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 experience significant employment growth, particularly among small and young firms. The performance effects, however, are heterogeneous: long-term gains in revenue and productivity are concentrated among firms that seize the opportunity to hire high-skill workers and make complementary technology investments. These results highlight a crucial, yet often overlooked, externality: disruptions in the tech sector labor market can spur technology adoption and growth in less dynamic sectors through the reallocation of skilled human capital.

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

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

*We sincerely appreciate invaluable comments and suggestions from John Graham, Denis Sosyura, Liu Yang, Elena Simintzi, David Denis, Shan Ge, Sherry Xue, Jianzhang Lin and conference/seminar participants at the 2025 Labor and Finance Group Conference, 2025 FSRDC Conference, 2025 FMA, 2025 SFA, the 3rd FWFS-GNY Conference, Bentley University, University of Western Ontario, UMass Amherst, and Northeastern University. We thank Shital Sharma and Sari Kerr for their diligent assistance with the data and clearance requests. Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number BR02396 (CBDRB-FY24-P2396-R11323). This research uses data from the Census Bureau's Longitudinal Employer-Household Dynamics Program, which was partially supported by the following National Science Foundation Grants SES-9978093, SES-0339191, and ITR-0427889; National Institute on Aging Grant AG018854; and grants from the Alfred P. Sloan Foundation.

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1 Introduction

Over the past two decades, the U.S. technology sector 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.[1] Public narratives have focused largely on displaced tech workers' struggles: enduring longer job searches, exiting the industry, and accepting lower pay. Yet emerging anecdotal evidence hints at an untold story: non-tech firms may have been quietly absorbing this talent windfall to advance their technology and improve long-term financial performance.[2] Do disruptions in the tech sector spur growth in non-tech sectors? Despite the importance of this question, the empirical evidence remains sparse.

In this paper, we shed light on this question by studying how local non-tech firms respond when the tech sector undergoes mass layoffs. We focus on the large-scale labor displacements that occurred in the early 2000s during the dot-com bubble burst, which provide a natural experiment in technological labor reallocation and the time horizon needed to evaluate effects that take years to materialize as firms adjust human capital and technology. Understanding these effects is crucial because local labor market shocks can propagate through regional firm networks and substantially amplify their economic impact (Giroud et al., 2024).

The U.S. tech sector is characterized by a concentration of workers whose technological expertise has become increasingly valuable as technology adoption spreads across the economy (Autor et al., 2003; Goos et al., 2014). Mass tech layoffs may offer a unique opportunity for non-tech firms to access talent that would otherwise be out of reach. This leads us to ask two central questions in this paper: Do non-tech firms expand their workforce during periods of contraction in the tech sector? And if so, how does this influx

[1] CBS News reported that the U.S. information technology sector experienced a loss of 403,300 jobs between March 2001 and April 2004. Based on Layoffs.fyi, a crowdsourced tracker that aggregates tech industry layoffs, about 701,000 tech employees were laid off between January 2022 and December 2025.

[2] In a 2006 interview with *Computerworld*, Dan Reynolds, CEO of a staffing services firm, remarked 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."

of human capital shape their technology adoption and long-term performance?

To answer our first question, we use data from the Longitudinal Business Database (LBD) and examine employment changes in non-tech firms. Because job searches and worker mobility are predominantly local (e.g., Enrico, 2011; Molloy et al., 2014), we exploit a difference-in-differences design comparing the employment of non-tech firms in regions experiencing mass tech layoffs with that of similar firms in regions that do not. Following Jacobson et al. (1993), we identify regions that experience mass tech layoffs as commuting zones containing at least one high-tech firm with over 50 employees that reduced employment by 30% or more in a given year between 2001 and 2004. Given that firms are not randomly distributed across locations, we match control firms to treated firms based on their ex-ante characteristics, including industry, employment size, firm age, and the local employment share of high-tech firms.

Our analysis suggests that, relative to the matched control group, non-tech firms experience a significant employment growth in the years following mass tech layoffs. After controlling for firm age, firm fixed effects, industry-by-year fixed effects, and state-by-year fixed effects, we estimate an average 2.5% increase in employment among non-tech firms in layoff-affected commuting zones within three years of the shock. Moreover, a visual inspection of the dynamic event-study coefficients around the layoff years reveals no significant pre-treatment differences between treated and control firms, providing support for the validity of the parallel trends assumption underlying our identification strategy.

Interestingly, we find that the employment effects are concentrated among small non-tech firms with fewer than 50 employees. On average, we document increases of 2.1% to 3.4% in employment among these firms in the aftermath of tech layoffs. Given the large number of small firms in the U.S. economy, this increase is not only statistically significant but also economically meaningful.[3] In contrast, larger non-tech firms exhibit more mixed responses: firms with 51 to 100 employees experience a 3.5% decline in employment, while those with more than 100 employees show a 2.6% increase. However, neither of these

[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.

effects is statistically significant, underscoring that the primary employment response to mass tech layoffs occurs among the smaller firms.

When we categorize firms by age, we find that the employment response is particularly pronounced among young firms: those under three years old experience a significant 4% increase in employment following mass tech layoffs, while the effects for more established firms are small and statistically insignificant. We also document statistically significant employment gains in wholesale, retail, service, and construction industries, indicating that the spillover extends across a broad set of non-tech sectors. Taken together, these patterns suggest that mass tech layoffs generate positive employment spillover effects on non-tech firms, particularly those that are typically less competitive in attracting skilled labor during periods of tech-sector expansion.

Whether the influx of human capital ultimately benefits non-tech firms is not immediately clear. On the one hand, hiring displaced tech workers may introduce advanced technological expertise that allows these firms to upgrade their technology. This mechanism predicts that non-tech firms experiencing substantial post-layoff employment gains to increase their technology investment and, over time, realize improvements in labor productivity. On the other hand, non-tech firms, particularly smaller ones, may match with less-skilled individuals who lack the capacity to implement meaningful technological improvements. Moreover, these firms may also face financial constraints that limit their ability to invest in new technologies. Under such circumstances, we would expect limited or even reduced technology investment in the short term and minimal long-term gains in labor productivity.

To assess whether non-tech firms benefit from post-tech-layoff hiring, we track changes in their revenue and labor productivity over a nine-year period following the layoff events.[4] Using firm-level revenue data from the U.S. Census, we replicate our baseline empirical design for revenue and for revenue per worker — the latter serving as our measure of labor productivity, following Duchin et al. (2010), Barth et al. (2016), and Tate and Yang (2024). In our sample, we observe an average 2.5% increase in revenue and a

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

2.2% decline in labor productivity, although neither estimate is statistically significant. These modest patterns are consistent with the fact that only a subset of non-tech firms expanded their workforce in response to the tech layoffs, and among larger firms, the marginal impact of new hires may be relatively limited. We therefore turn to small firms that experienced significant employment increases following tech layoffs and examine their long-run performance in greater detail.

Among treated small firms, we observe substantial heterogeneity in long-term revenue performance. For firms with 11–50 employees, we find that real revenue increases by 20.5% and labor productivity rises by 15.9%, on average, nine years after mass tech layoffs. When scaled to the sample means for this size category, these effects correspond to an average increase of $6.9 million in real revenue and $35,171 in labor productivity. In contrast, firms with fewer than 10 employees experience an average decline of 3.6% in revenue and a 10% decline in labor productivity, despite exhibiting statistically significant employment growth. Taken together, these findings indicate that the benefits of post-layoff hiring are unevenly distributed: while firms with 11-50 employees appear able to convert new hires into performance gains, the smallest firms struggle to translate employment growth into improved revenue or productivity.

The heterogeneity in the long-term performance of small non-tech firms may be explained by differences in the quality of new hires and in investments in new technologies. Firms with fewer than 10 employees may struggle to attract high-skill tech talent while balancing the costs of upgrading technology, as they tend to face the tightest financial constraints (Beck et al. 2005). In contrast, firms with 11-50 workers may benefit from hiring skilled workers who transfer tech-related knowledge and facilitate technology adoption. To test this hypothesis, we examine both technology investment patterns and the role of worker quality.

First, we use the Annual Capital Expenditures Survey (ACES) from the U.S. Census Bureau to examine changes in firms' capital spending, focusing on components that directly reflect technology investment. Relative to the control group, treated firms with fewer than 10 employees reduce spending on new capital and new equipment by 15% and

11.4%, respectively, over the three years following mass tech layoffs. We also observe a 9.2% decline in the ratio of new equipment to employment, indicating that the smallest firms fail to complement employment growth with technology investment. In contrast, firms with 11–50 employees increase capital expenditure by 18.1% on average, with the bulk directed toward new equipment and software. These technology investments likely contribute to the significant long-term revenue growth observed among firms in this size category.

In the second test, we examine heterogeneity in firm performance by the quality of new hires. Due to the complementary nature of skilled workers and technology (Goldin and Katz 2008; Autor et al. 2003; Goos and Manning 2007, we should expect firms, regardless of their size, that hire highly skilled workers from tech sectors to outperform their counterparts. Utilizing employer-employee matched data from the Longitudinal Employer-Household Dynamics (LEHD), we identify new hires at non-tech firms, and estimate their skills that are portable across firms following Abowd et al. (1999) and skills that are tech-related based on workers' tenure in high-tech sectors. We find supporting evidence that tech layoffs create positive spillover effects on a subset of small non-tech firms by facilitating knowledge transfer. Specifically, while firms with fewer than 10 employees, on average, experience declines in long-term revenue and labor productivity, those that hired relatively higher-skilled workers experience gains in both revenue and productivity after tech layoffs. For 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-skilled workers.

