Local Economic Impacts of Food Manufacturing Plant Closures in the Midwest

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Abstract

This paper provides the first systematic evidence on the local economic impacts of food manufacturing plant closures across Midwestern counties between 2010 and 2024. Using synthetic difference-in-differences, I find that a food plant closure reduces total county employment by about 8.1 percent for strongly treated counties, equivalent to an average loss of 528 jobs compared with an average layoff size of 418. Manufacturing employment falls as expected, and non-manufacturing employment erodes more gradually, suggesting spillover effects that accumulate over time. The unemployment rate spikes immediately after closures and remains elevated for several months. The effects are uneven, with employment losses disproportionately large among minority groups, especially Hispanic and Black workers. These groups also experience local population decline. Food manufacturing plant closures have important local economic impacts, including multiplier effects that extend beyond directly displaced workers and unequal burdens within and across rural and small-town counties.

Keywords: Plant closures, Food manufacturing, Local labor markets, Employment Dynamics, Population dynamics, Wages
JEL Classification: L66, J21, J63, R11, R23

1. Introduction

Manufacturing plant closures can have profound ripple effects on local economies, especially in regions heavily dependent on a single employer or industry. The Midwest has long relied on food processing, such as meatpacking, dairy, and grain processing, as a jobs engine. For example, in Iowa, over 59,000 workers are employed in food manufacturing, roughly one-quarter of the state's manufacturing workforce, according to the Iowa Workforce Development's 2022 Industry Profile for Manufacturing. Recent industry trends make this topic especially timely. In 2023–2024, meatpacking plants closed at an unprecedented rate, with 15 shutdowns each year, and this is the highest number in a decade, reported by Investigate Midwest.

Food manufacturing plant closures have particularly profound consequences for rural communities. Food processing facilities have historically provided stable jobs for immigrants and low-skilled workers and served as critical links in agricultural supply chains (Huffman and Miranowski, 1996; Kandel and Parrado, 2005). In recent years, however, structural transformations within the food industry, including consolidation among large firms, technological innovations that reduce labor needs, and rising market concentration, have increased the risk of shutdowns (MacDonald et al., 2023). COVID-19 disruptions further underscored the sector's fragility. Broad Leib et al. (2020) emphasize legal and supply chain vulnerabilities, while Ramsey, Goodwin, and Haley (2023) show that pandemic-era shocks revealed both flexibility and exposure to labor disruptions. The consequences of closures are likely to be especially severe in smaller communities where alternative employment opportunities are limited and where a single plant may account for a substantial share of local economic activity (Davis et al., 2023).

The broader displaced-worker literature demonstrates that plant closures and mass layoffs often have long-lasting consequences for workers. Jacobson, LaLonde, and Sullivan (1993) document large and persistent earnings losses following job separations, while subsequent studies show significant wage declines (Couch and Placzek, 2010; von Wachter et al., 2011) and even higher mortality risks (Sullivan and von Wachter, 2009). At the regional level, research on the China shock finds persistent employment and earnings declines in affected areas (Autor, Dorn, and Hanson, 2013). These findings underscore the potential severity of food manufacturing plant closures, especially in rural areas with limited outside options.

Beyond labor markets, plant closures can also affect population, housing, and community well-being. Standard spatial equilibrium models predict out-migration after local shocks (Blanchard and Katz, 1992), but empirical evidence suggests that such responses are often modest and selective (Autor et al., 2014; Greenland, Lopresti, and McHenry, 2019). Declines in employment and population may weaken housing markets and local public finances (Feler and Senses, 2017). Large-scale layoffs have also been linked to broader social costs, including family instability (Charles and Stephens, 2004), public health risks (Venkataramani et al., 2020), and reduced student achievement (Ananat et al., 2011). These channels highlight that the consequences of closures may extend well beyond the directly displaced workers.

A few previous studies underscore the economic and demographic role of food processing facilities in rural areas. Artz, Orazem, and Otto (2007) show that meatpacking plant expansions increased overall employment but put downward pressure on average wages. Artz, Jackson, and Orazem (2010) find that industry growth attracted substantial immigration and increased the demand for bilingual educational services, though without raising local government spending or poverty. Kandel and Parrado (2005) highlight how expansions reshaped rural demographics by drawing large flows of immigrant labor.

Evidence on food manufacturing plant closures largely comes from case studies, which illustrate their potentially severe consequences but remain focused on individual locations. Burrows, Cheney, and Rahn (2002) estimate that shutting down a Sara Lee turkey facility in Michigan led to output losses over $80 million and affected growers and suppliers. Dudensing et al. (2019) document that the closure of a large Cargill beef packing plant in Texas resulted in more than 2,500 lost jobs and nearly $1 billion in output reductions. Stevens, Hodges, and Mulkey (2003) find that the direct loss of 627 jobs at a Tyson poultry plant in Florida ultimately produced more than 1,600 job losses in the region. Most recently, an Iowa State Extension study of the 2024 Tyson pork plant closure in Perry, Iowa, revealed how a single shutdown can devastate a small town of 8,000 residents. (Schulz and Crespi, 2024) While informative, these case studies remain focused on individual communities or specific shocks, leaving open the question of how closures affect local economies more broadly across regions and over time.

This paper contributes to the literature by providing the first systematic evidence on the local economic impacts of food manufacturing plant closures across Midwestern counties. While informative, prior case studies remain descriptive. Their findings illustrate the potential severity of plant closures but do not provide causal estimates, since they lack a clear counterfactual of how local economies would have evolved in the absence of closure. My analysis addresses this limitation by applying the synthetic difference-in-differences (SDID) method that compares observed outcomes for treated counties to counterfactual counties (Arkhangelsky et al., 2021). This framework constructs a counterfactual by weighting control counties to match the pre-closure trajectory of treated counties, thereby enabling credible causal inference about the local economic impacts of food manufacturing plant closures. The results indicate that food plant closures reduce total county employment by about 8.1 percent for strongly treated counties, corresponding to an average loss of roughly 528 jobs, compared with an average layoff size of 418 workers. Manufacturing employment falls by more than 23 percent, with significant spillovers into non-manufacturing sectors. The effects are not evenly distributed. Both the employment and population responses are especially pronounced among minority groups, pointing to unequal burdens across communities.

In addition to average treatment effects, I estimate event-study dynamics to trace the timing and magnitude of impacts. The results show that food manufacturing employment falls sharply at the closure date, reflecting direct job losses, while total county employment continues to erode in subsequent months as spillover effects spread into non-manufacturing sectors. Unemployment spikes immediately after closure and remains elevated for several months before showing signs of gradual decline. These dynamic patterns underscore both the immediacy of direct displacement and the slower adjustment of broader local labor markets.

