Creative Destruction? Mass Layoffs and Innovation Spillovers

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[Preliminary Draft]

Abstract

Mass layoffs are typically viewed as harmful to regional economies. However, they may also connect otherwise disconnected innovation hubs by reallocating skilled workers and facilitating the flow of ideas across firms. This paper examines the causal effect of displaced inventors on the innovative productivity of their new coworkers. I construct a novel dataset linking LinkedIn job histories to USPTO patent records, enabling inventor-level tracking of mobility and innovation outcomes over time. To address endogeneity in inventor mobility, I use an instrumental variable based on geographic proximity to mass layoff events. The results show that incumbent inventors experience sizable increases in patent output and citations after being exposed to displaced inventors. These gains emerge quickly, persist over several years, and are concentrated among incumbents with lower pre-exposure productivity. In contrast, high-productivity incumbents experience little benefit or modest declines. The paper discusses potential mechanisms, including access to new technological knowledge and expanded external collaborative networks.

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1 Introduction

Mass layoffs are typically viewed as harmful shocks to workers, firms, and regional economies. A large body of research documents persistent earnings losses among displaced workers, declines in productivity at affected firms, and broader slowdowns in local economic activity following mass layoff events. (Blien, Dauth, & Roth, 2021; Brand, 2015; Couch & Placzek, 2010; Davis & Von Wachter, 2011; Farber, 2017; Foote, Grosz, & Stevens, 2019; Glitz, 2017; Hellerstein, Kutzbach, & Neumark, 2019; Huttunen, Møen, & Salvanes, 2018; Jacobson, LaLonde, & Sullivan, 1993; Lachowska, Mas, & Woodbury, 2020; Paul, Malgouyres, et al., 2022; Ruhm, 1991; Samson, 2023). These findings have shaped the dominant view of mass layoffs as purely disruptive labor market shocks. However, mass layoffs also trigger large-scale reallocations of high-skilled labor, particularly in knowledge-intensive industries. When skilled workers move across firms, they carry with them ideas, technologies, and organizational practices acquired at their former employers. As a result, mass layoffs not only destroy employment relationships, but also reorganize innovative activity. Despite this, existing research has focused almost exclusively on the outcomes of displaced workers themselves or on spillovers measured at the firm or regional level, largely due to data limitations (Arquié & Grjebine, 2024; Bai, Li, & Ma, 2024; Gathmann, Helm, & Schönberg, 2020; Tian, 2025). Surprisingly little is known about how the arrival of displaced workers affects the innovation of the coworkers they join.

To fill this gap, this paper provides the first individual-level evidence on the spillover effects of mass layoffs on incumbent workers' innovation in receiving firms. When a firm hires a displaced inventor, that worker brings not only technical expertise, but also exposure to new technological trajectories, professional networks, and problem-solving approaches acquired at the former employer. Through collaboration and knowledge recombination, the forced

reallocation of inventors may therefore reshape the innovative activity of existing employees.

To examine this question, I construct a novel dataset that links LinkedIn employment histories with USPTO patent records. This dataset enables me to track individual mobility and patenting activity over time. To identify displaced inventors, I use Worker Adjustment and Retraining Notification (WARN) Act notices. These notices are publicly available mass layoff records that firms submit to state labor departments, containing firm names, locations, and official notice dates. My analysis centers on layoffs that occurred between 2000 and 2015. Within this window, I focus on incumbent inventors, defined as those who were already employed at a firm before a displaced inventor joined. I then examine how their patenting activity changes following this inflow.

The procedure yields a longitudinal dataset of approximately 320,000 inventors based in the United States between 1990 and 2024. I identify 5,300 displaced inventors who leave their firms within 60 days of a mass-layoff notice. I further restrict the sample to 494 displaced inventors who have at least one patent in the five years prior to layoff and at least one patent in the five years after joining a new firm. Following reemployment, these displaced inventors collaborate with 2,016 incumbent inventors on patented inventions. These incumbent inventors constitute the main analysis sample.

