistics for Tech Workers Who Leave and Stay
This table reports summary statistics of tech workers' characteristics in the year prior to their employers' mass layoff by leavers who left tech firms and joined non-tech firms in our sample (column 1) and stayers at tech firms (column 2) that had mass layoffs. The workers with less than two quarters of tenure at the year prior to the layoff are excluded to limit the effect of temporary workers on our analysis. Workers employed at firms undergoing mass layoffs are classified as leaver if they exit the firm within four quarters following the layoffs and do not return to the same firm for at least two years. Workers who stay at the same employer before and after the layoffs are stayers. Tenure is the number of years a worker worked at the firm. Age represents a worker's age. Female is equal to one for female workers, zero otherwise. College Education is equal to one for workers who have at least some college education or above. Quarterly Earnings is the quarterly earnings in constant 2018 dollars. Earning growth is the percentage change in quarterly earnings between the years right before and after the mass tech layoff. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	(1) Leaver	(2) Stayer
Age	37.82	43.43
Female	0.4314	0.3814
College Education	0.6203	0.7257
Tenure (years)	1.222	2.416
Quarterly Earnings (2018$)	9,492	17,230
Earning Growth	0.0180	0.0534
Number of Observations	10,500	35,000

Table 3
Mass Tech Layoffs and Local Non-tech Firms' Employment
This table presents estimates of changes in employment of non-tech firms in commuting zones undergoing mass tech layoffs, compared to control firms in commuting zones with no tech layoffs during the same period. The effects are estimated using Equation 1. The dependent variable is the logarithm of firm employment in a given commuting zone. $Layoff_c$ equals one if a firm locates in a commuting zone where at least one tech firm with over 50 employees reduced its workforce by 30% or more between 2001 and 2004, and zero otherwise. $Layoff_c$ is absorbed by fixed effects. Firm age is estimated but not reported for brevity. Industries are classified by 4-digit SIC codes. The sample consists of non-tech firms in treated commuting zones and those of matched control non-tech firms from 1996 to 2007. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by ***, **, and * and correspond to the 1%, 5%, and 10% significance levels, respectively. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	(1)	(2)	(3)	(4)
	Log (Employment)			
$Post_{c,t} \cdot Layoff_c$	0.0177***	0.0309***	0.0179***	0.0253***
	(0.0067)	(0.0056)	(0.0067)	(0.0060)
$Post_{c,t}$	0.0002	-0.0025	-0.0002	-0.0015
	(0.0036)	(0.0030)	(0.0033)	(0.0030)
Observations	114,200,000	114,200,000	114,200,000	114,200,000
R^2	0.9164	0.9168	0.9186	0.9188
Firm Age	Yes	Yes	Yes	Yes
Firm-Czone FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	
State × Year FE		Yes		Yes
Industry × Year FE			Yes	Yes

Table 4
Mass Tech Layoffs and Local Non-tech Firms' Employment by Size
This table presents estimates of changes in employment of non-tech firms in commuting zones undergoing mass tech layoffs, compared to control firms in commuting zones that had no tech layoffs during the same period. We present estimates by firm employment size. Firms are categorized into four groups based on their employment in a given commuting zone: fewer than 10 employees, 11-50 employees, 51-100 employees, and over 100 employees. The effects are estimated using Equation 1 for each group. The dependent variable is the log of employment. $Layoff_c$ equals one if a firm locates in a commuting zone where at least one tech firm with over 50 employees reduced its workforce by 30% or more between 2001 and 2004, and zero otherwise. $Layoff_c$ is absorbed by fixed effects. Firm age is estimated but not reported for brevity. Industries are classified by 4-digit SIC codes. The sample consists of non-tech firms in treated commuting zones and those of matched control non-tech firms from 1996 to 2007. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by ***, **, and * and correspond to the 1%, 5%, and 10% significance levels, respectively. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	Fewer than 10 employees	11-50 employees	51-100 employees	Over 100 employees
	(1)	(2)	(3)	(4)
$Post_{c,t} \cdot Layoff_c$	0.0206***	0.0343***	-0.0348	0.0255
	(0.0064)	(0.0130)	(0.0218)	(0.0216)
$Post_{c,t}$	0.0192***	-0.0658***	-0.0418***	-0.0354***
	(0.0035)	(0.0075)	(0.0121)	(0.0083)
Observations	81,040,000	27,740,000	2,792,000	2,670,000
R^2	0.7897	0.7408	0.6687	0.8788
Firm Age	Yes	Yes	Yes	Yes
Firm-Czone FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes

Table 5
Mass Tech Layoffs and Local Non-tech Firms' Employment by Age
This table presents estimates of changes in employment of non-tech firms in commuting zones undergoing mass tech layoffs, compared to control firms in commuting zones that had no tech layoffs during the same period. We present estimates by firm age. Firms are categorized into four groups based on their age in a given commuting zone: 0-3 years, 4-9 years, 10-16 years, and older than 16 years. The effects are estimated using Equation 1 for each group. The dependent variable is the log of employment. $Layoff_c$ equals one if a firm locates in a commuting zone where at least one tech firm with over 50 employees reduced its workforce by 30% or more between 2001 and 2004, and zero otherwise. $Layoff_c$ is absorbed by fixed effects. Firm age is estimated but not reported for brevity. Industries are classified by 4-digit SIC codes. The sample consists of non-tech firms in treated commuting zones and those of matched control non-tech firms from 1996 to 2007. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by ***, **, and * and correspond to the 1%, 5%, and 10% significance levels, respectively. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	0-3 years	4-9 years	10-16 years	Older than 16 years
	(1)	(2)	(3)	(4)
$Post_{c,t} \cdot Layoff_c$	0.0397***	0.0094	0.0077	-0.0014
	(0.0132)	(0.0095)	(0.0119)	(0.0089)
$Post_{c,t}$	-0.0065	-0.004	-0.0055	0.0048
	(0.0095)	(0.0059)	(0.0069)	(0.0038)
Observations	18,070,000	31,080,000	31,450,000	33,640,000
R^2	0.9052	0.9062	0.9108	0.9470
Firm Age	Yes	Yes	Yes	Yes
Firm-Czone FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes

Table 6
Mass Tech Layoffs and Local Non-tech Firms' Revenue Performance

This table presents estimates of changes in non-tech firms' revenue performance in commuting zones undergoing mass tech layoffs, compared to control firms in commuting zones that had no tech layoffs during the same period. Firm performance is measured using the logarithm of total revenue made by all domestic establishments of a given firm and the ratio of revenue to employment (i.e., productivity) plus one. Revenue is in thousand and adjusted to 2018 constant dollars. The results are presented for all firms in Columns 1-2 and by firm size in a given commuting zone, with firms having fewer than 10 employees in Columns 3-4 and firms having 11-50 employees in Columns 5-6. The effects are estimated using Equation 1 for each group. $Layoff_c$ is absorbed by fixed effects. Firm age is estimated but not reported for brevity. Industries are classified by 4-digit SIC codes. The sample consists of non-tech firms in treated commuting zones and those of matched control non-tech firms from 1996 to 2013. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by ***, **, and * and correspond to the 1%, 5%, and 10% significance levels, respectively. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	All		Fewer than 10		11-50 employees	
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Revenue)	Log(Prod)	Log(Revenue)	Log(Prod)	Log(Revenue)	Log(Prod)
$Post_{c,t} \cdot Layoff_c$	0.0248	-0.0221	-0.0358	-0.0993***	0.2050***	0.1591**
	(0.0472)	(0.0452)	(0.0345)	(0.0332)	(0.0751)	(0.0668)
$Post_{c,t}$	-0.0228	0.0014	-0.0216	-0.0124	-0.0331	0.0243
	(0.0219)	(0.0194)	(0.0245)	(0.0218)	(0.0536)	(0.0332)
Observations	27,160,000	27,160,000	19,630,000	19,630,000	6,500,000	6,500,000
R^2	0.8223	0.8626	0.8119	0.8318	0.8758	0.8935
Firm Age	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Czone FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7
Mass Tech Layoffs and Technology Investment