The remainder of the paper is organized as follows: Section 2 outlines the theoretical framework, Section 3 describes the data, Section 4 presents the empirical strategy, Section 5 reports the results, Section 6 discusses robustness checks, and Section 7 concludes.

2. Theoretical Framework

2.1 A Spatial Equilibrium Model of Local Labor Market Adjustment

To study the local economic impacts of food manufacturing plant closures, I present a spatial equilibrium framework inspired by Roback (1982) and Blanchard and Katz (1992). Workers choose their residential location based on local wages, housing rents, amenities, and demographic-specific migration costs. Let the indirect utility function for a worker of demographic group *d* in region *i* be:

$$U_{i,d} = w_{i,d} - r_{i,d} + A_{i,d} - C_{i,d}$$

where $w_{i,d}$ denotes local wages, $r_{i,d}$ denotes local rents for demographic group *d*, $A_{i,d}$ denotes local amenities for demographic group *d*, and $C_{i,d}$ represents location-specific migration frictions for demographic group *d*. It reflects the cost of settling in region *i*, such as limited information, language barriers, or weak social networks for certain groups.[1]

In equilibrium, workers achieve equal utility across locations, such that:

$$w_{i,d} - r_{i,d} + A_{i,d} - C_{i,d} = w_{j,d} - r_{j,d} + A_{j,d} - C_{j,d}$$

However, this assumption is strong and unlikely to hold in the short run. In rural communities, where food manufacturing plants often account for a large share of employment, workers typically face barriers that constrain mobility. These include credit constraints, social ties, incomplete information, and group-specific limitations. To incorporate such frictions, I relax the equilibrium condition and instead assume that migration occurs only when the expected utility gain exceeds a threshold $\kappa_{i,j,d}$:

$$U_{j,d} - U_{i,d} > \kappa_{i,j,d}$$

This inequality reflects real-world inertia in migration decisions and allows for persistent spatial utility differentials. This adjustment captures the inertia that often constrains migration, even in the face of large shocks.

[1] A more realistic specification would allow for bilateral migration costs, $C_{i,j,d}$, since frictions often depend on both the origin and destination (e.g., distance, networks, or state policies). For tractability, I use location-specific costs $C_{i,d}$, which captures group-specific barriers to settling in region *i*. This simplification aligns with standard spatial equilibrium frameworks and avoids the added complexity of modeling unobserved bilateral frictions.

Plant closure acts as a productivity shock, decreasing local labor demand and subsequently reducing equilibrium wages in the affected area. As a result, some workers may migrate to other locations where they can have higher utility. Local labor demand is explicitly composed of demand from existing firms and potential new firm entries:

$$L_i^D = L_{old,i}^D + L_{new,i}^D$$

where total local labor demand L_i^D is the sum of existing firm employment $L_{old,i}^D$ and new firm employment $L_{new,i}^D$.

While many closures lead to persistent economic distress, in some cases, new firms enter the market or acquire and reopen closed facilities. For example, after Conagra closed its food manufacturing plant in Trenton, Missouri, in early 2018, Nestlé acquired and reopened the facility within two months, rehiring many former workers and resuming production. In 2025, JBS announced plans to build a new \$135 million sausage plant in Perry, Iowa, the site of a recent Tyson plant closure, projected to create 500 jobs. These events highlight the potential for partial recovery or structural shifts in local labor markets. These real-world cases motivate the inclusion of firm entry and adjustment frictions in my theoretical framework, which allows for both short-term disruptions and long-run re-equilibration.

Firm entry in the region typically responds gradually due to entry and adjustment frictions, governed by:

$$L_{new,i,t}^D = \rho L_{new,i,t-1}^D + (1-\rho)\gamma(w_{i,t-1}, r_{i,t-1}, X_i), \qquad 0 < \rho < 1,$$

where ρ captures the realistic delay in local labor market adjustment, and $\gamma(\cdot)$ is a function determining new firm entry or expansions, negatively influenced by local wages $w_{i,t-1}$, rents

$r_{i,t-1}$, and positively influenced by local conditions such as infrastructure, workforce quality, and market access, captured in X_i.

Labor supply depends on local population N_i and labor force participation $LFPR_i$:

$$LS_i = N_i \times LFPR_i$$

In equilibrium, wages adjust to balance local labor demand and supply. A negative shock to labor demand leads to excess supply in the short run, reflected in rising unemployment or falling wages. Over time, adjustments occur through: a) wage flexibility: lower wage makes the region more attractive to firms; b) out-migration: reduces population, tightening the labor market, and c) firm entry: gradually increases labor demand, absorbing excess supply. This dynamic interaction ensures that the labor market eventually re-equilibrates at a new level of wages, employment, and population.

The housing market clears when housing demand equals housing supply:

$$D^r(N_i, w_i) = S^r(r_i)$$

As population increases, housing demand rises, putting upward pressure on rents. Conversely, a decline in local population due to job loss or out-migration reduces housing demand, leading to falling rents and increased vacancy rates. Housing adjustments occur more slowly than labor market changes due to fixed supply in the short run. Over time, developers may adjust supply through new construction or disinvestment, but in the short run, rents serve as the primary equilibrating mechanism. Falling rents in the aftermath of a plant closure reflect both declining population and reduced local economic opportunity, potentially reinforcing further out-migration and disinvestment. While lower rents reduce the cost of living, they also signal weak demand and deteriorating local conditions, which can discourage new residents and investment.

2.2 Multiplier Effects

The consequences of food plant closures extend beyond the directly displaced workers. Economists often describe these broader impacts through the concept of a local employment multiplier, which measures how total county employment changes relative to the initial loss of food manufacturing jobs.

Formally, let $E_{i,t}$ denote total employment in county *i* at time *t*, and let $E_{F,i,t}$ represent employment in food manufacturing. Define the local employment multiplier, μ, as:

$$\mu = \frac{dE_{i,t}}{dE_{F,i,t}}$$

In empirical applications, this is observed as the change in total employment relative to the change in food manufacturing employment. This parameter captures the total local employment effect of a one-job change in food manufacturing. If $\mu > 1$, job losses in food manufacturing lead to broader employment losses across the local economy, indicating the presence of multiplier effects. If $\mu = 1$, the job loss is fully contained within the manufacturing sector. If $\mu < 1$, the local economy partially absorbs the shock, possibly through commuting adjustments, sectoral reallocation, or inflows of outside employment. For example, $\mu = 1.5$ implies that losing one food manufacturing job reduces total local employment by 1.5 jobs, while $\mu = 0.7$ implies that the employment loss is smaller than the direct shock, suggesting limited or no spillover and some local absorption.