A key empirical concern is selection: displaced inventors may self-select into systematically more innovative firms or be assigned to high-performing teams, which would make incumbent workers in those firms appear more innovative even in the absence of spillovers. To address this, I implement an instrumental variables based on geographic proximity. Specifically, I construct an average inverse-distance measure between each displaced inventor's former employer and the employers of all inventors. The intuition is that workers are substantially more likely to join geographically closer firms due to lower search and relocation costs

(Molloy, Smith, & Wozniak, 2017; Morkutė, 2019; Park et al., 2019). This inverse-distance measure predicts whether inventors in a given firm are exposed to displaced coworkers (relevance). At the same time, geographic distance should not directly affect the subsequent innovation outcomes of incumbent inventors except through the arrival of displaced workers (exclusion).

Using this design, I find that the arrival of displaced inventors substantially increases incumbent innovation. Coworkers' patent quantity rises by approximately 30 percent, and patent quality by about 40 percent. These effects are strongest among incumbents whose pre-period productivity is lower than that of the displaced inventors. The gains persist for up to four years and gradually fade thereafter.

This paper contributes to two core strands of the literature. First, it contributes to the literature on mass layoffs. Most existing studies examine the consequences of mass layoffs for displaced workers and contracting firms, documenting substantial negative effects on outcomes such as wages, unemployment, housing prices, and productivity (Blien et al., 2021; Brand, 2015; Couch & Placzek, 2010; Davis & Von Wachter, 2011; Farber, 2017; Foote et al., 2019; Glitz, 2017; Hellerstein et al., 2019; Huttunen et al., 2018; Jacobson et al., 1993; Lachowska et al., 2020; Paul et al., 2022; Ruhm, 1991; Samson, 2023). A smaller set of studies examines spillovers to local labor markets or neighboring firms, showing that mass layoffs affect regional employment, wages, and housing markets, and can also alter productivity in surrounding firms (Arquié & Grjebine, 2024; Gathmann et al., 2020; vom Berge & Schmillen, 2023). While this literature has begun to explore spillovers beyond displaced workers, these effects are almost exclusively measured at the firm or regional level. To my knowledge, no prior work examines how mass layoffs affect innovation at the level of individual incumbent workers due to data limitations. This paper fills this gap by focusing

on innovation and providing the first individual-level evidence on the spillover effects of mass layoffs on incumbent coworkers in receiving firms.

Second, this paper contributes to the literature on labor mobility and innovation. A large body of research documents knowledge spillovers from inventor mobility, but this literature has primarily focused on voluntary moves, such as job changes by star scientists or strategic job hopping (Agrawal, Cockburn, & McHale, 2006; Braunerhjelm, Ding, & Thulin, 2018; Breschi & Lissoni, 2009; Kaiser, Kongsted, & Rønde, 2015; Møen, 2005; Singh & Agrawal, 2011; Song, Almeida, & Wu, 2003). In contrast, this paper provides the first inventor-level evidence on innovation spillovers generated by involuntary mobility induced by mass layoffs. By studying forced reallocation, the paper shows how the arrival of displaced inventors reshapes the innovative activity of their new coworkers.

The paper is organized as follows: Section 2 discusses the relevant literature, Section 3 provides an overview of the context and institutional details about school closures in Texas, while Section 4 presents on the data employed in the analysis. Section 5 explains the methodology for selecting non-closed schools as the control group, and Section 6 presents the empirical specification. The main findings are explored in Section 7, with a discussion on the varied effects across different groups in Section 8. Section 9 delves into the underlying mechanisms behind our observations. Finally, the paper concludes with Section 10.

2 Literature Review

A large body of research documents the adverse consequences of mass layoffs for displaced workers themselves. Studies using administrative and survey data show that job loss, including plant closures and mass-layoff events, is associated with long-run employment losses,

scarring in earnings trajectories, and difficulties returning to jobs commensurate with prior skill levels (Blien et al., 2021; Brand, 2015; Couch & Placzek, 2010; Davis & Von Wachter, 2011; Farber, 2017; Foote et al., 2019; Glitz, 2017; Huttunen et al., 2018; Jacobson et al., 1993; Lachowska et al., 2020; Paul et al., 2022; Ruhm, 1991). Some studies further show that job loss reduces individual productivity or innovative output in subsequent jobs, either because displaced workers move into lower-productivity firms or because they are unable to fully utilize accumulated human capital (Hellerstein et al., 2019).