This table presents estimates of changes in technology investment of non-tech firms in commuting zones undergoing mass tech layoffs, compared to control firms in commuting zones that had no tech layoffs during the same period. The effects are estimated using Equation 1 for firms with fewer than 10 employees in Panel A and 11-50 employees in Panel B. The dependent variables in Columns 1-3 are the logarithm of one plus total capital spending for new structures and equipment (*New TCE*), capital spending for new equipment (*New EQ*), and capital spending for new equipment per employee. The dependent variables in Columns 4-5 are the share of spending on new equipment in total capital expenditures (New EQ/TCE) and the share of software spending in total capital expenditure (*SW/TCE*). $Layoff_c$ equals one if a firm locates in a commuting zone where at least one tech firm with over 50 employees reduced its workforce by 30% or more between 2001 and 2004; zero otherwise, and is absorbed by fixed effects. The firm age is estimated but not reported for brevity. The sample consists of non-tech firms in treated commuting zones and those of matched control non-tech firms from 1996 to 2007. Standard errors are reported in parentheses and clustered at the firm level. Industries are classified by 4-digit SIC. Significance levels are indicated by ***, **, and * and correspond to the 1%, 5%, and 10% significance levels, respectively. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	Panel A: Fewer than 10 employees					Panel B: 11-50 employees				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	New TCE	New EQ	New EQ/Emp	New EQ/TCE	SW/TCE	New TCE	New EQ	New EQ/Emp	New EQ/TCE	SW/TCE
$Post_{c,t} \cdot Layoff_c$	-0.1496***	-0.1141**	-0.0919**	0.0384***	0.0106	0.1813**	0.2832***	0.0814*	0.0294*	0.0128*
	(0.0543)	(0.0551)	(0.0388)	(0.0121)	(0.0074)	(0.0775)	(0.0986)	(0.0478)	(0.0169)	(0.0067)
$Post_{c,t}$	0.0357***	0.0271**	0.0114	-0.0036	-0.0011**	-0.0252**	-0.0236	-0.0246	0.0083	0.0030
	(0.0137)	(0.0138)	(0.0070)	(0.0025)	(0.0005)	(0.0108)	(0.0154)	(0.0185)	(0.0067)	(0.002)
Observations	112,000	112,000	112,000	105,000	59,500	184,000	184,000	184,000	183,000	82,500
R^2	0.9927	0.9910	0.9854	0.9386	0.9471	0.9928	0.9914	0.9920	0.9616	0.8977
Firm Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Czone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8

Heterogeneity of Effects on Revenue Performance: New Hire Quality

This table presents estimates of changes in non-tech firms' revenue performance in commuting zones undergoing mass tech layoffs, further interacting $Post_{c,t} \cdot Layoff_c$ with $HighQuality_i$. The effects are estimated using Equation 4. Firm performance is measured using the logarithm of total revenue made by all domestic establishments of a given firm and the ratio of revenue to employment (i.e., productivity) plus one. Revenue is adjusted to 2018 constant dollars. $HighQuality_i$ equals one if the average quality of new hires of a given firm i is above the sample medium, and zero otherwise. The results are presented for all firms in Columns 1-2 and by firm size in a given commuting zone, with firms having fewer than 10 employees in Columns 3-4 and firms having 11-50 employees in Columns 5-6. $Layoff_c$ is absorbed by fixed effects. Firm age is estimated but not reported for brevity. Industries are classified by 4-digit SIC codes. The sample consists of non-tech firms in treated commuting zones and those of matched control non-tech firms from 1996 to 2013. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by ***, **, and * and correspond to the 1%, 5%, and 10% significance levels, respectively. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	All		Fewer than 10		11-50 employees	
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Revenue)	Log(Prod)	Log(Revenue)	Log(Prod)	Log(Revenue)	Log(Prod)
$Post_{c,t} \cdot Layoff_c \cdot HighQuality_i$	0.3638***	0.5622***	0.2841***	0.6495***	0.5388***	0.4230***
	(0.0984)	(0.1753)	(0.0676)	(0.163)	(0.1064)	(0.0881)
Observations	598,000	598,000	401,000	401,000	167,000	167,000
R^2	0.9428	0.9553	0.9713	0.9651	0.9848	0.9821
Firm Age	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Czone FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Internet Appendix