These multipliers operate through several channels. On the downstream side, displaced workers lose income and reduce consumption, lowering demand for retail, hospitality, transportation, and other local service industries. On the upstream side, agriculture is directly tied to food processing activity:

$$E_{A,i} = h(E_{F,i}), \quad \frac{\partial E_{A,i}}{\partial E_{F,i}} > 0$$

where $E_{A,i}$ represents agricultural employment and $E_{F,i}$ represents food manufacturing employment. A reduction in food manufacturing employment therefore reduces demand for agricultural inputs, reinforcing local economic decline. Together, these downstream and upstream channels explain why the total impact of closures often exceeds the direct job loss at the shuttered facility.

Empirical studies highlight the variability of such multipliers. Moretti (2010) estimates that each additional manufacturing job in U.S. cities creates, on average, 1.6 additional jobs in the non-tradable sector, with stronger effects for high-skilled jobs (up to 2.5) and weaker effects for low-skilled jobs (around 1.0). In contrast, studies of large plant closures in Europe suggest more muted spillovers. Jofre-Monseny, Sánchez-Vidal, and Viladecans-Marsal (2018) find that each job lost in Spanish manufacturing led to 0.6 to 0.7 additional job losses within the same industry, while Celli, Cerqua, and Pellegrini (2023) document persistent within-industry losses in Italy but little effect on other sectors.

The empirical relevance of these multiplier effects is discussed in Section 5.1, where I provide estimates based on observed employment responses to closures.

2.3 Equilibrium Dynamics

Figure 1 presents a conceptual illustration of possible local unemployment dynamics following a food manufacturing plant closure. Immediately after the closure, denoted by the red vertical line, unemployment rises sharply from the pre-closure steady-state level U* to a higher level U, reflecting the direct displacement of workers. Over time, unemployment declines as some workers find alternative employment, migrate out of the region, or exit the labor force. However, in this baseline scenario, the local labor market stabilizes at a new, higher unemployment rate, indicating a persistent adverse effect of the closure.

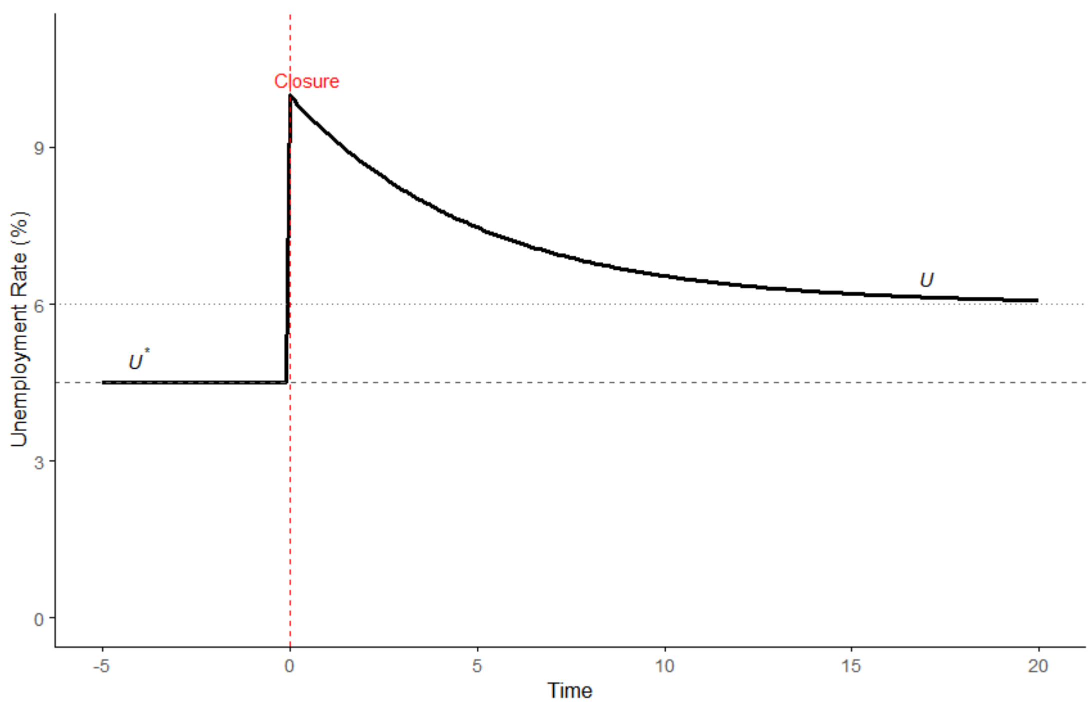

Figure 1. Conceptual Dynamics of Local Unemployment Following Plant Closure.

This persistence is consistent with findings in the literature. A substantial body of work shows that local shocks, such as mass layoffs and trade exposure, can generate long-term economic scarring at the regional level. For example, Autor, Dorn, and Hanson (2013) document that U.S. regions exposed to import competition suffered persistent declines in employment and wages, with limited recovery over a decade. Blanchard and Katz (1992) show that regional unemployment spikes following local shocks and the recovery can be slow. More recently, Celli, Cerqua, and Pellegrini (2023) find that large layoffs in Europe lead to enduring local employment losses. Greenland, Lopresti, and McHenry (2019) show that population responses to labor market shocks are modest and delayed, especially among low-income and less-mobile populations. These studies highlight the role of adjustment frictions, skill mismatch, and structural change in slowing or preventing recovery.

However, not all communities necessarily experience permanent distress. Under certain conditions, such as new firm entry, infrastructure investment, or in-migration, local economies may eventually recover. For example, Diamond (2016) finds that mobile, high-skilled workers tend to move toward recovering areas, while Notowidigdo (2020) emphasizes the role of local labor market fundamentals in absorbing shocks. Kline and Moretti (2014) and Austin, Glaeser, and Summers (2018) highlight how place-based policies can stimulate new investment and support economic revitalization. Figure 2 presents an alternative scenario in which unemployment gradually returns to its original level over time, reflecting the possibility of a full restoration of the pre-shock equilibrium.