A second strand of research examines how mass layoffs affect outcomes beyond the displaced workers, focusing on spillovers to local labor markets and firms. Several studies analyze how job destruction propagates across the labor market, showing that mass layoffs alter employment, unemployment, and wages in surrounding firms through shifts in local labor-market conditions and labor supply (Arquié & Grjebine, 2024; Gathmann et al., 2020; vom Berge & Schmillen, 2023). More recently, research has begun to examine the effects of mass layoffs on firm- or region-level productivity and growth, including changes in output and value-added among neighboring establishments (Bai et al., 2024; Kim, Roychowdhury, & Zheng, 2025)

To my knowledge, however, existing research has not examined how mass layoffs shape innovation at the individual level—especially among incumbent workers in firms that absorb displaced employees. This distinction is important. Innovation is produced by individuals, not firms, and aggregate outcomes can conceal major shifts within organizations. When skilled newcomers arrive, they may spark learning and collaboration. But they can also displace others from leadership roles or inventive work. Understanding who gains, who loses, and why requires tracking outcomes at the person level.

To fill this gap, this paper examines how mass layoffs affect the innovative activity of

individual incumbents in receiving firms. It provides new evidence on how large workforce disruptions reshape innovation from within organizations.

3 Data

To conduct the analysis, I construct a novel individual-level panel dataset by combining three data sources: LinkedIn employment histories (provided by Revelio Labs), patent records from the U.S. Patent and Trademark Office (USPTO), and mass layoff information from WARN notices. This merged dataset enables me to track inventors over time, capturing their employers, office locations, displacement events, and patenting activity.

3.1 Employment Data (LinkedIn)

To capture detailed employment trajectories, I use structured resume data from LinkedIn, as processed and standardized by Revelio Labs. This dataset includes career histories for all LinkedIn users, though my focus is restricted to individuals who have ever worked in the United States. The dataset provides rich information on job titles, employer names, employment periods, geographic locations, and educational backgrounds. These records allow me to construct year-by-year career paths, identify firm affiliation in each period, and detect job transitions. Additionally, the LinkedIn data offers contextual firm-level characteristics, such as firm size, industry classification, and location, which help characterize the environments into which workers transition. Crucially, the dataset includes employment information even in years without patenting activity, providing a more complete view of inventor career dynamics.

3.2 Patent Data (USPTO)

To measure innovation output, I use comprehensive utility patent records filed with the United States Patent and Trademark Office (USPTO) from 2000 to 2024. These records include detailed information on inventor names, application and grant dates, assignee organizations, technology classifications, and forward citations. I focus on patents granted to U.S.-based inventors across all sectors. Using disambiguated inventor identifiers, I am able to track patenting activity longitudinally across time and employers. Based on this data, I construct annual measures of innovation output, including the number of patents filed, forward citations (adjusted for year and technology class), and indicators for novelty and breakthrough innovations.

3.3 Mass Layoff Data (WARN)

To identify displaced workers, I rely on mass layoff events reported under the Worker Adjustment and Retraining Notification (WARN) Act in the United States. Enacted in 1988 and effective from February 1989, the WARN Act requires employers to provide affected workers with at least 60 days' advance written notice prior to large-scale layoffs or plant closures. The law applies to both full-time and part-time employees and imposes penalties such as back pay, continued benefits, and civil fines on firms that fail to comply. Several states have since introduced their own versions of the WARN Act, commonly referred to as Mini-WARN laws, which expand protections for workers. For instance, New York and New Jersey require a 90-day notice period, while California enforces daily fines of 500 dollars for violations. Some states also adopt broader definitions of mass layoffs. Whereas the federal threshold applies to layoffs involving more than 500 employees, states like Illinois extend coverage to cases where as few as 25 workers are affected. Despite these state-level differences, the federal

WARN Act continues to serve as a foundational framework for layoff notification requirements (U.S. Bureau of Labor Statistics, n.d.). WARN notices are compiled and published by individual state labor departments. These records are publicly accessible and can typically be downloaded from state government websites. Each notice includes detailed information such as the company name, the number of workers displaced, the location (including the metropolitan area and state), and the official notice date of the layoff. I use mass layoff data aggregated by Revelio Labs, which collects and standardizes WARN filings across states to enable consistent tracking of displacement events over time.

3.4 Data Construction

To address this research question, I construct a novel panel dataset containing annual observations on inventors' geographic locations, employers, and patenting activity. I begin by linking USPTO patent records with detailed LinkedIn career histories, using inventors' home addresses reported on patent applications. The matching procedure relies on four key elements: the inventor's name, state of residence, assignee listed on the patent, and the requirement that the patent application date falls within the inventor's employment period reported in their LinkedIn profile. I ensure consistency across these dimensions by verifying that the name matches the LinkedIn profile, the state aligns with the employment location, and the employer corresponds to the assignee. This approach yields approximately 320,000 successful matches—representing about 32% of all U.S.-based inventors who have resided exclusively within the United States.