Alternatively, reduced consumer demand resulting from nearby tech-sector layoffs could plausibly explain the observed declines in revenue and labor productivity growth among small firms with 1-10 workers, particularly if these firms are overrepresented in non-tradable and service sectors serving local markets. If so, one would expect immediate declines in revenue right after tech layoffs, as well as significant employment cuts in non-tradable and service sectors. However, our analysis finds little evidence supporting this alternative explanation.

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 et al. 1993; Stevens 1997; Eliason and Storrie 2006; Schmieder et al. 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), and health condition (Black et al., 2015). These existing studies focus on the consequences of displaced workers, whereas we focus on the spillover effects of job displacement on other firms. To our knowledge, ours is the first study to investigate how mass tech layoffs affect non-tech firms' employment, technology investment policies, and long-term performance.

We also build on the literature examining the spillover effects of financial distress and mass layoffs. For instance, Bernstein et al. (2019) document a negative spillover effect of bankruptcy on the local employment of non-bankrupt firms, particularly within non-tradable and service sectors. We instead focus on the cross-sector spillover effect of mass tech layoffs and document a positive effect on employment in small non-tech firms. More importantly, we show that firms experiencing significant revenue and productivity gains are the ones that hired higher-quality workers from tech firms and increased technology investment post-layoffs, suggesting knowledge transfer from the tech sector to non-tech sectors. Building on the positive spillover effects identified by Babina (2019), who shows that financial distress at firms can drive talented individuals to launch successful startups, our study highlights a complementary spillover: the positive impact of a larger pool of displaced tech workers on non-tech firms.

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 driven by variations in technology adoption and the quality of new hires. Altogether, our study offers valuable insights into the potential consequences of the ongoing 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, Jaffe et al. (1993), Peri (2005) and Matray (2021) document the spillover effects of innovation on R&D activities of neighboring firms and inventors. Our study contributes to this literature by showing how tech sector contractions create a novel channel of knowledge diffusion, as mass layoffs at local high-tech firms generate human capital windfalls that benefit a subset of non-tech firms. Relatedly, Tambe and Hitt (2014) documents that IT labor flows are positively correlated with productivity among connected publicly listed firms. We contribute by extending the analysis to private small firms and studying cross-sector spillover effects of tech layoffs on technology investment, which addresses their call to develop a better understanding of how IT spillovers are distributed across firms in different industries.

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 construction of samples in detail below.

2.1 Longitudinal Business Database

To identify mass layoffs in the tech sector and track employment changes at local non-tech firms over time, we use establishment-level employment 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). Besides employment, it also contains unique establishment identifiers that allow us to track establishment-level 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) and we expect the spillover effects of tech layoffs to be concentrated within the same local labor markets, we aggregate establishment-level data to the firm-commuting zone level. Commuting zones (CZs) reflect the local economies where people live and work and are widely adopted in the labor literature (e.g., Autor et al. 2013; Chetty et al. 2014; Matray 2021).[5] Specifically, we aggregate establishment-level employment for each firm-commuting zone by summing the employment of a firm's establishments in a given commuting zone. Following Haltiwanger et al. (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 positive employment in that commuting zone. All variables used in our analysis are defined in Appendix A.

To define high-tech versus non-tech firms, we first classify each firm's industry in a given commuting zone using 4-digit SIC codes based on the largest share of payroll in that zone, following the Statistics of U.S. Businesses Program. We then identify high-tech firms as those in computer hardware, communication equipment and services, electronics, navigation equipment, measuring and controlling devices, and software, following Ljungqvist and Wilhelm (2003). Appendix B lists the high-tech industries and corresponding 4-digit SIC codes. Firms not in high-tech industries are considered non-tech firms.

Following Jacobson et al. (1993), we define mass tech layoff events as instances where high-tech firms with over 50 employees reduce their workforce by 30% or more in a given commuting zone-year between 2001 and 2004. Over this period, the U.S. high-tech sector

[5] 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/.

consistently experienced net job losses, resulting in a 17.8% decline in its workforce by 2004, according to Bureau of Labor Statistics data (Gascon and Karson 2017).

To construct our sample, we first define non-tech firms in commuting zones with at least one mass tech layoff event as treated, with the year of the earliest event designated as the treatment year. We track each firm-commuting zone five years before and three years after the treatment year. We adopt a shorter post-period to avoid capturing the labor market effects of the 2008 financial crisis. Our baseline sample spans from 1996 to 2007.

We then sample control firms from non-tech firms in commuting zones that did not experience mass tech layoffs during our sample period. To ensure treated and control firms are not systematically different in characteristics that may affect their exposure to tech-sector layoffs and employment growth, we employ a two-step matching procedure. First, we match treated and control firm-CZs by industry and employment decile in the year before treatment to account for sector-specific trends and size-related differences in employment growth. Second, within each matched group, we keep up to four control firm-CZs with the nearest propensity scores constructed using a linear probability model based on pre-treatment log employment, firm age, and commuting zone-level high-tech employment share.[6]

Table 1 presents summary statistics of non-tech firms in our firm-commuting zone-year level sample.[7] Columns 1-3 report observation counts, sample means, and standard deviations of key variables used in our analysis. We report the same statistics, but for the pre-treatment period and post-treatment period separately in columns 4-6 and columns 7-9. Panel A shows that, in our sample, the average firm is 12 years old and has 16 employees. Compared with 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 the commuting zones in which they are located and aggregate employment across a firm's establishments within a given commuting zone. Importantly, columns 5 and 8

[6]Similar matching approaches have been used in the literature, such as by Graham et al. (2023), Lagaras (2024), and Ma et al. (2025).

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

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 that has firm-year-level revenue data from the revenue-augmented LBD.[8] Revenue data are adjusted for inflation using the 2018 GDP deflator. Following Duchin et al. (2010), 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 consistency with how revenue is calculated.[9] 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 A of Table 1 reports summary statistics of firm domestic revenue and labor productivity. Firms in our sample have an average revenue of $18.1 million and an average labor productivity of $0.64 million.

2.2 Annual Capital Expenditures Survey

We obtain data on business capital expenditures in structures, equipment, and capitalized computer software from the Annual Capital Expenditures Survey (ACES). ACES is an annual, mandatory survey conducted by the Census Bureau since 1994 and provides the only comprehensive estimates of annual U.S. capital expenditure data for 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, and the Bureau of Labor Statistics, to refine estimates of investment and stock in structures and equipment.[10]

[8]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).

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

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

We link ACES data to our baseline sample through Census internal firm identifiers, yielding a technology investment sample spanning 1996 to 2007. Panel B of Table 1 reports summary statistics for key variables in this sample and Appendix A provides detailed variable definitions.[11] On average, firms in our sample spend \$85 million on new structures 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 investments that is consistent with the trend reported by Department of Commerce (2003).

2.3 Longitudinal Employer-Household Dynamics

To track worker flows from high-tech to non-tech firms, we use quarterly employer-employee-matched data from the Census Longitudinal Employer-Household Dynamics (LEHD) Program, which covers about 95% of U.S. private-sector jobs. We have access to LEHD for 27 participating U.S. states.[12] Within the covered states, the LEHD program records workers' quarterly earnings, locations, and industries across employers.[13] The program also provides detailed information on various demographic characteristics such as education, age, gender, and race.[14] We link workers from LEHD to firms in our samples described in Section 2.1 using the Business Register Bridge, following Babina (2019) and Ma (2024).

We identify displaced tech workers as those who exit a high-tech firm within four quarters following a mass layoff and do not return to the same firm for at least two years. Among displaced workers, those who join non-tech firms in our baseline sample in the year of or one year after the layoff are defined as new hires at non-tech firms (or leavers

[11]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.

[12]The exclusion of certain states from the dataset available to researchers is primarily due to preexisting state laws, suggesting that the available states can be considered as a random sample.

[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, limiting our ability to assess job-specific impacts.

at high-tech firms). In contrast, tech workers who remain at the same high-tech firm for at least four quarters following the layoff are defined as stayers. To limit the influence of temporary workers on our analysis, we exclude tech workers with fewer than two 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 layoff to account for potential retirements.

Table 2 reports characteristics of two groups of tech workers: leavers who left tech firms and joined non-tech firms after tech layoffs (column 1) and stayers who remained at the same high-tech firm for at least four quarters (column 2). Within our sample, displaced tech workers tend to be female, younger, less educated, have shorter tenure, and earn lower earnings. Furthermore, the earnings growth between the years right before and after the mass tech layoff is also lower for tech workers who moved to non-tech sectors (1.8%) than stayers (5.3%), consistent with findings in Bartel and Borjas (1981) and Neal (1995).

After mass layoffs, where do tech workers go? Figure 1 plots the distribution of displaced workers in our sample who left tech firms during mass layoffs and joined non-tech firms by two-digit SIC sectors of their new employers. The figure shows that the majority of displaced tech workers joined the services sector, which includes 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 also absorbed a significant share of displaced tech workers, while wholesale trade and construction experienced a moderate influx.