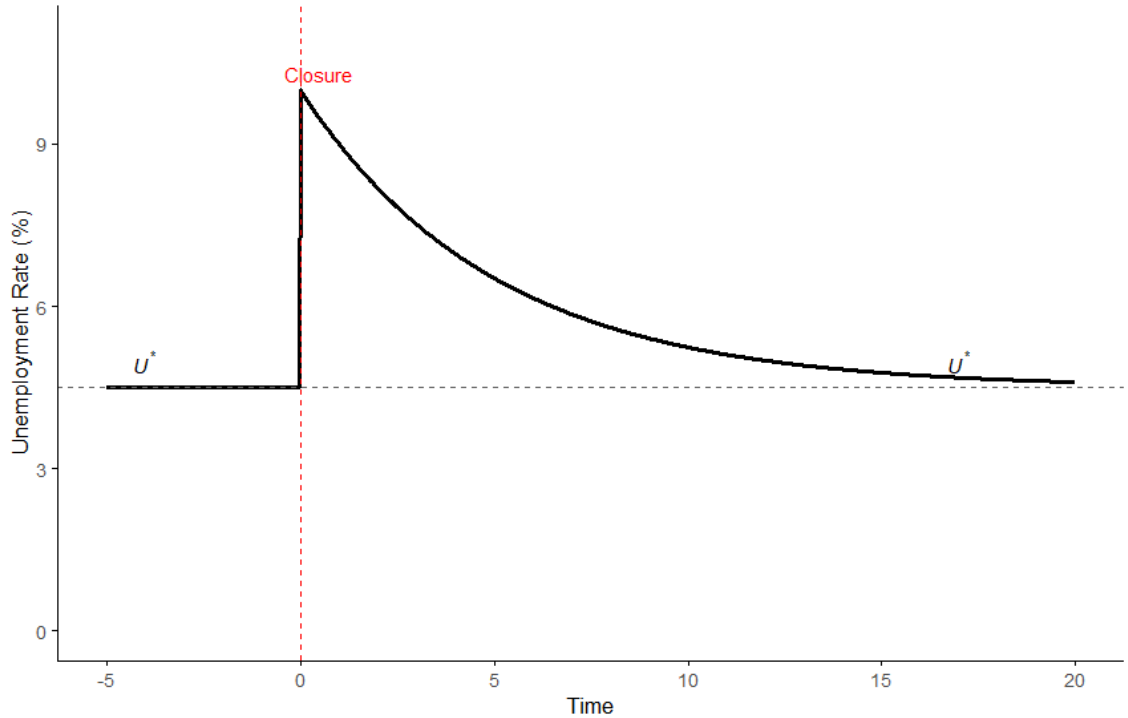

Figure 2: Alternative Adjustment Paths Following a Plant Closure

Together, these conceptual figures emphasize that recovery trajectories can vary substantially across locations. They provide useful benchmarks for interpreting heterogeneity in local outcomes.

3. Data

3.1 Employment, wage, and population data

This study draws on multiple datasets to measure labor market and demographic outcomes at the county level. For employment, I use 2010-2024 monthly data from the Quarterly Census of Employment and Wages (QCEW), published by the U.S. Bureau of Labor Statistics (BLS). The QCEW provides nearly universal coverage of workers covered by unemployment insurance programs, reporting employment counts by county and industry. These data allow me to track short-run changes in local labor markets at a monthly frequency. In addition, I employ the Local Area Unemployment Statistics (LAUS) data from the BLS, which provides county-level monthly unemployment rates.

For wage outcomes, I use quarterly data on average weekly wages from QCEW, which are available at the county-industry level. This enables the analysis of broader earnings dynamics over time, while smoothing short-term volatility. Sector-specific employment and wage outcomes, such as those for manufacturing and non-manufacturing sectors, are constructed using industry-level QCEW data. In some cases, wage or employment values are not publicly reported because of confidentiality restrictions in the QCEW data. The BLS withholds county–industry cells when the number of establishments is small enough that individual employers could be identified. I exclude the suppressed county–months or quarters from the analysis to maintain a balanced panel dataset, which is required for the estimation framework applied in this study.[2]

To capture more detailed labor market dynamics, this study also uses the Census Bureau's Quarterly Workforce Indicators (QWI) data, derived from the Longitudinal Employer-Household Dynamics (LEHD) program. QWI provides rich quarterly information on local job flows, including new hires, separations, job creation, job destruction, and earnings for different worker groups. Crucially, QWI offers detailed demographic breakdowns, such as race and ethnicity, enabling the assessment of heterogeneous impacts of plant closures across different subpopulations within counties. While the QCEW and LAUS datasets provide monthly information, the QWI dataset's quarterly structure provides complementary insights into labor market dynamics and distributional effects.

[2] Two strongly treated counties have missing manufacturing employment data. In one case, six months of values are missing well prior to the closure; I impute these using QWI data. In the other case, manufacturing employment is missing for the entire period. Because QWI data are reported with a two-quarter lag relative to QCEW, I exclude this county from the main analysis for employment.

For population measures, I use annual county-level estimates from the U.S. Census Bureau. Because population data are available only on a yearly basis, all population-related analyses are conducted at the annual frequency. In addition to the total population, I utilize Census demographic breakdowns by race and ethnicity, which allow for heterogeneity analyses across subpopulations. This enables me to assess whether food plant closures are associated with changes in the size or composition of minority populations, who are disproportionately represented in food manufacturing employment.

3.2 WARN and Closures

This study uses data from the Worker Adjustment and Retraining Notification (WARN) system to identify large-scale closures of food manufacturing facilities. The WARN Act requires employers with 100 or more full-time employees to provide at least 60 days' advance notice to state agencies before a mass layoff, defined as affecting at least 50 employees at a single site. I construct an event-level database of food manufacturing plant closures across the Midwest U.S. from 2010 to 2024, identifying 113 permanent closures during this period. I focus on the Midwest, where food manufacturing employment is especially concentrated and where many counties remain dependent on a small number of large plants.

I focus specifically on counties where a closure represents a significant local employment shock. Using 2010 QCEW data as a baseline, I calculate the relative layoff size for each event, defined as the number of laid-off workers divided by the county's total 2010 employment. The primary treatment group consists of the 12 counties in which the relative layoff size exceeds 3 percent.[3] This threshold ensures that the analysis centers on economically meaningful closures: in a typical rural and small-town county, a 3 percent layoff translates into several hundred jobs lost, large enough to disrupt the local labor market. The choice is also supported by the distribution of observed events. In the sample, the largest closure below the cutoff affected 2.26 percent of county employment, leaving a clear gap between the "large" closures classified as treatment and the remaining, smaller shocks. Closures below this threshold are excluded from the treatment sample. In section 5.1, I also examined smaller closures with a relative layoff size of 1 to 3 percent, which are defined as a moderate treatment group.

Given the geographic scale of my analysis, closures are assigned to counties based on reported plant locations in the WARN records. In cases where the effective layoff date is missing, I impute the treatment date as 60 days after the notification date, in accordance with WARN's statutory notice period.[4] I also use local news to confirm the date of closures.

Among the primary treatment group, only one closure is observed in each county. The simple mean for the number of workers laid off is 549.2, and the mean for relative layoff size is 6.15%. The average treatment year in this group is 2022, which is notably more recent than the overall sample average of 2018. This pattern suggests that more recent closures tend to involve larger layoffs.