I then merge this dataset with WARN notice data to identify displaced inventors. Displaced inventors are defined as individuals who were employed at a firm in the same metropolitan statistical area (MSA) at the time of a WARN-covered layoff (between 2000

and 2015) and who left the firm within 60 days of the layoff notice. This process identifies approximately 5,300 displaced inventors. I further restrict the sample to inventors with at least one patent in the five years before displacement and at least one patent in the five years after joining a new firm, resulting in a final sample of 494 displaced inventors.

To identify the coworkers affected by these inflows, I select inventors who are co-inventors on patents with the displaced worker after reemployment and who were already employed at the receiving firm prior to the displaced worker's arrival. This procedure yields a set of approximately 2,016 incumbent inventors, who form the main analysis sample.

4 Empirical Analysis

This section examines how mass layoffs affect the innovation performance of incumbent inventors at receiving firms. A key empirical challenge is endogeneity: displaced inventors may disproportionately move to firms that are already highly innovative, confounding the effect of their arrival on incumbent outcomes. To address this, I implement an instrumental variable (IV) strategy based on geographic proximity between firms.

4.1 IV Estimates of the Impact of Exposure to Displaced Workers on Innovation Outcomes

The instrument is an Average Inverse Distance. It is defined as the average of one over the distance between each displaced inventor's previous employer and all inventor-hiring firms in the same state. The idea is that workers are more likely to join nearby firms because of lower search and relocation costs (Molloy et al., 2017; Morkutė, 2019; Park et al., 2019). This measure helps predict which firms become exposed to displaced inventors, satisfying

the relevance condition. Conditional on labor market controls, distance to a layoff should not affect incumbents' innovation except through the hiring of displaced coworkers. This supports the exclusion restriction.

Formally the first stage is specified as:

$$\text{Exposure}_{i,t} \;=\; \pi_0 \;+\; \pi_1 \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \frac{1}{\text{Distance}\big(\text{Firm}(i,t), \text{Firm}(j,t)\big)} \;+\; \gamma_i \;+\; \delta_t \;+\; \mu_{m,t} \;+\; \nu_{i,t} \tag{1}$$

where $\text{Exposure}_{i,t}$ indicates whether inventor i becomes a coworker of at least one displaced inventor in year t. Ni,t denotes the number of firm–firm distance pairs between inventor i's employer in year t and the employers of all displaced workers j in year t who experienced a mass layoff. $\text{Firm}(i,t)$ identifies the firm employing inventor i in year t and $\text{Firm}(j,t)$ denotes the original firm of displaced worker j. The inventor fixed effects γ_i absorb all time invariant characteristics of individual inventors that could confound innovation outcomes such as innate research ability field specialization patenting skill baseline productivity and long term career trajectories. The year fixed effects δ_t control for aggregate macro level shocks that affect all inventors in a given year such as national economic conditions USPTO processing changes or technological cycles that drive patenting waves. The metro by year fixed effects $\mu_{m,t}$ account for local labor market shocks that vary by region over time such as city level economic growth university R&D investment local policy changes and cluster specific innovation trends. Including these fixed effects ensures that identification comes only from within inventor changes in exposure over time and not from differences across inventors cohorts or regions.

The second stage estimates the impact of predicted exposure on innovation outcomes:

$$Log(Y_{i,t}) \;=\; \alpha \;+\; \beta\, \widehat{\text{Exposure}}_{i,t} \;+\; \gamma_i \;+\; \delta_t \;+\; \mu_{m,t} \;+\; \varepsilon_{i,t} \tag{2}$$

where $Y_{i,t}$ represents the innovation outcomes of inventor i in year t measured by the number of patents, the citation count of patents and the novelty of patented technologies. $\widehat{\text{Exposure}}i, t$ is the predicted exposure obtained from equation (1). As in the first stage inventor fixed effects γ_i year fixed effects δ_t and metro by year fixed effects $\mu_{m,t}$ are included to absorb time-invariant inventor characteristics aggregate macro trends and region specific shocks.