Thy Bust, My Boom: Micro Evidence on Small Firms' Tech Evolution after Dot Com Bubble

Appendix A Variable Definitions

Employment is the number of employees of a firm in a given commuting zone. *Source*: LBD

Firm Age is the number of years since a firm has had any positive employment in a given commuting zone. *Source*: LBD

Revenue is the total revenue generated by all domestic establishments of a given firm. Revenue is in thousand and adjusted to 2018 constant dollars. *Source*: LBD

Productivity is calculated as the ratio of total domestic revenue to total domestic employment. Revenue is in thousand and adjusted to 2018 constant dollars. *Source*: LBD

New Capex is the business expenditures (in thousand and adjusted to 2018 constant dollars) for the new structure (exclude land) and equipment of a given firm. *Source*: ACES

New Capex on Equip is the spending (in thousand and adjusted to 2018 constant dollars) on new equipment of a given firm. Examples of equipment include machinery, fixtures, computers, computer software, website development, and transportation equipment used in the production and distribution of goods and services or in office functions. *Source*: ACES

Capitalized Software is the capital expenditure (in thousand and adjusted to 2018 constant dollars) for computer software developed or obtained for internal use by a given firm. *Source*: ACES

$New\ TCE$ is the logarithm of new capital expenditure plus one. *Source*: ACES

$New\ EQ$ is the logarithm of the spending on new equipment plus one. *Source*: ACES

New/TCE is the share of spending on new equipment in new capital expenditures. *Source*: ACES

SW/TCE is the share of software spending in total capital expenditure. *Source*: ACES.

Age represents a worker's age. *Source*: LEHD

Female is equal to one for female workers, zero otherwise. *Source*: LEHD

College Education equals one for workers with some college education or above. *Source*: LEHD

Quarterly Earnings is the quarterly earnings in constant 2018 dollars. *Source*: LEHD

Earning growth is the percentage change in quarterly earnings between the years right before and after the mass tech layoff. *Source*: LEHD

Post equals one for the year at and after the earliest mass tech layoffs in a given commuting zone, zero otherwise. *Source*: LBD

$Post_1$ equals one for the year and next three years after mass tech layoffs, zero otherwise. *Source*: LBD

$Post_2$ equals one for the fourth to the sixth years after mass tech layoffs, zero otherwise. *Source*: LBD

$Post_3$ equals one for the seventh to the ninth years after mass tech layoffs, zero otherwise. *Source*: LBD

Layoff equals one if a firm locates in a commuting zone where at least one tech firm with over 50 employees reduced its employment by 30% or more in a given year between 2001 and 2004. *Source*: LBD

HighQuality equals one if the average quality of new hires of a given firm is above the medium, zero otherwise. *Source*: LEHD and LBD

Appendix B High-tech Industry SIC Codes

Computer Hardware

3571: Electronic Computers
3572: Computer Storage Devices
3575: Computer Terminals
3577: Computer Peripheral Equipment, Not Elsewhere Classified
3578: Calculating and Accounting Machines, Except Electronic Computers