Table 1 summarizes the plant closure events that constitute the basis of this study, providing information on each closure event, including the firm name, county location, month and year of closure, and total number of layoffs. The closures involve prominent food

[3] A small number of strongly treated counties are technically part of metropolitan statistical areas (MSAs), but none are central metro counties. Only Dallas County, IA exceeds 50,000 residents, which should be considered as a metro county. I do robustness check regarding this issue in Section 6.4.
[4] In the primary treatment group, only one treated county has a missing effective date, and I impute it using notification date plus 60 days. I double check with the local news that the closure date is accurate.

manufacturing firms, such as Tyson Foods, ConAgra, General Mills, and Smithfield Foods, occurring primarily across Midwestern counties from 2013 to 2025. The closures are ranked by the relative size of the layoff. The main empirical analysis exploits this categorization to investigate differences in local economic adjustments across varying intensities of treatment.

Table 1. Information on Food Manufacturing Plant Closures

Food manufacturer	Location	Date	Number of workers	Relative size
Tyson Foods	McDonald County, MO	Oct 2023	1,513	22.31%
ConAgra Foods	Grundy County, MO	Mar 2018	282	8.30%
Tyson Foods	Stoddard County. MO	Oct 2023	683	6.57%
Tyson Foods	Lyon County, KS	Feb 2025	809	5.38%
Tyson Foods	Crawford County, IA	Aug 2015	404	5.37%
Missouri Prime Beef Packers	Polk County, MO	Apr 2024	335	4.38%
Tyson Foods	Dallas County, IA	Jun 2024	1,276	4.12%
West Liberty Foods	Henry County, IA	Dec 2022	350	3.89%
Smithfield Foods	Sullivan County, MO	Oct 2023	92	3.52%
General Mills Operations	Buchanan County, Iowa	Oct 2023	217	3.51%
Tyson Foods	Harrison County, IN	Mar 2024	368	3.40%
Tyson Foods	Union County, SD	July 2023	262	3.04%
Dean Foods Company of Indiana	Fulton County, IN	Oct 2015	138	2.26%
Richelieu Foods	Grundy County, IA	Feb 2023	81	2.10%
Twin Rivers Foods	Newton County, MO	Jun 2016	330	1.69%
DFA Dairy Brands Ice Cream	Adams County, IN	Dec 2021	176	1.46%
Del Monte Foods	Green Lake County, WI	Apr 2024	90	1.41%
General Mills	Floyd County, IN	Aug 2016	343	1.22%
Unilever Ice Cream Manufacturing	Huntington County, IN	Jul 2013	157	1.15%

Table A.1 provides descriptive statistics on food manufacturing plant closures in the 113 treated counties across the Midwest between 2010 and 2024. On average, each closure affected approximately 200 workers. Several cases affect a large number of workers; for example, the maximum is 1,513, which accounts for a 22 percent decrease in employment. Treated counties experienced an average of 2.17 closures during the sample period, with some counties seeing as many as seven closure events. The average closure occurred in 2018, with events spanning from 2012 to 2025.

3.3 Additional data

I also compile annual county-level data from the Federal Housing Finance Agency's (FHFA) House Price Index (HPI), which tracks changes in single-family home values based on repeat-sale and refinance transactions. In addition, I draw on supplementary indicators such as health measures and SNAP participation, which are described in Appendix C.

4. Empirical strategy

To estimate the causal effects of food manufacturing plant closures on local labor markets, population, and average wages and earnings, I employ the synthetic difference-in-differences (SDID) method developed by Arkhangelsky et al. (2021). The SDID estimator combines the strengths of two widely used approaches in program evaluation: difference-in-differences (DID) and the synthetic control method (SCM). The SDID framework allows for credible identification of treatment effects while improving robustness to violations of parallel trends assumptions common in traditional DID designs.

In contrast to standard DID, which assumes that treated and control units would follow parallel trends in the absence of treatment, SDID constructs a weighted synthetic control group for each treated unit based on its pre-treatment outcome history. These weights are used to adjust for baseline differences in levels and trends. The method then applies a difference-in-differences estimator comparing post-treatment outcomes between treated units and their synthetic controls, producing estimates that are doubly robust to time-varying confounders and unit-specific shocks.

The SDID framework is particularly well-suited for this study for three reasons. First, the treatment, closure of large food manufacturing plants, is implemented at different times across counties, which SDID can flexibly accommodate. Arkhangelsky et al. (2021) indicate how synthetic DID can be applied to a staggered treatment setting by applying the SDID estimator repeatedly, once for every initial treatment year and then aggregating. Second, the small number of treated counties raises concerns about standard DID assumptions and statistical power. SDID improves estimation precision through partial pooling and the use of outcome-based weighting. Third, many economic outcomes of interest, such as wages, population, and house prices, may evolve along different trends across counties, particularly between rural and urban areas. SDID's design-based weights mitigate this concern by matching on pre-treatment trajectories.

More formally, SDID works as follows:

$$\left(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = arg \min_{\tau,\mu,\alpha,\beta} \{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - D_{it}\tau)^2 \hat{w}_i^{sdid} \hat{\lambda}_t^{sdid} \}.$$

Here τ is the average treatment effect on the treated (ATT) of interest and $\hat{\tau}^{\mathrm{sdid}}$ is its SDID estimate. Y_{it} refers to the outcome variable for unit *i* in time period *t*, D_{it} refers to the treatment variable, $\hat{w}_i^{sdid}$ is the optimal weight for individual units, and $\hat{\lambda}_t^{sdid}$ is the optimal weight for time periods. The parameters α_i, β_t, and μ respectively capture unit fixed-effects, time fixed-effects, and a reference intercept.

The primary outcomes examined in this study include the natural log of monthly employment, annual population, and quarterly average weekly wages at the county level. These variables are selected to capture key dimensions of local economic activity and community well-being, potentially affected by large-scale food manufacturing plant closures. I use the bootstrap procedure to construct the standard errors.[5]

I report results for both log and level specifications. Logs are useful for proportional interpretation and for making outcomes more comparable across counties of different sizes, while levels provide direct policy relevance by quantifying effects in headcounts or dollar amounts. Together, these complementary specifications provide a fuller picture of the local adjustments following closures.

I also conduct event study estimates based on the SDID framework, implemented using the sdid_event Stata package introduced by Ciccia (2024). This procedure estimates cohort-specific effects for each event year, defined relative to the timing of treatment, and then aggregates them using cohort weights to produce average treatment effect estimates by event time. I report the window from 36 months before to 24 months after closure (20 pre-closure and 8 post-closure quarters for quarterly data), because beyond two years the number of treated counties drops sharply and the confidence intervals widen, making longer-run estimates too noisy to interpret reliably.[6]

This empirical design allows me to test the main theoretical predictions from Section 2 that closures cause immediate employment losses, possible multiplier effects in non-manufacturing, and adjustments in population and average wages.