4.2 Dynamic Effects of Exposure to Displaced Workers on Innovation Outcomes

To complement the IV estimates, I additionally estimate a dynamic event-study specification that includes a full set of leads and lags relative to the first year in which an inventor becomes exposed to displaced coworkers. This design allows me to assess the validity of the identifying assumptions by visually testing for pre-trends, and to decompose the estimated effects into their dynamic adjustment pattern. Formally, the specification is given by:

$$\log(Y_{i,t}) = \alpha + \sum_{k=-6}^{7} \beta_k \cdot P_{i,t}^{(k)} + \gamma_i + \delta_t + \mu_{m,t} + \theta_i t + \varepsilon_{i,t}, \tag{3}$$

$\log(Y_{i,t})$ denotes the innovation output of inventor i in year t. $P_{i,t}^{(k)}$ is an indicator equal to one if inventor i is k periods relative to the first year of exposure, where $k = -1$ is

omitted as the reference period. The coefficients β_k trace out the dynamic effects of exposure k years relative to the event. The specification includes a rich set of fixed effects: inventor fixed effects γ_i, year fixed effects δ_t, and metro-area-by-year fixed effects $\mu_{m,t}$, which control for time-invariant inventor heterogeneity, aggregate shocks, and local economic conditions, respectively. In addition, $\theta_i t$ denotes inventor-specific linear trends, allowing each inventor to follow a distinct underlying trajectory in innovation over time.

5 Results

5.1 IV Estimates

Having established that firms located closer to mass layoff origins are more likely to hire displaced inventors, I apply an instrumental variable approach to estimate the causal effect of exposure to displaced inventors on the innovative output of incumbent coworkers. The results of this IV analysis are presented in Table 1. For reference, the first-stage estimates show that geographic proximity predicts exposure: a one-unit increase in the average inverse-distance measure increases the likelihood of hiring a displaced inventor by approximately 8%. The reduced-form results indicate that proximity to layoffs is also associated with substantial gains in innovation outcomes.

Columns 3 and 4 of the table report the OLS and IV estimates, respectively. In the OLS specification, exposure to a displaced inventor is associated with a 43% increase in the number of patents and a 62% increase in patent citations. However, these estimates may be upward biased if displaced inventors tend to match with already highly innovative firms. The IV estimates, which leverage geographic proximity as a source of exogenous variation, suggest that the true causal effects are smaller but still substantial: exposure increases patent

output by 38% and citations by 49%.

To examine the timing and persistence of these effects, the next section turns to an event-study analysis of innovation trajectories surrounding displacement.

Table 1: OLS and IV Estimates of the Effect of Exposure to Displaced Inventors on Incumbent Innovation

Panel A. Log(Number of patents)				
	First stage	Reduced Form	OLS	IV
Exposed to displaced worker			0.3552***	0.3217***
			(0.0196)	(0.0430)
Average (1/distance)	8.0984***	2.6054***		
	(0.2471)	(0.3673)		
Mean (Y)			0.512	0.512
Observations	308,453	308,453	308,453	308,453
Kleibergen-Paap F-statistic	9,212.10			
Panel B. Log(Number of citations)				
	First stage	Reduced Form	OLS	IV
Exposed to displaced worker			0.4775***	0.4028***
			(0.0334)	(0.0771)
Average (1/distance)	8.0984***	3.2622***		
	(0.2471)	(0.6421)		
Mean (Y)			0.760	0.760
Observations	308,453	308,453	308,453	308,453
Kleibergen-Paap F-statistic	9,212.10			

Note: This table reports OLS and IV estimates of the effect of exposure to displaced inventors on the innovative output of incumbent inventors. The dependent variables are the annual number of patents and patent citations at the inventor-year level. All regressions include inventor, year, and metro company-by-year fixed effects. Standard errors, shown in parentheses, are clustered at the inventor level.
† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