3 Non-tech firm employment

We first examine how non-tech firms' employment responds to nearby mass tech layoffs. Such layoffs release skilled workers into local labor markets, enabling non-tech firms to hire tech talent they would otherwise be unable to attract or afford. If so, we should expect positive employment effects at non-tech firms in treated commuting zones.

Alternatively, non-tech firms may be negatively affected by the tech-sector contraction and are financially constrained from expanding their workforce. If so, we should expect muted or even negative employment effects at local non-tech firms. To test our hypotheses, we estimate the following equation:

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

where $y_{i,c,t}$ represents the log employment of firm i in commuting zone c and year t; $Post_{c,t}$ equals one for the year of and after the earliest mass tech layoff in commuting zone c, and zero otherwise; $Layoff_c$ equals one for commuting zones experiencing at least one mass tech layoff between 2001 and 2004, and zero otherwise. $\alpha_{i,c}$ represents firm-commuting zone fixed effects, and α_t represents year fixed effects; $X_{i,c,t}$ represents firm age in a given commuting zone-year. In more restrictive specifications, we further control for 4-digit SIC industry-by-year fixed effects ($\alpha_{j,t}$) to absorb time-varying industry shocks and for state-by-year fixed effects ($\alpha_{s,t}$) to absorb time-varying local shocks. We cluster standard errors at the firm level to account for correlation in outcomes across multiple establishments of the same firm and over time.

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-commuting zone fixed effects and year fixed effects. The estimated effect is statistically significant at the 1% level. We next add industry-by-year fixed effects (column 2), state-by-year fixed effects (column 3), and both (column 4) to absorb industry-specific and local economic shocks that might coincide with the timing of mass tech layoffs and non-tech industry expansions. The estimated effects remain robust through all specifications. The most stringent specification (column 4) documents an average employment increase of 2.5%, equivalent to 1 million additional jobs, at non-tech firms in treated commuting zones.[15]

A key identification challenge is that firms' location choices and local exposure to tech

[15] In our sample, there are 2.5 million unique treated firm-commuting zones with an average pre-treatment employment of 16. This translates to an average employment increase of approximately 1 million jobs (= 2.5% $\times$ 16 $\times$ 2.5 million) at non-tech firms following mass tech layoffs.

layoffs may not be random, potentially confounding our estimates. We address this in two ways. First, as discussed in section 2.1, we match treated and control firms on industry, size, age, and local tech worker share, ensuring comparability on observables that predict both location and employment growth. Second, we examine whether both treated and control firm-commuting zones follow parallel trends before mass tech layoffs. Specifically, we create separate indicator variables for each year relative to treatment. 1_{Pre_n} equals 1 for the n^{th} year before the mass tech layoff event and 0 otherwise, while 1_{Post_n} equals 1 for the n^{th} year after the mass tech layoff event and 0 otherwise. The first year before the mass tech layoff event is set as the benchmark year and omitted from the estimation. We augment our baseline specification by interacting these variables with $Layoff_c$ and plot the dynamic coefficient estimates in Figure 2.

Figure 2 shows statistically and economically insignificant changes in the employment of non-tech firms in treated commuting zones before the event year, supporting the parallel trends assumption and suggesting a causal interpretation of our findings. In contrast, we observe a significant and persistent increase in employment at treated non-tech firms following the mass tech layoffs. Overall, our results suggest that mass tech layoffs reallocate human capital from high-tech sector to nearby non-tech firms.

What types of non-tech firms hire tech workers during mass tech layoffs? During the tech bubble, smaller and younger non-tech firms likely faced a disadvantage in competing for tech talent due to less attractive compensation and benefits (Oi and Idson 1999; Brown and Medoff 2003; Babina et al. 2021). Following the bubble's collapse, tech workers likely lowered their wage expectations, bringing them within the range that smaller and younger non-tech firms could afford. In contrast, larger and more established firms may have experienced less change in their ability to attract tech workers. We therefore expect the spillover effect to be stronger among smaller and younger firms. To test this hypothesis, we first categorize firms into four groups based on their employment size in a given commuting zone in the year before the mass tech layoffs: fewer than 10 employees, 11-50 employees, 51-100 employees, and over 100 employees.[16,17] We estimate Equation 1 for each group with industry-by-year fixed effects and state-by-year fixed effects controlled.

Table 4 reports the employment changes at non-tech firms around the time of mass tech layoffs by firm employment size. The coefficients of $Post_{c,t} \times Layoff_c$ for firms with fewer than 10 employees (column 1) and firms with 11-50 employees (column 2) indicate a 2.1% and 3.4% increase in employment, 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 coefficient of $Post_{c,t} \times Layoff_c$ for firms with 51-100 employees in column 3 is statistically insignificant and negative, suggesting no notable employment growth for nearby 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% (column 4). This change is statistically insignificant and likely too small to meaningfully influence large firms' investment decisions or performance.

In the next test, we repeat our analysis in Table 4 but categorize firms by age into four groups: under 3 years, 4-9 years, 10-16 years, and older than 16 years.[18] Table 5 presents employment changes at local non-tech firms around the time of mass tech layoffs by firm age. We find that young non-tech firms experience significant employment growth of 3.97% (column 1) post-layoffs. In contrast, the effects are muted at more established firms, as evidenced by the insignificant interaction coefficients in Columns 2-4. Taken together, employment in the treated non-tech firms increases overall, but this growth is primarily driven by smaller and younger firms.

Lastly, we examine heterogeneity in employment changes across industries to better understand where tech workers go after the mass tech layoffs. 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.[19] Our

[16] 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 https://www.bls.gov/bdm/bdmfirmsize.htm.

[17] Appendix Table C1 reports summary statistics of key variables by employment size group.

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

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

results indicate employment growth among local firms across the non-farm agriculture, construction, transportation, wholesale, retail, and service sectors, although the effects are not statistically significant for the agriculture and transportation sectors.[20] Interestingly, while Figure 1 shows a notable share of tech workers transitioning to finance sectors following the layoffs, Figure 3 shows a muted effect in the finance sector in our difference-in-differences analysis. One possible explanation for this inconsistency is that finance firms were not financially constrained and had already been actively recruiting tech talent ex ante, given the sector's high demand for quantitative skills. As a result, the supply shock may have had little marginal effect on finance hiring patterns.

4 Non-tech firm long-term performance

So far, our analysis shows employment growth at non-tech firms, particularly smaller ones, in commuting zones experiencing mass tech layoffs. The next natural question is whether this influx of human capital benefits non-tech firms. On the one hand, hiring tech workers may introduce advanced IT skills that facilitate technology adoption and enhance productivity. If so, non-tech firms with significant employment growth should increase technology investment following tech layoffs and, over time, experience improvements in financial performance. On the other hand, financially constrained firms, particularly the smallest ones, may struggle to complement new hires with necessary technology investments. These firms may also be more likely to attract less qualified workers with limited ability to enhance productivity. In such cases, the costs of expansion may outweigh the benefits, leading to reduced technology investment and weaker financial performance.

To answer this question, we examine changes in firms' financial performance during mass tech layoffs using a subset of firms with reported revenues in LBD. Given that technology investments, fueled by human capital development, typically take 5-7 years

[20]Examples of tech jobs in construction include building information modeling specialists, who design and manage 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 manage online operations, including website maintenance and order processing. They also need tech professionals to develop and use software tools to improve inventory and distribution efficiency.

to fully translate into productivity gains (Romer 1990; Brynjolfsson and Hitt 2003), we extend the post-treatment period to nine years. We estimate changes in revenue and changes in revenue per worker—a proxy for labor productivity—around mass tech layoffs with Equation 1. Table 6 presents the results.

Columns 1 and 2 show that, relative to control firms, treated firms experience an average increase of 2.5% in revenue and an average decline of 2.2% in labor productivity, though neither effect is statistically significant. These modest changes are not surprising, given that only small firms experience significant employment growth in response to tech layoffs, as shown in Section 3. Moreover, in larger firms, newly hired workers represent a small share of the workforce and may have limited impact on overall performance. We therefore turn to small firms to examine their long-term outcomes.

We repeat our analysis for small firms, which experience significant employment growth in commuting zones with mass tech layoffs. Results are reported in columns 3–6 of Table 6. Interestingly, we observe heterogeneous outcomes among small firms. Columns 3–4 show that the smallest firms (fewer than 10 employees), on average, experience a revenue decline of 3.6% and a labor productivity decline of 9.9% over the nine years following mass tech layoffs. This deterioration may reflect adverse selection, as these firms may have hired less qualified workers unable to implement necessary upgrades, or financial constraints that prevented complementary technology investments. In contrast, columns 5–6 show that treated small firms with 11–50 employees experience average increases of 20.5% in revenue and 15.9% in labor productivity relative to control firms. The improved financial performance may reflect these firms' ability to attract and deploy talent effectively, facilitating technology adoption. We will explore the mechanisms underlying this performance heterogeneity in Section 6.