Communications Equipment

3661: Telephone and Telegraph Apparatus
3663: Radio and Television Broadcasting and Communications Equipment
3669: Communications Equipment, Not Elsewhere Classified

Electronics

3674: Semiconductors and Related Devices

Navigation Equipment

3812: Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Systems and Instruments

Measuring and Controlling Devices

3823: Industrial Instruments for Measurement, Display, and Control of Process Variables; and Related Products
3825: Instruments for Measuring and Testing of Electricity and Electrical Signals
3826: Laboratory Analytical Instruments
3827: Optical Instruments and Lenses
3829: Measuring and Controlling Devices, Not Elsewhere Classified

Communication Services

4899: Communications Services, Not Elsewhere Classified

Software

7370: Services—Computer Programming, Data Processing, and Other Computer Related Services
7371: Computer Programming Services

7372: Prepackaged Software
7373: Computer Integrated Systems Design
7374: Computer Processing and Data Preparation and Processing Services
7375: Information Retrieval Services
7378: Computer Maintenance and Repair
7379: Computer Related Services, Not Elsewhere Classified

Appendix C Tables

Table C1
Summary Statistics for Non-tech Firms by Size
This table reports the mean and standard deviation of key variables from the Longitudinal Business Database (LBD) administered by the U.S. Census Bureau. Firms are categorized into four groups based on their employment in a given commuting zone: fewer than 10 employees, 11-50 employees, 51-100 employees, and over 100 employees. Employment is the number of employees of a firm in a given commuting zone. Firm Age is the number of years since a firm has positive employment in a given commuting zone. Revenue is the total revenue made by all domestic establishments of a given firm in thousand and adjusted to 2018 constant dollars. Productivity is calculated as the ratio of revenue and employment at the “firm level. Columns 1-3 present summary statistics for all firms. Columns 4-6 and 7-9 present summary statistics for firms before and after mass tech layoffs, respectively. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	All Firms			Firms before Layoffs			Firms after Layoffs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.
				Fewer than 10 employees					
Employment	81,040,000	3.975	8.448	46,020,000	3.897	4.676	35,020,000	4.079	11.68
Firm Age	81,040,000	12.35	8.244	46,020,000	11.15	7.805	35,020,000	13.91	8.537
Revenue (thousand $)	19,630,000	9,964	775,000	9,250,000	4,670	269,200	10,380,000	14,680	1,035,000
Productivity (thousand $)	19,630,000	793.9	19,430	9,250,000	764.9	11,050	10,380,000	819.8	24,600
				11-50 employees					
Employment	27,740,000	18.98	18.42	15,640,000	18.72	18.75	12,100,000	19.31	17.96
Firm Age	27,740,000	13.74	8.257	15,640,000	12.29	7.828	12,100,000	15.61	8.418
Revenue (thousand $)	6,500,000	36,060	565,200	2,889,000	33,630	562,700	3,611,000	38,000	567,100
Productivity (thousand $)	6,500,000	241.8	7,221	2,889,000	221.2	6,998	3,611,000	258.2	7,394

	All Firms			Firms before Layoffs			Firms after Layoffs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.
	51-100 employees								
Employment	2,792,000	64.63	31.06	1,570,000	62.84	29.43	1,222,000	66.94	32.91
Firm Age	2,792,000	14.98	8.431	1,570,000	13.39	7.968	1,222,000	17.04	8.567
Revenue (thousand $)	582,000	57,250	539,800	273,000	37,910	486,900	30,900	74,370	582,200
Productivity (thousand $)	582,000	288.5	8,386	273,000	208.1	5,468	30,900	359.7	10,300
	Over 100 employees								
Employment	2,670,000	302.8	598.9	1,473,000	294.1	581.4	1,197,000	313.4	619.6
Firm Age	2,670,000	15.51	8.613	1,473,000	14.06	8.101	1,197,000	17.31	8.882
Revenue (thousand $)	457,000	66,620	614,100	207,000	70,810	695,700	250,000	63,160	537,300
Productivity (thousand $)	457,000	101.4	2,440	207,000	126.4	1,566	250,000	80.81	2,974