5.2 Dynamic Difference-in-Differences Results

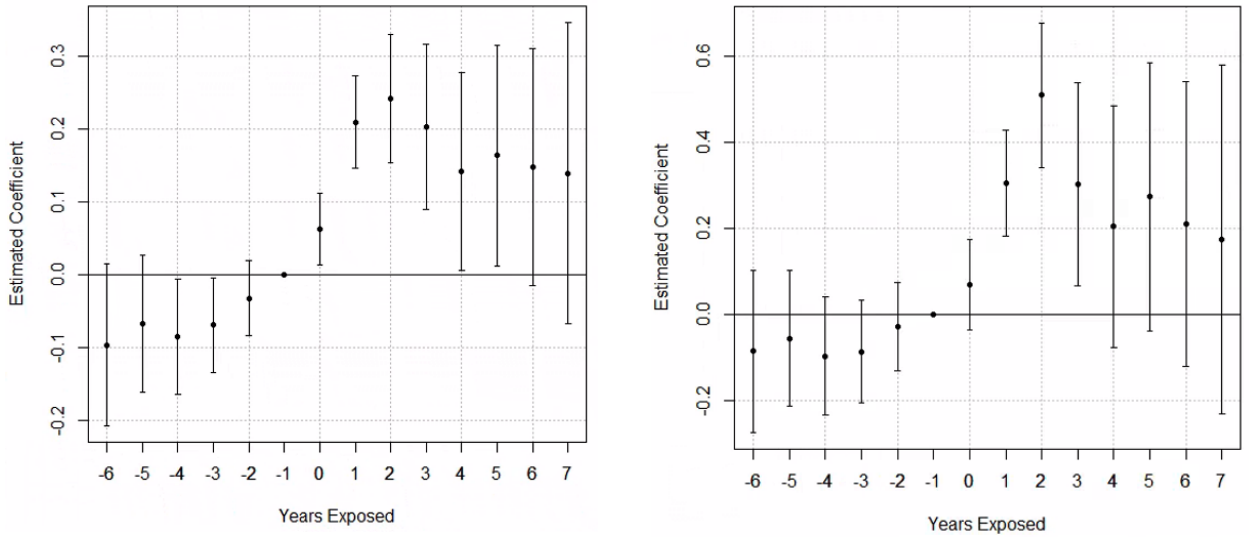
The IV estimates establish an average causal effect of exposure, but they do not show when spillovers emerge or whether they persist. To examine the dynamics, I estimate a dynamic difference-in-differences specification given in equation 3, with leads and lags around the exposure year (period 0) and using period -1 as the reference year. This design allows me to assess pre-trends and trace out how the effects evolve over time.

Figure 1 shows that incumbent patenting increases after exposure. Effects become visible by $k = 1$ and peak between $k = 2$ and $k = 4$ at roughly 0.20–0.30 log points (about a 20–30 percent increase), remaining positive through $k = 6$. Citation outcomes respond more strongly: citations rise after exposure, reaching about 0.40–0.50 log points by $k = 2$, and remain elevated thereafter.

Overall, there is no evidence of differential pre-trends, and the post-exposure increases are persistent across all outcomes. The effects are strongest for citations, followed by patent counts.

6 Heterogeneous Effects

The aggregate effects may mask important differences across incumbent workers. In particular, spillovers may operate through complementary human capital—benefiting some workers but not others. To investigate this possibility, I examine how the impact of exposure varies by incumbents' pre-exposure productivity. Productivity is measured as the inventor's average patent output in the five years prior to first exposure. Inventors above the median of this distribution are classified as high-productivity, while those below the median are categorized as low-productivity incumbents.



(a) Number of Patents **(b) Patent Citations**

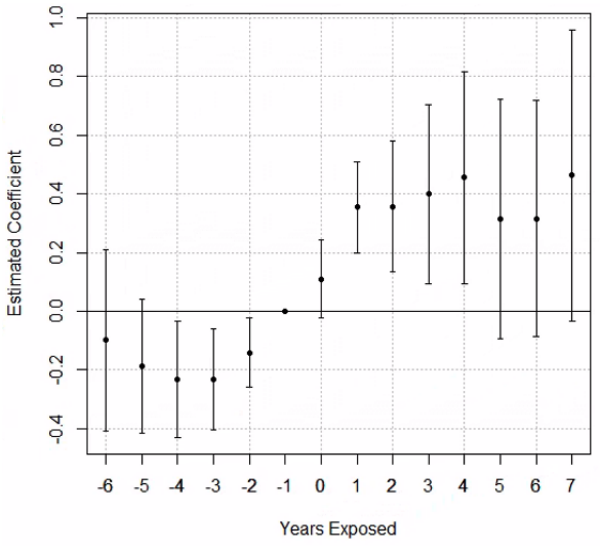
Figure 1: Spillover effects of exposure to displaced inventors on incumbent innovation

Notes: This figure plots event-study coefficients and 95% confidence intervals from regressions estimating the effect of exposure to displaced inventors. Event time is centered at $t = 0$, the year when an incumbent is first exposed to a displaced inventor. All regressions include inventor fixed effects, year fixed effects, firm-by-year fixed effects, and inventor-specific linear trends. Standard errors are clustered at the inventor level.