To better understand the dynamics of these effects, we decompose the post-treatment period into three stages: the event year through year 3, years 4-6, and years 7-9. If the revenue decline at the smallest firms were driven primarily by reduced local consumer demand following mass tech layoffs, we would expect this effect to appear immediately and potentially disappear over time as the local economy recovers. In contrast, if the effects operate through hiring displaced tech workers and subsequent technology investments, we would expect performance to enhance gradually, consistent with the documented fact that such investments take 5-7 years to fully translate into productivity gains (Romer 1990; Brynjolfsson and Hitt 2003). To empirically distinguish these hypotheses, 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 or the logarithm of one plus labor productivity. $Post_{n,c}$ (n=1,2,3) equals one for the event year through year 3, years 4–6, and years 7–9 after mass tech layoffs, respectively, and zero otherwise. $Layoff_c$ equals 1 if a commuting zone experiences at least one mass tech layoff, and 0 otherwise. Control variables are the same as the ones described in Equation 1. Standard errors are clustered at the firm level.

We plot the estimated coefficients of $Post_{n,c} \times Layoff_c$ (i.e., θ_n) in Figure 4 for revenue (Panel A) and labor productivity (Panel B). Firms with 11–50 employees experience revenue increases of 16.84%, 22.78%, and 34.79% in each successive post period, relative to control firms (light grey bars in Panel A). Labor productivity at these firms exhibits a similar upward trend (light grey bars in Panel B). In contrast, firms with fewer than 10 employees do not realize substantial revenue gains over either the short or long term, despite experiencing employment growth that drives a lasting decline in labor productivity (dark grey bars). While these smallest firms do show a short-term revenue decline, the magnitude is negligible and statistically insignificant, suggesting that reduced local consumer demand is not the primary driver of our results. Instead, the gradual and heterogeneous performance effects among small firms support a human capital reallocation channel, whereby firms that effectively integrate displaced tech workers realize sustained improvements.

5 Robustness tests

Variation in the size of tech layoffs across commuting zones allows us to examine whether effects on employment and revenue performance scale with treatment intensity, which can further support a causal interpretation (Meyer 1995). To this end, we re-estimate Equation 1 but replace the binary treatment variable ($Layoff_c$) with a continuous treatment variable ($Layoff\ Size_c$) that captures the total number of workers displaced during mass tech layoffs in each commuting zone-year.[21] Appendix Table C3 reports the estimated effects on employment, revenue, and labor productivity of all non-tech firms in our sample (columns 1-3), firms with fewer than 10 workers (columns 4-6), and firms with 11-50 workers (columns 7-9).

Overall, the direction of effects is consistent with our binary treatment results reported in Tables 3, 4, and 6. Across all firms in our sample, on average, a one standard deviation increase in the size of local tech layoffs is associated with a 0.7% increase in employment, with insignificant effects on revenue and labor productivity. Among small firms, we continue to observe significant increases in employment alongside heterogeneous effects on their long-term revenue and labor productivity. While these results are reassuring, we choose the binary treatment for our baseline specification because continuous treatment raises challenges for interpretation due to selection bias not ruled out by the parallel trends assumption (Callaway et al., 2024).

As discussed in Section 2.1, while employment is measured at the firm-commuting zone level, revenue in the LBD is reported only at the firm level. This creates a potential bias for multi-establishment firms operating in both treated and untreated commuting zones, as we cannot directly attribute revenue to specific locations. To address this concern, we construct an adjusted measure of revenue by weighting firm-level revenue by the firm's employment share in each commuting zone. This adjustment assumes that a firm's revenue in a given commuting zone is proportional to its employment there. Appendix Table C4 presents these results. Our coefficient estimates remain robust to

[21]For ease of interpretation, $Layoff\ Size_c$ is standardized to have a mean of 0 and a standard deviation of 1.

this adjustment, alleviating the concern.

Lastly, due to the presence of both skewness and zeros in the revenue data, we transform the data by taking the logarithm of one plus revenue (or labor productivity) in tests reported in section 4. To address the concern that such transformation may distort the interpretation of the data (Cohn et al., 2022), we follow Chen and Roth (2023) and calculate the percentile rank of revenue (or labor productivity) within the regression sample, which requires no distributional property assumptions. In Appendix Table C5, we replace the dependent variables with percentile ranks and replicate the tests in Table 6. Consistent with our baseline findings, we observe statistically insignificant changes in revenue and labor productivity among all firms within our sample. We continue to find heterogeneous effects among small firms. Specifically, on average, for those with 1-10 workers, we observe insignificant changes in revenue but a statistically significant decline in labor productivity by 1.2 percentage points. In contrast, firms with 11-50 workers exhibit statistically significant increases, with revenue rising by 3.3 percentage points and labor productivity by 1.6 percentage points, on average.

6 Mechanism

In this section, we explore the mechanisms through which mass tech layoffs affect non-tech firm performance. Our baseline results reveal heterogeneous effects among firms that experienced employment gains: firms with 11–50 employees see sustained revenue and productivity growth, while the smallest firms show no improvement or even declines in performance. We consider two channels that may explain these patterns.

The first is a human capital reallocation channel: displaced tech workers bring specialized skills and knowledge to their new employers in the non-tech sector, facilitating technology adoption and enhancing productivity (Cohen and Levinthalz 1989; Autor et al. 2003; Kogan et al. 2017). This channel generates several testable predictions. First, if hiring tech workers enables technology adoption, we would expect firms experiencing employment growth to increase technology investment, which ultimately contributes to long-run performance gains. Second, if knowledge matters, firms that hire more skilled tech workers should experience stronger performance gains, while those hiring less qualified workers may see limited or no improvement. We test these predictions by examining heterogeneity in technology investment across firm size categories and by investigating whether firm performance varies with the quality of displaced workers hired.

The second is a local demand channel: mass tech layoffs may reduce consumer demand in affected areas, disproportionately harming firms that serve local markets, which tend to be smaller and concentrated in service and non-tradable sectors (Bernstein et al. 2019). This channel generates its own testable predictions. First, if reduced local demand is the primary driver of performance declines at the smallest firms, we would expect revenue to fall immediately following the shock as consumer spending contracts. Second, firms in service and non-tradable sectors should be more adversely affected than those in tradable sectors, and we would expect employment contraction rather than growth in these sectors. We test these predictions by examining the timing of revenue effects and by comparing employment outcomes across tradable, service, and non-tradable sectors.

6.1 Human Capital Reallocation

6.1.1 Technology Investment

If technology investment is a key mechanism linking human capital acquisition to productivity gains, we would expect firms with 11–50 employees — those experiencing both employment growth and improved performance — to increase technology spending. In contrast, the smallest firms, which show employment growth but no performance improvement, may see muted changes in technology investment. To test this prediction, we incorporate ACES data on capital expenditures (CapEx), which include spending that directly reflects technology investment, such as machinery, computers, computer software, and website development. Within the technology investment sample described in section 2.2, we estimate Equation 1 with various capital expenditure metrics as the dependent variables. Panels A and B of Table 7 present the results for firms with fewer than 10 workers and those with 11-50 workers, respectively.

Overall, we find results supporting our prediction. Panel A shows that treated firms with fewer than 10 employees reduce technology investment following mass tech layoffs. Specifically, these firms experience a decline of 14.96% in total new capital expenditures (column 1) and 11.41% in new equipment spending (column 2), with similar results for equipment per worker (column 3). While columns 4–5 show modest increases in the share of capital spending allocated to new equipment (3.8 percentage points) and software (1.1 percentage point), these likely reflect declining total expenditure as shown in column 1 rather than technology upgrading.

Panel B reveals a contrasting pattern for firms with 11–50 employees. Within this size group, treated firms increase total new capital expenditures by 18.13% (column 1), new equipment spending by 28.32% (column 2), and equipment per worker by 8.14% (column 3), relative to control firms. Moreover, columns 4–5 show increases of 2.9 percentage points in the share of new equipment spending and 1.3 percentage points in the share of software spending, indicating a meaningful shift toward technology investment. Taken together, these results suggest that mass tech layoffs affect non-tech firm performance through human capital reallocation and complementary technology investment.

6.1.2 Talent Acquisition

Given the complementary nature of skills and technology (Goldin and Katz 1998, 2008; Autor et al. 2003; Goos and Manning 2007), skilled workers are more likely to transfer tech-related knowledge from tech firms to non-tech firms and facilitate technology adoption that enhances long-term performance. Thus, if knowledge matters, we would expect non-tech firms that hire more skilled workers to experience stronger performance gains. This should hold across firm size groups, even among the smallest firms.

We measure worker skills in two ways. First, following Abowd et al. (1999) and Card et al. (2013), we use employer-employee matched data from LEHD-LBD and estimate worker fixed effects (α_k) capturing time-invariant portable skills (e.g., talent or experiences obtained before workers' first jobs):

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

where $y_{k,t}$ denotes the log earnings of worker k in year t. ψ_i represents firm i's fixed effects. η_t are year fixed effects that absorb time-varying macro trends. $X_{k,t}$ includes year-by-education fixed effects and worker age-education interactions. Second, following D'Acunto et al. (2025), we assume that workers accumulate industry-specific human capital over time and measure tech-related skills as the number of years spent in high-tech industries before joining a non-tech firm.[22]

We identify new hires as workers who leave a high-tech firm within one year of a mass layoff, do not return to that employer for at least two years, and join a non-tech firm in the year of or immediately following the layoff. $HighQuality_i$ as one if the average skill of new hires at firm i exceeds the sample median, and zero otherwise.[23] We then test whether the performance improvements of non-tech firms vary by new hire quality 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 the logarithm of one plus labor productivity of firm i located in commuting zone c in year t. $Post_{c,t}$ equals one for years of and after the first mass tech layoff event in commuting zone c, zero otherwise; $Layoff_c$ equals one for commuting zones 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.