[5] The current version reports estimates with 500 bootstrap draws. Results are insensitive to using more than 500 bootstrap draws.
[6] The control group is still created based on the entire pre-closure period. I only display a 3-year window for monthly data and a 5-year window for quarterly data for clarity.

5. Results

5.1 Employment

Table 2 presents the SDID estimates of the impact of food manufacturing plant closures on local employment using QCEW monthly employment data. County-level total employment declines by about 8.1 percent, corresponding to an average loss of roughly 528 jobs per county. Within manufacturing, employment falls by 23.2 percent, or about 374 jobs, while non-manufacturing employment contracts by 3.7 percent, or about 153 jobs. These results confirm that the consequences of a single closure extend beyond the plant itself, with meaningful spillover effects on the broader local economy.

A useful comparison comes from juxtaposing the estimated manufacturing decline of 374 jobs with the average treatment of 418 jobs, calculated using SDID time weights.[7] The two figures are not statistically different given the standard error of 107 jobs on the manufacturing estimate. Still, the fact that the estimated sectoral decline is somewhat smaller than the measured shock is notable. One possible explanation is that some displaced food manufacturing workers found reemployment in other parts of the manufacturing sector that expanded, so the net contraction within manufacturing was less than the gross number of displaced jobs.

These estimates also allow us to assess the local employment multiplier, defined in Section 2.2 as the ratio of the change in total employment to the change in food manufacturing employment. In practice, there are two natural ways to calculate this. Using the imputed direct shock of 418 jobs as the denominator yields a multiplier of about 1.26, meaning that each plant job lost corresponds to about 1.26 total jobs lost in the county. Alternatively, using the realized decline in manufacturing employment of 374 jobs produces a multiplier of about 1.41,

[7] Calculated with the number of laid off workers in Table 1. Details of the formula are provided in Appendix B.

suggesting that each observed manufacturing job lost is associated with an additional 0.41 jobs lost elsewhere. Both measures are informative, but the first provides a more natural benchmark when assessing the total community impact of a closure, while the second offers a complementary perspective on how broader employment adjusts relative to realized sectoral contraction.

Table 2. SDID ATT Estimates for Employment

	Logs	Levels
Total employment	-0.081***	-528.48***
	(0.015)	(106.38)
Manufacturing	-0.232***	-374.18***
	(0.043)	(107.43)
Non-manufacturing	-0.037***	-153.31***
	(0.011)	(46.05)

Note: ATT estimates are in the top row, bootstrapped standard errors are in parentheses. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

The event-study estimates in Figures 3–5 provide evidence on the dynamics of employment adjustment. Figure 3 shows that total employment tracks the synthetic control closely in the pre-closure period, supporting the validity of the design. At the time of closure, total employment drops sharply, and this immediate decline reflects the direct displacement of workers from the shuttered food manufacturing plant.[8] However, employment continues to decline gradually in the following periods, suggesting the presence of broader spillover effects and indicating that the shock produces an immediate drop followed by additional cumulative losses over time.

[8] In QCEW data, employment is measured during the pay period including the 12th of the month. As a result, the first month of a closure may not fully capture the displacement if workers remain on payroll for part of the period or receive severance payments. The full employment decline typically appears in the following month.

Figure 4 highlights that the immediate adjustment is concentrated in manufacturing. Employment in this sector falls steeply at the closure date and stabilizes at a lower level, consistent with the direct displacement of food processing workers.

Figure 5 shows a slower adjustment path in non-manufacturing. Employment in these sectors trends downward more gradually, with losses emerging in the quarters after the closure. Although less sharp than the manufacturing response, the pattern suggests spillover effects, suggesting that the consequences of plant closures extend into other parts of the local economy beyond the directly affected sector, but with some lag.