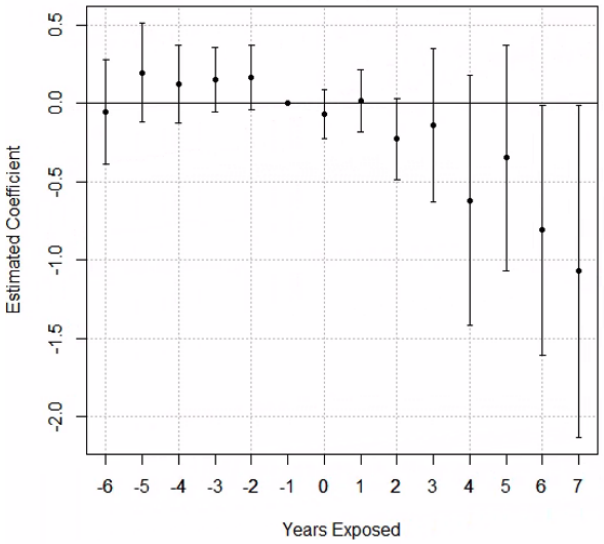
Figure 2 reports the dynamic estimates for low-productivity incumbents. Their innovation outcomes respond strongly following exposure: coefficients rise beginning in $k = 1$ and peak between $k = 2$ and $k = 4$ at approximately 0.30–0.50 log points, with confidence intervals excluding zero for several post-event horizons. These results imply that displaced inventors disproportionately raise the performance of initially underperforming incumbents, consistent with organizational learning or skill-complementarity mechanisms in which new knowledge diffuses to workers who previously lacked exposure to similar ideas or networks.

In contrast, Figure 2 shows that high-productivity incumbents experience little to no improvement after exposure. Their pre-period coefficients remain flat, but post-period estimates gradually decline and become negative around $k \approx 3$, reaching roughly -0.50 log points by $k = 6$. This pattern suggests that highly productive incumbents may already operate near their innovation frontier, leaving limited room for spillover-driven gains. Alternatively, incoming displaced workers may induce internal reallocation—drawing managerial attention, resources, or collaboration opportunities away from top performers.

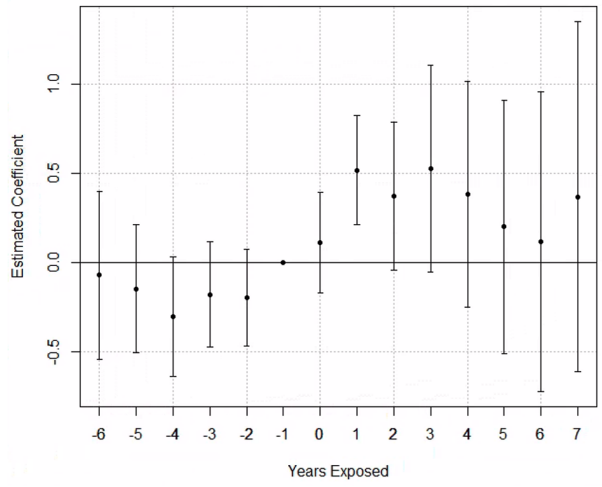
Overall, the heterogeneous effects demonstrate that mass-layoff-induced talent inflows do not raise all boats equally. Spillovers are concentrated among low-productivity incumbents, while high-productivity inventors experience no gains and may even be adversely affected. These findings are consistent with a reallocation channel in which external knowledge inflows reshape internal team dynamics by elevating lagging workers while potentially diluting the relative position of top performers.