Table 8 presents results with $HighQuality_i$ defined by average worker fixed effects

[22] LEHD does not track occupation, making tech industry tenure a more reliable measure for tech-specific knowledge in our setting.

[23] If there are no new hires, $HighQuality_i$ is set to zero.

(Panel A) and average tenure in high-tech industries (Panel B). Columns 1–2 report estimates for all firms using revenue and labor productivity as dependent variables. Columns 3–4 restrict the sample to firms with fewer than 10 employees, and columns 5–6 focus on firms with 11–50 employees. Among all firms, those that hire higher-skilled workers during mass tech layoffs experience higher increases in revenue and labor productivity relative to firms that hire lower-skilled workers or do not hire (columns 1–2). This pattern holds across firm size groups: both the smallest firms (columns 3–4) and firms with 11–50 employees (columns 5–6) show stronger performance when they hire higher-quality workers. Overall, these results support the human capital reallocation channel, in which knowledge transfer from skilled tech workers enhances non-tech firm performance.

6.2 Consumer Demand Reduction

An alternative explanation is that consumer demand reduction induced by nearby tech layoffs drives the observed decline in revenue and labor productivity among the smallest firms. If reduced local demand is the primary channel, we would expect revenue to decline immediately following mass tech layoffs, and employment to contract, particularly in non-tradable and service sectors that depend on local demand (Enrico 2011). Neither pattern is evident in our data.

As discussed in Section 4, firms with 1–10 workers experience only a 2.5% revenue decline during the first three years post-layoff, and this change is statistically insignificant (Figure 4). To further test the demand channel, we examine whether employment declines in non-tradable and service sectors relative to tradable sectors by interactions of $Post_{c,t} \times Layoff_c$ and sector indicators in Equation 4.[24] Table 9 shows that nearby tech layoffs do not significantly reduce employment in non-tradable and service industries relative to tradable sectors. Collectively, these patterns suggest that consumer demand reduction is not the primary channel through which mass tech layoffs affect small firm performance.

[24] We classify tradable, non-tradable, and service sectors following Mian and Sufi (2014) and Bernstein et al. (2019). Non-tradable sectors include retail trade (SIC 52–59), accommodation and food services (SICs 5813 and 7011), which primarily serve local demand. Tradable sectors include manufacturing (SIC 20–39), and service sectors include the remaining industries.

7 Conclusion

This paper uses comprehensive micro-level datasets on employment, technology investment, and revenue from the Census Bureau to investigate the effects of mass tech layoffs on local non-tech firms. We find that mass tech layoffs lead to employment growth at nearby non-tech firms, driven primarily by small and young firms. However, the performance implications of this growth are heterogeneous among small firms. Firms with 11–50 employees experience significant and long-term gains in revenue and labor productivity, while the smallest firms with fewer than 10 employees see employment growth but no improvement in long-term performance.

We provide evidence on the mechanisms underlying this heterogeneity. Consistent with a human capital reallocation channel, firms that experience both employment growth and performance improvement also increase technology investment, particularly in new equipment and software. Moreover, worker quality matters: firms that hire higher-skilled tech workers outperform, regardless of firm size. These findings suggest that the benefits of absorbing tech workers during mass layoffs depend critically on a firm's ability to make complementary technology investments and attract high-quality human capital.

Our study offers timely insights into the potential consequences of the ongoing wave of tech layoffs in the U.S. A key implication is that mass layoffs in the tech sector can facilitate productive reallocation of human capital to firms positioned to leverage it. However, our findings also underscore that not all firms benefit equally, and the smallest firms may face barriers to translating new hires into performance gains. Lastly, we note a caveat of our analysis: our results apply to non-tech firms that survived for at least one year following a mass tech layoff event, and do not extend to firms that exited before or shortly after such events.

References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Reviews*, 103(6):2121–2168.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Babina, T. (2019). Destructive creation at work: How financial distress spurs entrepreneurship. *The Review of Financial Studies*, 33(9):4061–410.

Babina, T., Ma, W., Moser, C., Ouimet, P., and Zarutskie, R. (2021). Pay, employment, and dynamics of young firms. Working Paper, Kenan Institute of Private Enterprise.

Bartel, A. P. and Borjas, G. (1981). Wage growth and job turnover: An empirical analysis. In *Studies in Labor Markets*, pages 65–90. National Bureau of Economic Research, Inc.

Barth, E., Bryson, A., Davis, J. C., and Freeman, R. (2016). It's where you work: Increases in the dispersion of earnings across establishments and individuals in the United States. *Journal of Labor Economics*, 34(S2):S67–S97.

Beck, T., Demirgüç-Kunt, A., and Maksimovic, V. (2005). Financial and legal constraints to growth: Does firm size matter? *The Journal of Finance*, 60(1):137–177.

Bernstein, S., Colonnelli, E., Giroud, X., and Iverson, B. (2019). Bankruptcy spillovers. *Journal of Financial Economics*, 133(3):608–633.

Bertheau, A., Acabbi, E. M., Barceló, C., Gulyas, A., Lombardi, S., and Saggio, R. (2023). The unequal consequences of job loss across countries. *American Economic Review: Insights*, 5(3):393–408.

Black, S. E., Devereux, P. J., and Salvanes, K. G. (2015). Losing heart? The effect of job displacement on health. *ILR Review*, 68(4):833–861.

Brown, C. and Medoff, J. L. (2003). Firm age and wages. *Journal of Labor Economics*, 21(3):677–98.

Brynjolfsson, E. and Hitt, L. (2003). Computing productivity: Firm-level evidence. *The Review of Economics and Statistics*, 85(4):793–808.

Callaway, B., Goodman-Bacon, A., and Sant'Anna, P. H. C. (2024). Difference-in-differences with a continuous treatment. Working Paper 32117, National Bureau of Economic Research.

Card, D., Heining, J., and Kline, P. (2013). Workplace heterogeneity and the rise of west german wage inequality. *The Quarterly Journal of Economics*, 128(3):967–1015.

Charles, K. K. and Melvin Stephens, J. (2004). Job displacement, disability, and divorce. *Journal of Labor Economics*, 22(2):489–522.

Chen, J. and Roth, J. (2023). Logs with zeros? Some problems and solutions. *The Quarterly Journal of Economics*, 139(2):891–936.

Chetty, R., Hendren, N., Kline, P., and Saez, E. (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *The Quarterly Journal of Economics*, 129(4):1553–1623.

Cohen, W. M. and Levinthalz, D. A. (1989). Innovation and learning: The two Faces of R&D. *The Economic Journal*, 99(397):569.

Cohn, J. B., Liu, Z., and Wardlaw, M. I. (2022). Count (and count-like) data in finance. *Journal of Financial Economics*, 146(2):529–551.

D'Acunto, F., Tate, G., and Yang, L. (2025). Entrepreneurial teams: Diversity of skills and early-stage growth. Management Science.

Department of Commerce (2003). Digital economy 2003, u.s. department of commerce. https://www.commerce.gov/sites/default/files/migrated/reports/dig_econ_2003.pdf.

Duchin, R., Ozbas, O., and Sensoy, B. A. (2010). Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics*, 97(3):418–35.

Eliason, M. and Storrie, D. (2006). Lasting or latent scars? Swedish evidence on the long-term effects of job displacement. *Journal of Labor Economics*, 24(4):831–856.

Enrico, M. (2011). Local labor markets. In Card, D. and Ashenfelter, O., editors, *Handbook of Labor Economics*, pages 1237–313. Amsterdam, the Netherlands: Elsevier.

Foster, L., Haltiwanger, J. C., and Krizan, C. J. (2001). *Aggregate Productivity Growth: Lessons from Microeconomic Evidence*, pages 303–372. University of Chicago Press.

Gascon, C. S. and Karson, J. C. (2017). Growth in tech sector returns to glory days of the 1990s. Regional Economist, Federal Reserve Bank of St. Louis.

Gathmann, C., Helm, I., and Schönberg, U. (2020). Spillover Effects of Mass Layoffs. *Journal of the European Economic Association*, 18(1):427–468.

Giroud, X., Lenzu, S., Maingi, Q., and Mueller, H. (2024). Propagation and amplification of local productivity spillovers. *Econometrica*, 92(5):1589–1619.

Goldin, C. and Katz, L. F. (1998). The origins of technology-skill complementarity. *The Quarterly Journal of Economics*, 113(3):693–732.

Goldin, C. and Katz, L. F. (2008). *The race between education and technology*. Harvard University Press.

Goos, M. and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The Review of Economics and Statistics*, 89(1):118–133.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8):2509–26.

Graham, J. R., Kim, H., Li, S., and Qiu, J. (2023). Employee costs of corporate bankruptcy. *The Journal of Finance*, 78(4):2087–2137.