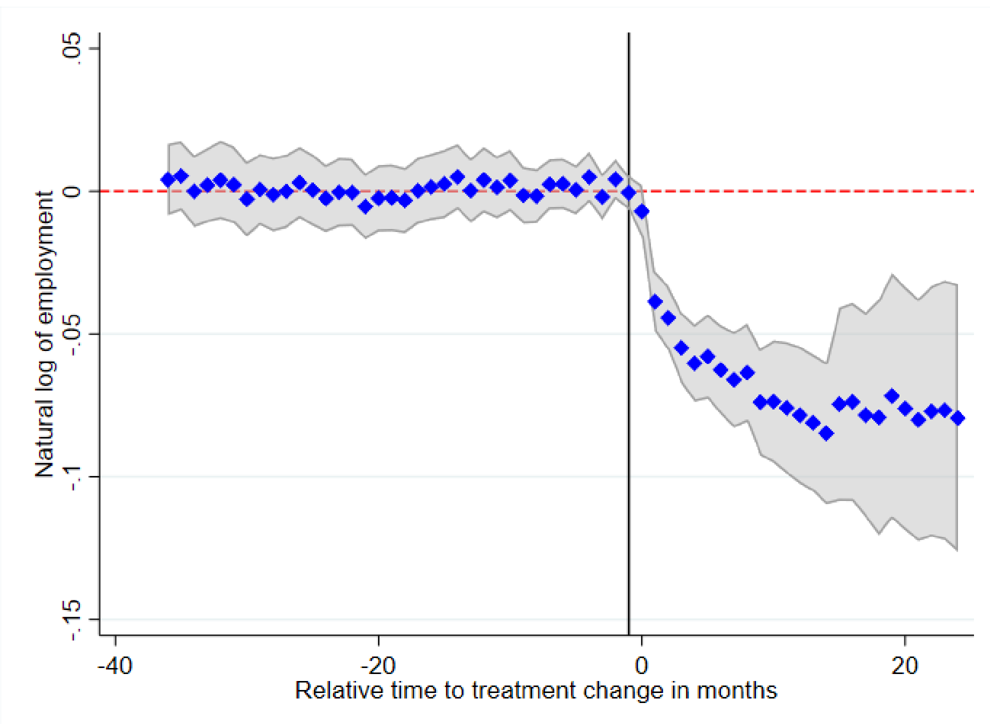

Figure 3. SDID Event Analysis Estimates for Natural Log of Employment

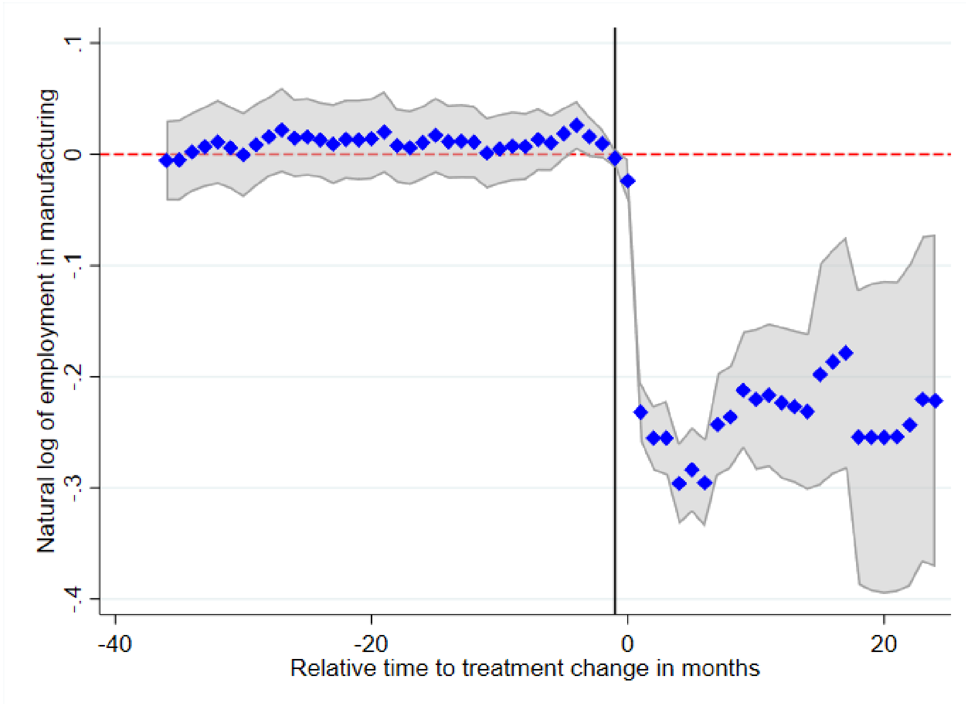

Figure 4. SDID Event Analysis Estimates for Natural Log of Employment in Manufacturing

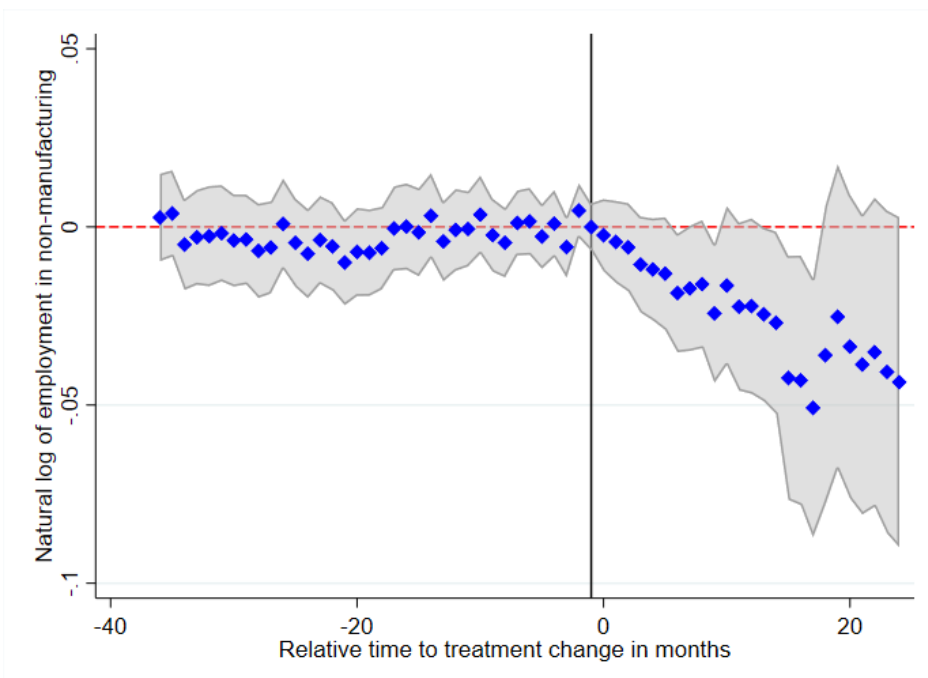

Figure 5. SDID Event Analysis Estimates for Natural Log of Employment in Non-manufacturing

I also estimated effects for moderate treated counties, as defined in Section 3.2. The results are reported in Appendix Table A.2. Unlike the large closures emphasized in the main analysis, these estimates do not show a decline in overall county employment. Manufacturing employment falls significantly, consistent with the direct impact of the closure, but this reduction may be offset by small and imprecise gains in non-manufacturing sectors, leaving total employment essentially unchanged. This pattern suggests that moderate closures may be insufficient to generate broad local effects.

5.2 Racial and Demographic Heterogeneity

Panel A of Table 3 reports employment effects by race. The results show that closures have a disproportionately large impact on minority workers. White employment declines by about 5.9 percent, corresponding to roughly 178 jobs. Hispanic and Black employment fall by 16 percent, or about 118 jobs, and 14.8 percent, or about 41 jobs, respectively. For Asian workers, the estimates point to large proportional declines around 21 percent, but the corresponding changes in absolute numbers are not significant.

To illustrate these dynamics, Figure 6 presents the event study for Hispanic workers, who represent a large share of the food manufacturing workforce in the Midwest and experience the largest relative employment losses. The trajectory shows a clear declining trend in the first three quarters after closure, then the loss seems to be stable over the subsequent quarters. Although the confidence intervals are wide after three quarters due to smaller number of treated counties, the overall downward trend remains clear.

Table 3. SDID ATT Estimates for Employment and Population by Race

	Logs	Levels
A. Employment		
White	-0.059***	-177.57**
	(0.017)	(78.95)
Hispanic	-0.160***	-117.96**
	(0.060)	(58.63)
Black	-0.148***	-40.51**
	(0.048)	(18.48)
Asian	-0.209***	-61.45
	(0.053)	(37.43)
B. Population		
All	-0.003	-273.46***
	(0.005)	(100.26)
White	-0.007	139.10
	(0.008)	(111.90)
Hispanic	-0.055***	-79.13
	(0.020)	(49.83)
Black	-0.060	-124.28**
	(0.037)	(53.97)
Asian	-0.029	-55.96*
	(0.069)	(28.95)

Notes: Estimate in top row, SE in parentheses below. The sample includes all counties with non-missing values in Midwest. Standard errors are bootstrapped. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

Appendix Figures A1–A3 provide the corresponding event studies for White, Black, and Asian workers. Decrease in White employment is more stable but with a smaller magnitude. Black and Asian employment have similar patterns to Hispanic employment that the employment decreases significantly in the first three quarters and then become noisier.