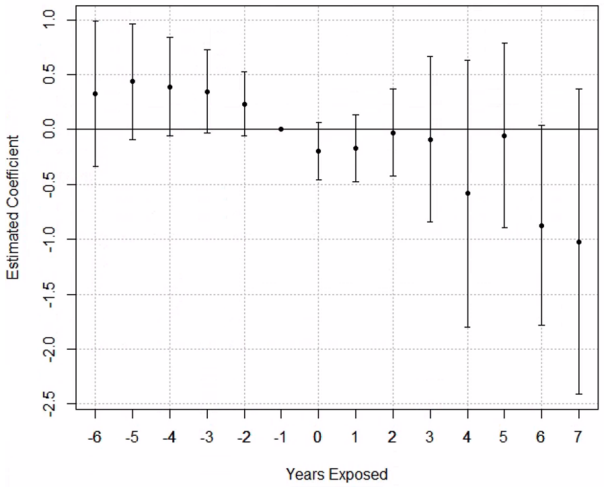
(a) Low baseline productivity: Patents



(b) High baseline productivity: Patents



(c) Low baseline productivity: Citations



(d) High baseline productivity: Citations

Figure 2: Heterogeneous spillover effects of exposure to displaced inventors on incumbent innovation

Notes: These figures plot event-study coefficients and 95% confidence intervals from regressions estimating the effects of exposure to displaced inventors on incumbent innovation. Event time is centered at $t = 0$, the year an incumbent is first exposed to a displaced inventor. Panels (a) and (b) show effects on patent counts for incumbents with low and high baseline productivity, respectively. Panels (c) and (d) show effects on patent citations. All regressions include inventor fixed effects, year fixed effects, firm-by-year fixed effects, and inventor-specific linear trends. Standard errors are clustered at the inventor level.

7 Mechanism

This section outlines a set of analyses designed to shed light on the mechanisms through which exposure to displaced inventors affects incumbent workers' innovation outcomes. In particular, I plan to examine whether the effects operate through social networks and collaboration, or through direct channels of knowledge transfer.

Social networks and collaboration. I will study the role of social connections by tracking cross-firm patent co-authorships before and after exposure. Specifically, I will examine whether incumbent inventors become more likely to coauthor patents with displaced workers or with former colleagues of displaced workers following their arrival. An increase in cross-firm or newly formed collaborations would suggest that social networks facilitate knowledge exchange and the diffusion of ideas across organizational boundaries.

Knowledge transfer. To assess whether exposure operates through direct knowledge transmission, I will analyze changes in the technological composition of displaced workers' and incumbents' patents. In particular, I will test whether patents produced after reemployment are more likely to overlap in technology classes with the displaced workers' prior work. Evidence of increased technological overlap would be consistent with the transfer of specific technical knowledge, rather than purely general spillovers.

8 Conclusion

Mass layoffs are commonly viewed as destructive labor market shocks, associated with job loss, earnings declines, and local economic disruption. This paper shows that they also generate an important and previously undocumented channel of knowledge reallocation.

Using novel linked LinkedIn and USPTO data and an instrumental variables design based on geographic proximity, I provide the first individual-level evidence that the arrival of displaced inventors raises the innovative output of incumbent workers in receiving firms.

The results show that exposure to displaced inventors substantially increases incumbent patenting and citations. These gains emerge shortly after exposure, persist for several years, and are concentrated among incumbents with lower pre-exposure productivity. In contrast, high-productivity incumbents experience little benefit and may even face declines, consistent with internal reallocation of innovative activity. Together, these findings indicate that labor reallocation triggered by mass layoffs does not simply destroy or preserve innovation, but reshapes who produces it within organizations.

By shifting the focus from displaced workers to their new coworkers, this paper contributes to the literature on mass layoffs, labor mobility, and innovation. Existing work has emphasized the direct costs of displacement and the aggregate consequences for firms and regions. This study complements that evidence by documenting a micro-level spillover channel operating through individual workers inside firms. The results highlight the importance of measuring innovation at the person level, where gains, losses, and reorganization can be observed directly rather than inferred from firm aggregates.

From a policy perspective, the findings suggest a more nuanced interpretation of mass layoffs. Although they impose substantial costs on displaced workers, they may also generate positive externalities when skilled workers are reallocated into new environments where their knowledge can be recombined with that of incumbents. Policies that facilitate efficient matching, mobility, and integration of displaced high-skilled workers—such as job search assistance, relocation support, or platforms that connect workers to innovative firms—may help amplify these spillovers and accelerate the diffusion of ideas following economic shocks.

Future work can further investigate the mechanisms through which these spillovers arise, including the roles of collaboration networks and direct knowledge transfer, and examine how organizational structure or team composition shapes the distribution of gains and losses. More broadly, understanding when labor reallocation enhances innovation and when it merely redistributes it remains central for evaluating the long-run innovative consequences of economic restructuring.

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