Table C2
Summary Statistics for Non-tech Firms by Age
This table reports the mean and standard deviation of key variables from the Longitudinal Business Database (LBD) administered by the U.S. Census Bureau. Firms are categorized into four groups based on their age: younger than 3 years old, 4-9 years old, 10-16 years old, and above 16 years old. Employment is the number of employees of a firm in a given commuting zone. Firm Age is the number of years since a firm has positive employment in a given commuting zone. Columns 1-3 present summary statistics for all firms. Columns 4-6 and 7-9 present summary statistics for firms before and after mass tech layoffs, respectively. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	All Firms			Firms before Layoffs			Firms after Layoffs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.
				0-3 years					
Employment	18,070,000	10.76	54.44	7,385,000	10.19	53.65	10,685,000	11.16	54.98
Firm Age	18,070,000	3.148	1.734	7,385,000	1.598	0.719	10,685,000	4.218	1.387
				4-9 years					
Employment	31,080,000	13.29	89	18,650,000	12.64	85.16	12,430,000	14.27	94.45
Firm Age	31,080,000	6.034	2.907	18,650,000	4.359	2.061	12,430,000	8.55	2.052
				10-16 years					
Employment	31,450,000	13.5	65.84	18,860,000	12.88	58.59	12,590,000	14.44	75.41
Firm Age	31,450,000	13.94	3.811	18,860,000	12.17	3.185	12,590,000	16.6	3.054
				Older than 16 years					
Employment	33,640,000	23.93	151.7	19,810,000	22.74	143.4	13,830,000	25.65	163
Firm Age	33,640,000	23.25	2.863	19,810,000	21.43	1.947	13,830,000	25.85	1.749

Table C3

Robustness: Mass Tech Layoffs and Local Non-tech Firms' Performance

This table presents estimates of changes in revenue of non-tech firms in commuting zones undergoing mass tech layoffs, compared to control firms in commuting zones with no tech layoffs during the same period. Revenue at the commuting zone level ($Revenue\ CZ$) is the product of total revenue at firm level and employment share in a given commuting zone. Revenue is in thousand and adjusted to 2018 constant dollars. The dependent variable is the logarithm of $Revenue\ CZ$ plus one. Column 1 reports the effects on all firms in the sample. Columns 2-3 report effects by firm employment sizes in a given commuting zone: fewer than 10 employees and 11-50 employees. $Layoff_c$ equals one if a firm locates in a commuting zone where at least one tech firm with over 50 employees reduced its workforce by 30% or more between 2001 and 2004, and zero otherwise. $Layoff_c$ is absorbed by fixed effects. Firm age is estimated but not reported for brevity. Industries are classified by 4-digit SIC codes. The sample consists of non-tech firms in treated commuting zones and those of matched control non-tech firms from 1996 to 2013. Standard errors are reported in parentheses and clustered at the firm level. Significance levels are indicated by ***, **, and * and correspond to the 1%, 5%, and 10% significance levels, respectively. Appendix A defines the variables. All estimates and observation counts are rounded according to Census disclosure rules.

	(1)	(2)	(3)
	All	Fewer than 10 employees	11-50 employees
$Post_{c,t} \cdot Layoff_c$	0.0337	-0.0394	0.2414***
	(0.0471)	(0.0342)	(0.0745)
$Post_{c,t}$	-0.0245	-0.018	-0.0479
	(0.0218)	(0.0244)	(0.0535)
Observations	27,160,000	19,630,000	6,500,000
R^2	0.8129	0.8134	0.8570
Firm Age	Yes	Yes	Yes
Firm-Czone FE	Yes	Yes	Yes
Industry Year FE	Yes	Yes	Yes
State Year FE	Yes	Yes	Yes