Haltiwanger, J., Jarmin, R., Kulick, R., Miranda, J., and Penciakova, V. (2019). Augmenting the lbd with firm-level revenue. CES Technical Notes CES-TN-2019-02, US Census Bureau, Center for Economic Studies.

Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2013). Who creates jobs? Small versus large versus young. *The Review of Economics and Statistics*, 95(2):347–361.

Hoffman, T. (2006). Q&A: Where did the postbubble it layoff victims go? *Computerworld.*

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *The American Economic Review*, 83(4):685–709.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations*. *The Quarterly Journal of Economics*, 108(3):577–598.

Jarmin, R. S. and Miranda, J. (2002). The longitudinal business database. *Available at SSRN 2128793.*

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2):665–712.

Lagaras, S. (2024). M&As, employee costs and labor reallocation. *Journal of Finance, forthcoming.*

Ljungqvist, A. and Wilhelm, W. J. (2003). IPO pricing in the Dot-Com Bubble. *The Journal of Finance*, 58(2):723–752.

Ma, W. (2024). Employer dominance and worker earnings in Finance. *The Review of Corporate Finance Studies*, 13(4):1030–1079.

Ma, W., Ouimet, P., and Simintzi, E. (2025). Mergers and acquisitions, technological change and inequality. *Journal of Financial Economics.*

Matray, A. (2021). The local innovation spillovers of listed firms. *Journal of Financial Economics*, 141(2):395–412.

Melissa, C., Fort, T. C., Goetz, C., Goldschlag, N., Lawrence, J., Perlman, E. R., Stinson, M., and White, T. K. (2021). Redesigning the longitudinal business database. *Census Working Paper Number CES-21-08.*

Meyer, B. D. (1995). Natural and quasi-experiments in economics. *Journal of Business Economic Statistics*, 13(2):151–161.

Mian, A. and Sufi, A. (2014). What explains the 2007–2009 drop in employment? *Econometrica*, 82(6):2197–2223.

Molloy, R., Smith, C. L., and Wozniak, A. K. (2014). Declining migration within the U.S.: The role of the labor market. Working Paper, National Bureau of Economic Research.

Neal, D. (1995). Industry-specific human capital: Evidence from displaced workers. *Journal of Labor Economics*, 13(4):653–677.

Oi, W. and Idson, T. (1999). Firm size and wages. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, pages 2165–214. Amsterdam, the Netherlands: Elsevier.

Peri, G. (2005). Determinants of knowledge flows and their effect on innovation. *The Review of Economics and Statistics*, 87(2):308–322.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, 98(5):S71–S102.

Schmieder, J. F., von Wachter, T., and Bender, S. (2016). The effect of unemployment benefits and nonemployment durations on wages. *The American Economic Review*, 106(3):739–777.

Stevens, A. H. (1997). Persistent effects of job displacement: The importance of multiple job losses. *Journal of Labor Economics*, 15(1):165–188.

Sullivan, D. and von Wachter, T. (2009). Job displacement and mortality: an analysis using administrative data. *The Quarterly Journal of Economics*, 124(3):1265–1306.

Tambe, P. and Hitt, L. M. (2014). Job hopping, information technology spillovers, and productivity growth. *Management Science*, 60(2):338–355.

Tate, G. and Yang, L. (2024). The Human Factor in Acquisitions: Cross-industry Labor Mobility and Corporate Diversification. *The Review of Financial Studies*, 37(1):45–88.

Tsipursky, G. (2023). The silver lining of tech layoffs. *Forbes*.

Vilhuber, L. et al. (2018). LEHD infrastructure s2014 files in the FSRDC. *US Census Bureau, Center for Economic Studies Discussion Papers, CES*, 1(2):3.

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.

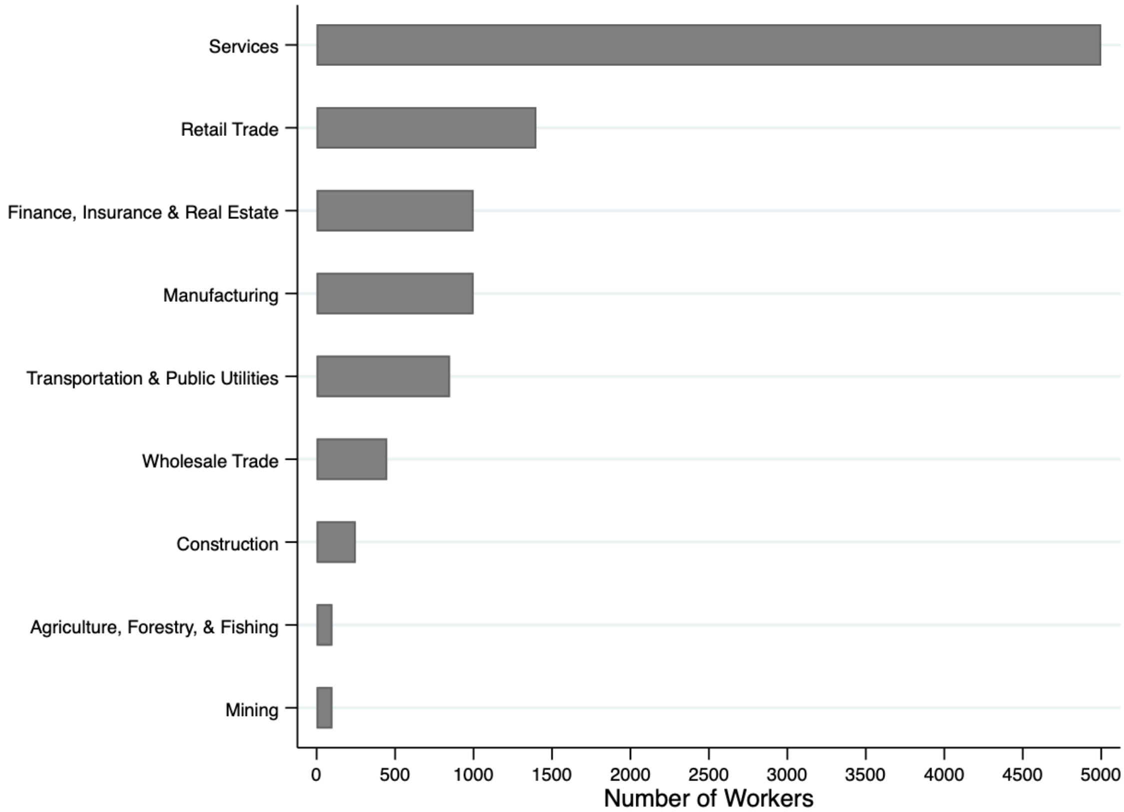


Figure 2. Dynamic Effects of Mass Tech Layoffs on Changes of Employment
This figure plots the dynamic effects of mass tech layoff on the employment at local non-tech firms estimated by the follow equation:

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

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 90% confidence intervals. Standard errors are clustered at the firm level.

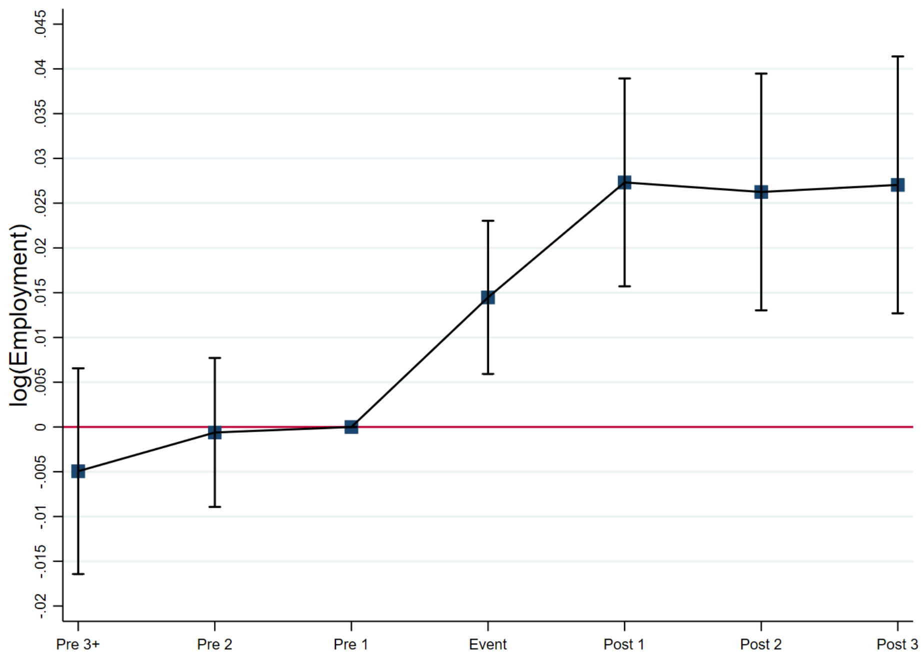


Figure 3. Mass Tech Layoff and Employment of Non-tech Firms by Industry
This figure plots the effects of mass tech layoffs on the employment of non-tech firms by industry group (SIC division). For each industry group, the effects on employment are estimated using the following equation:

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

where $y_{i,c,t}$ represents the logarithm of 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 90% confidence intervals by industry. Standard errors are clustered at the firm level.

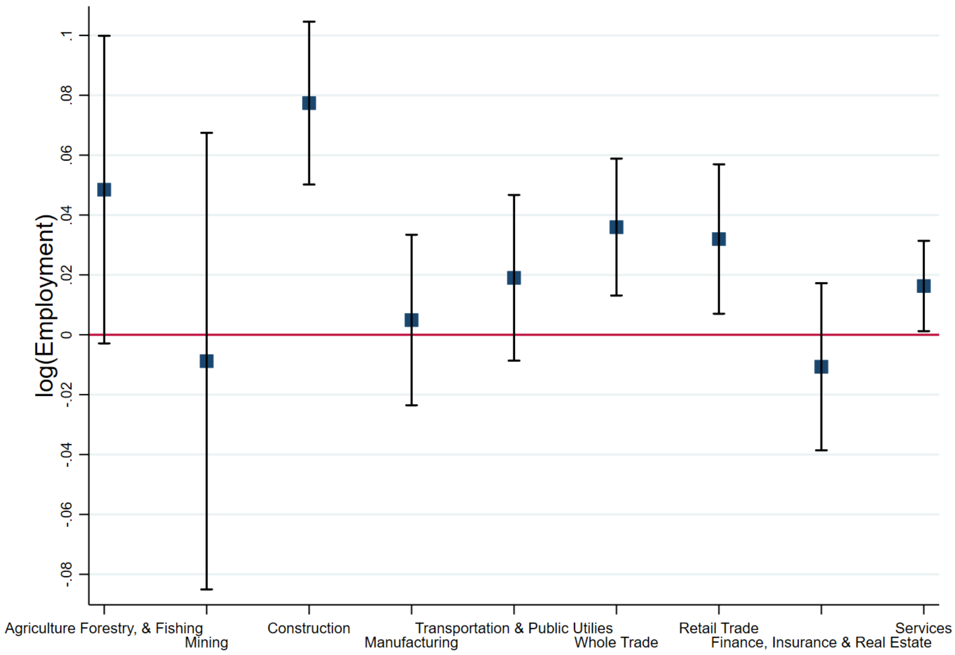
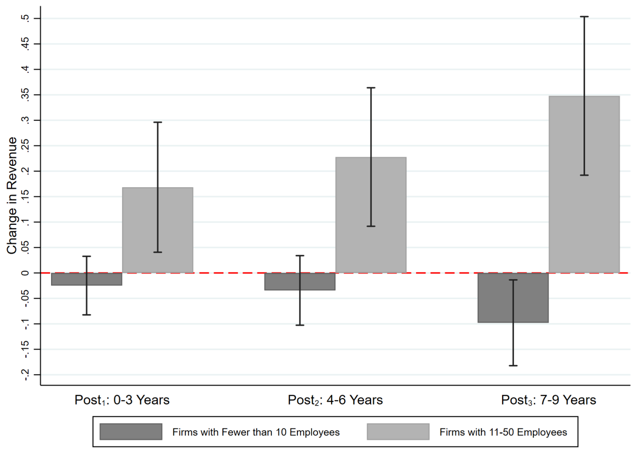


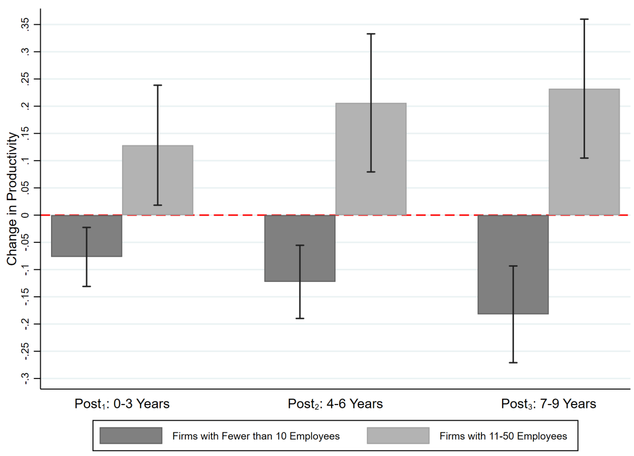
Figure 4. Mass Tech Layoff and Revenue of Non-tech Small Firms by Periods
This figure plots the effects of mass tech layoffs on non-tech small firms' revenue by post-periods. Small firms are categorized into two groups based on their employment in a given commuting zone: fewer than 10 employees and 11-50 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:

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

where $y_{i,c,t}$ represents the logarithm of one plus revenue (a) and the logarithm of one plus labor 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-commuting zone 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 90% confidence intervals. Standard errors are clustered at the firm level.



(a) Revenue



(b) Labor 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) and the Annual Capital Expenditures Survey (ACES) 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 had positive employment in a given commuting zone. Revenue is the total revenue made by all domestic establishments of a given firm in thousands 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 thousands and adjusted to 2018 constant dollars. New CapEx on Equipment is the spending on new equipment of a given firm in thousands 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 thousands 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 periods			Before Layoffs			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. LBD					
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
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 B. ACES					
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 $)	176,000	2,142	22,820	7,900	386.4	6,667	168,000	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 with at least some college education or above. Quarterly Earnings is the quarterly earnings in constant 2018 dollars. Earnings 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 (years)	37.82	43.43
Female	0.43	0.38
College Education	0.62	0.73
Tenure (years)	1.22	2.42
Quarterly Earnings (2018$)	9,492	17,230
Earnings Growth (%)	1.80	5.34
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. Firm age is estimated but not reported for brevity. $Layoff_c$ is absorbed by firm-commuting zone fixed effects. Staggered treatment timing generates variation in $Post_{c,t}$ that is estimated but not reported for brevity. The sample includes non-tech firms in treated commuting zones and matched control non-tech firms from 1996 to 2007. 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)
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
Year FE	Yes			
Firm-CZ FE	Yes	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. Firm age is estimated but not reported for brevity. $Layoff_c$ is absorbed by firm-commuting zone fixed effects. Staggered treatment timing generates variation in $Post_{c,t}$ that is estimated but not reported for brevity. The sample includes non-tech firms in treated commuting zones and matched control non-tech firms from 1996 to 2007. Industries are classified by 4-digit SIC codes. The sample includes non-tech firms in treated commuting zones and 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)
	log(Employment)	log(Employment)	log(Employment)	log(Employment)
$Post_{c,t} \cdot Layoff_c$	0.0206***	0.0343***	-0.0348	0.0255
	(0.0064)	(0.0130)	(0.0218)	(0.0216)
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-CZ 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. Firm age is estimated but not reported for brevity. $Layoff_c$ is absorbed by firm-commuting zone fixed effects. Staggered treatment timing generates variation in $Post_{c,t}$ that is estimated but not reported for brevity. The sample includes non-tech firms in treated commuting zones and matched control non-tech firms from 1996 to 2007. 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)
	log(Employment)	log(Employment)	log(Employment)	log(Employment)
$Post_{c,t} \cdot Layoff_c$	0.0397***	0.0094	0.0077	-0.0014
	(0.0132)	(0.0095)	(0.0119)	(0.0089)
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-CZ 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. The dependent variable is the logarithm of one plus total domestic revenue in columns 1, 3, and 5. The dependent variable is the logarithm of one plus the ratio of revenue to employment (i.e., productivity) in columns 2, 4, and 6. Revenue is 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. Firm age is estimated but not reported for brevity. $Layoff_c$ is absorbed by firm-commuting zone fixed effects. Staggered treatment timing generates variation in $Post_{c,t}$ that is estimated but not reported for brevity. The sample includes non-tech firms in treated commuting zones and matched control non-tech firms from 1996 to 2007. 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 employees		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)
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-CZ 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 expenditures (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. $Layoff_c$ is absorbed by firm-commuting zone fixed effects. Staggered treatment timing generates variation in $Post_{c,t}$ that 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)
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-CZ 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 and 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. 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. In Panel A, worker quality is measured using worker fixed effects estimated using Equation 3. In Panel B, worker quality is measured using the number of years worked in high-tech industries before joining the new firm. $Layoff_c$ is absorbed by firm-commuting zone fixed effects. Staggered treatment timing generates variation in $Post_{c,t}$ that is estimated but not reported for brevity. $Post_{c,t} \cdot Layoff_c$ and firm age are estimated but not reported for brevity. The sample includes non-tech firms in treated commuting zones and matched control non-tech firms from 1996 to 2007. 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 employees		11-50 employees	
	(1)	(2)	(3)	(4)	(5)	(6)
	Log(Revenue)	Log(Prod)	Log(Revenue)	Log(Prod)	Log(Revenue)	Log(Prod)
Panel A. Average worker FE of new hires						
$Post_{c,t} \cdot Layoff_c \cdot HighQuality_i$	0.1172	0.4284**	0.0897*	0.3494***	0.5860***	0.5903***
	(0.2195)	(0.1901)	(0.0507)	(0.0632)	(0.1326)	(0.1026)
Observations	1093000	1093000	752000	752000	266000	266000
R^2	0.945	0.958	0.961	0.965	0.976	0.964
Panel B. Average tenure in high-tech industries of new hire						
$Post_{c,t} \cdot Layoff_c \cdot HighQuality_i$	0.2202*	0.3067**	0.2808*	0.3801**	0.3799	0.4052*
	(0.1176)	(0.1348)	(0.1615)	(0.1714)	(0.2615)	(0.2384)
Observations	1,093,000	1,093,000	752,000	752,000	266,000	266,000
R^2	0.958	0.945	0.961	0.964	0.976	0.964
Firm Age	Yes	Yes	Yes	Yes	Yes	Yes
Firm-CZ 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 9
Heterogeneity of Effects on Employment: Tradable, Non-tradable and Service Sectors
This table presents estimates of changes in non-tech firms' employment in commuting zones undergoing mass tech layoffs, further interacting $Post_{c,t} \cdot Layoff_c$ with $Nontrade_{i,c}$ and $Service_{i,c}$. The effects are estimated using Equation 4 for all firms (column 1), firms having fewer than 10 employees (column 2), and firms having 11-50 employees (column 3). The dependent variable is the logarithm of employment. $Nontrade_{i,c}$ (or $Service_{i,c}$) equals one for firm-commuting zones in non-tradable (or service industries), and zero otherwise. Tradable, non-tradable, and service industries are classified following Mian and Sufi (2014) and Bernstein et al. (2019). Firm age is estimated but not reported for brevity. $Layoff_c$ is absorbed by firm-commuting zone fixed effects. Staggered treatment timing generates variation in $Post_{c,t}$ that is estimated but not reported for brevity. The sample includes non-tech firms in treated commuting zones and matched control non-tech firms from 1996 to 2007. 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) Log(Employment)	(2) Log(Employment)	(3) Log(Employment)
$Post_{c,t} \cdot Layoff_c \cdot Nontrade_{i,c}$	0.0058	0.0476	-0.0285
	(0.0255)	(0.0385)	(0.0372)
$Post_{c,t} \cdot Layoff_c \cdot Service_{i,c}$	-0.0053	0.0213	-0.0311
	(0.0216)	(0.0310)	(0.0347)
Observations	114,200,000	81,040,000	27,740,000
R^2	0.919	0.79	0.741
Firm Age	Yes	Yes	Yes
Firm-CZ FE	Yes	Yes	Yes
Industry ×Year FE	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes

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 thousands 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 thousands and adjusted to 2018 constant dollars. *Source*: LBD

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

New CapEx on Equip is the spending (in thousands 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 comprises costs (in thousands and adjusted to 2018 constant dollars) for materials and services related to software development or acquisition for internal use, compensation for employees directly involved in software development, and interest costs incurred during development. *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 capitalized software spending in total capital expenditure. *Source*: ACES.

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

Female equals one for female workers, and 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, and zero otherwise. *Source*: LBD

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

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

$Post_3$ equals one for the seventh to the ninth years after mass tech layoffs, and 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, and zero otherwise. We estimate worker skills that are portable across firms following Abowd et al. (1999) using Equation 3 and skills that are tech-related based on workers' ex-ante work tenure in high-tech sectors. High-tech sectors are identified using SIC codes, following the classification in Ljungqvist and Wilhelm (2003), which includes industries such as computer hardware, communication equipment and services, electronics, navigation equipment, measuring and controlling devices, and software. *Source*: LEHD and LBD

Nontrade equals one for firm-commuting zones in non-tradable industries, and zero otherwise. Non-tradable industries are classified following Mian and Sufi (2014) and Bernstein et al. (2019) and include retail trade (SIC 52-59), accommodation and food services (SICs 5813 and 7011), which primarily serve local demand. *Source*: LBD

Service equals one for firm-commuting zones in service industries, and zero otherwise. Service industries are classified following Mian and Sufi (2014) and Bernstein et al. (2019) and include all non-farming private industries excluding retail trade (SIC 52-59), accommodation and food services (SICs 5813 and 7011), or manufacturing (SIC 20-39). *Source*: LBD

Layoff Size is the continuous treatment measure of layoff intensity, defined as the total number of workers who left tech firms during mass layoffs in a given commuting zone. It is standardized to have a mean of 0 and a standard deviation of 1. *Source*: LBD

$Revenue_{cz}$ is a firm's revenue adjusted by its local employment share, i.e., the product of the total domestic revenue of a given firm and its employment share in a given commuting zone. Revenue is adjusted to 2018 constant dollars. *Source*: LBD

Revenue Rank is the within-sample percentile rank of firm revenues. *Source*: LBD

Prod Rank is the within-sample percentile rank of firm productivity. *Source*: 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 Appendix 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 periods			Before Layoffs			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. 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
Panel B. 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 periods			Before layoffs			After layoffs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.
	Panel C. 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
	Panel D. 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 periods			Before Layoffs			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. 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
	Panel B. 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
	Panel C. 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
	Panel D. 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
Heterogeneous Treatment Intensity

This table presents estimates of changes in employment and revenue performance of non-tech firms in commuting zones that experience different sizes of mass layoffs in local tech sectors. The effects are estimated using Equation 1 but with a continuous treatment measure, $Layoff\ Size_c$, representing the number of workers displaced by high-tech firms in a given commuting zone. Results are presented for all firms in the sample in columns 1-3, and by firm size in a given commuting zone, with firms having fewer than 10 employees in columns 4-6 and firms having 11-50 employees in columns 7-9. For each group, the dependent variables are the logarithm of firm employment in a given commuting zone, the logarithm of one plus total domestic revenue and the logarithm of one plus labor productivity (i.e., the ratio of revenue to employment), respectively. Firm age is estimated but not reported for brevity. Industries are classified by 4-digit SIC codes. $Layoff_c$ is absorbed by firm-commuting zone fixed effects. Staggered treatment timing generates variation in $Post_{c,t}$ that is estimated but not reported for brevity. The sample includes non-tech firms in treated commuting zones and 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.

	All firms			Fewer than 10 employees			11-50 employees		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log(Employment)	Log(Revenue)	Log(Prod)	Log(Employment)	Log(Revenue)	Log(Prod)	Log(Employment)	Log(Revenue)	Log(Prod)
$Post_{c,t} \cdot Layoff\ Size_c$	0.0067***	0.0062	0.0043	0.0050***	-0.0120**	-0.0155**	0.0110***	0.0601**	0.0587**
	(0.0017)	(0.0167)	(0.0161)	(0.0010)	(0.0060)	(0.0070)	(0.0050)	(0.0251)	(0.0243)
Observations	114,200,000	27,170,000	27,170,000	81,040,000	19,630,000	19,630,000	27,740,000	6,501,000	6,501,000
R^2	0.919	0.822	0.863	0.79	0.812	0.832	0.741	0.876	0.894
Firm Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-CZ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table C4
Robustness: Mass Tech Layoffs and Local Non-tech Firms' Revenue Adjusted by Local Employment Share
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. The dependent variable is the logarithm of $Revenue_{cz}$ plus one. $Revenue_{cz}$, is a firm's revenue adjusted by its local employment share, i.e., the product of the total domestic revenue of a given firm and its employment share in a given commuting zone. Revenue is adjusted to 2018 constant dollars. 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 is located 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. Firm age is estimated but not reported for brevity. $Layoff_c$ is absorbed by firm-commuting zone fixed effects. Staggered treatment timing generates variation in $Post_{c,t}$ that is estimated but not reported for brevity. The sample includes non-tech firms in treated commuting zones and matched control non-tech firms from 1996 to 2007. 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 employees	11-50 employees
	(1)	(2)	(3)
	$Revenue_{CZ}$	$Revenue_{CZ}$	$Revenue_{CZ}$
$Post_{c,t} \cdot Layoff_c$	0.0337	-0.0394	0.2414***
	(0.0471)	(0.0342)	(0.0745)
Observations	27,160,000	19,630,000	6,500,000
R^2	0.8129	0.8134	0.8570
Firm Age	Yes	Yes	Yes
Firm-CZ FE	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes

Table C5
Robustness: Mass Tech Layoffs and Local Non-tech Firms' Revenue Percentile Ranks
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. The dependent variable is the within-sample percentile rank of a firm's domestic revenue in columns 1, 3, and 5. The dependent variable is the within-sample percentile rank of a firm's domestic labor productivity (i.e., the ratio of revenue to employment) in columns 2, 4, and 6. Revenue is 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. Firm age is estimated but not reported for brevity. $Layoff_c$ is absorbed by firm-commuting zone fixed effects. Staggered treatment timing generates variation in $Post_{c,t}$ that is estimated but not reported for brevity. The sample includes non-tech firms in treated commuting zones and matched control non-tech firms from 1996 to 2007. 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 employees		11-50 employees	
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenue Rank	Prod Rank	Revenue Rank	Prod Rank	Revenue Rank	Prod Rank
$Post_{c,t} \cdot Layoff_c$	0.8788	-0.3941	0.0645	-1.1880***	3.2660***	1.6330*
	(0.6320)	(0.5567)	(0.4380)	(0.4086)	(0.9974)	(0.9203)
Observations	27,170,000	27,170,000	19,630,000	19,630,000	6,501,000	6,501,000
R^2	0.886	0.875	0.893	0.849	0.906	0.899
Firm Age	Yes	Yes	Yes	Yes	Yes	Yes
Firm-CZ 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