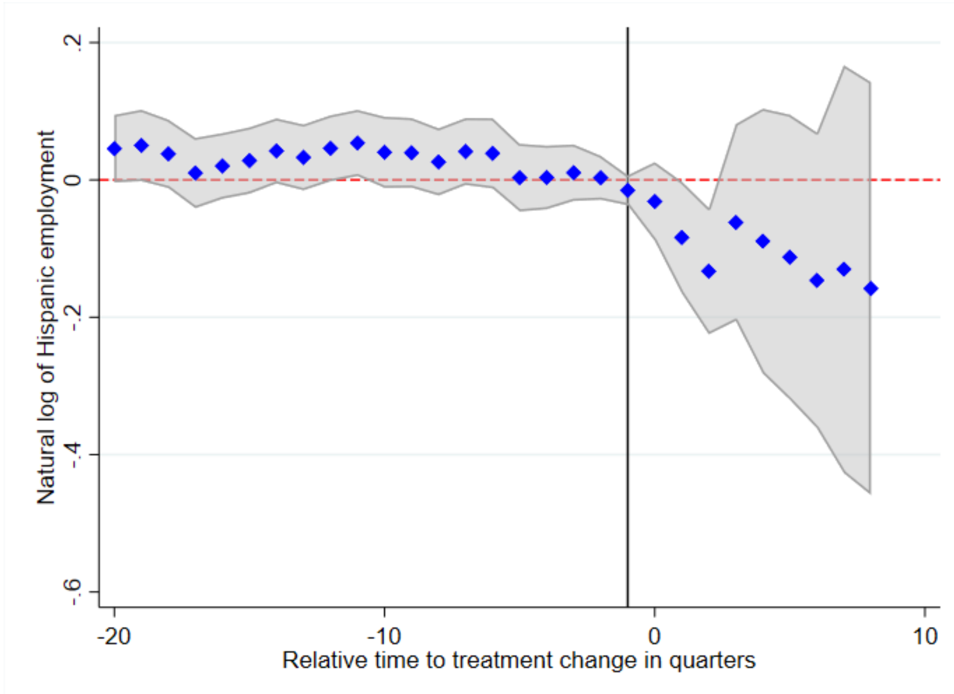

Figure 6. SDID Event Analysis Estimates for Natural Log of Hispanic Employment

Panel B of Table 3 examines population outcomes by race. For total population, the log estimates are statistically insignificant, and it may be because the proportional change is small relative to county size, but the level specification still detects a significant decline of about 273 residents. The effects are uneven across demographic groups. The Hispanic population declines by about 5.5 percent, consistent with the significant employment losses. The black population decreases by 6 percent at an almost statistically significant level, corresponding to a significant decline of 124 residents. A significant decrease of 56 Asian residents is also observed. The White populations show no measurable change.

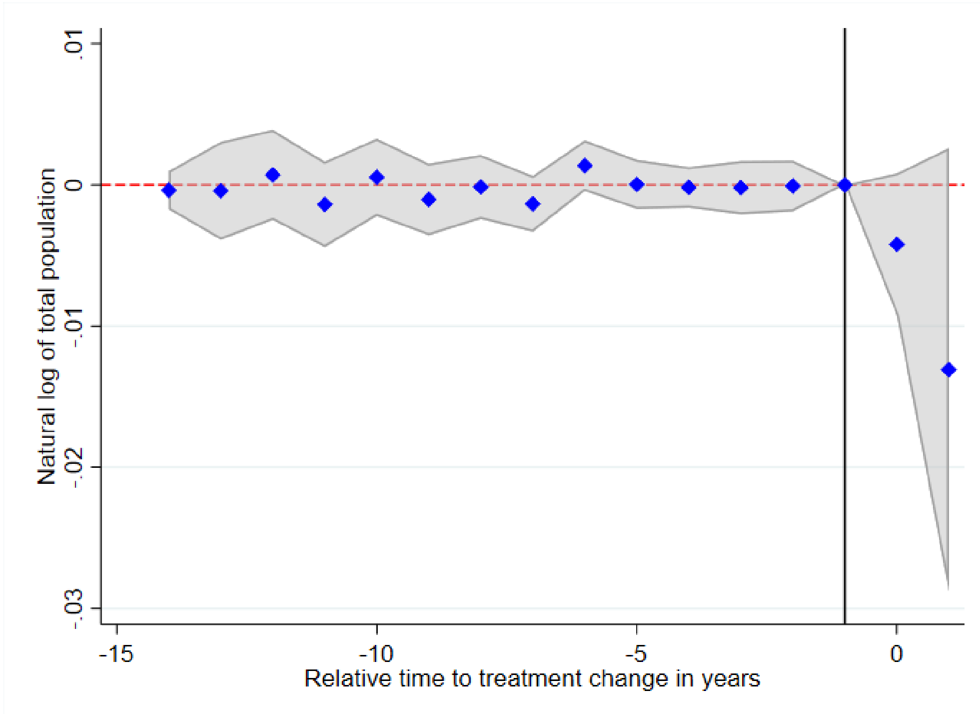

Figure 7. SDID Event Analysis Estimates for Natural Log Total Population

Figure 7 shows that total county population begins to decline following closures, although the estimates are not yet statistically significant in the second post-treatment year. The pattern points to a downward trend, which is plausible given that migration decisions typically occur with a lag relative to job loss. With more post-closure data, these estimates may become more precisely estimated and reveal larger long-run effects.

Appendix Figures A4–A7 provide the racial breakdowns. These show evidence of declines across all racial groups, with Hispanic residents experiencing largest proportional losses, while Black and Asian residents show significant decline at the treatment year. White residents display smaller proportional changes.

Together, these results suggest that closures not only disrupt local labor markets but also contribute to selective out-migration, with minority households more likely to leave affected counties. This reinforces the view that the costs of plant closures are unevenly distributed across communities.

I also examined population adjustments by age group. These results, reported in Appendix Table A.3. Among age groups, the most noticeable declines appear for prime-age adults aged 25-54 and seniors. The decline among prime-age adults is consistent with the decrease in employment, as displaced prime-age workers are the most likely to relocate in response to reduced job opportunities. The decline in the senior population may reflect selective out-migration after the spillovers in service industries. Given the limited number of post-treatment periods and the need for additional precision, I place these results in Appendix Table A.2 and treat them as suggestive.

5.3 Unemployment Rate

Closures also lead to a measurable increase in local unemployment. On average, the unemployment rate rises by about 0.5 percentage points, which is significant at the one percent level. This suggests that following a closure, a sizable share of displaced workers are not immediately reabsorbed into the labor market.

Figure 8 shows the corresponding event-study estimates. The unemployment rate closely tracks the synthetic control before the closure. At the closure date, the rate rises sharply and remains elevated in the following months. After about 5 months, the estimates begin to trend downward, suggesting a possible convergence back toward pre-closure levels. However, later periods after 15 months are based on relatively few treated counties, and the confidence intervals widen substantially. More post-closure data will be needed to determine whether unemployment stabilizes at a permanently higher level, consistent with the persistent scenario in Section 2.3, or gradually returns toward its baseline, consistent with the recovery scenario.

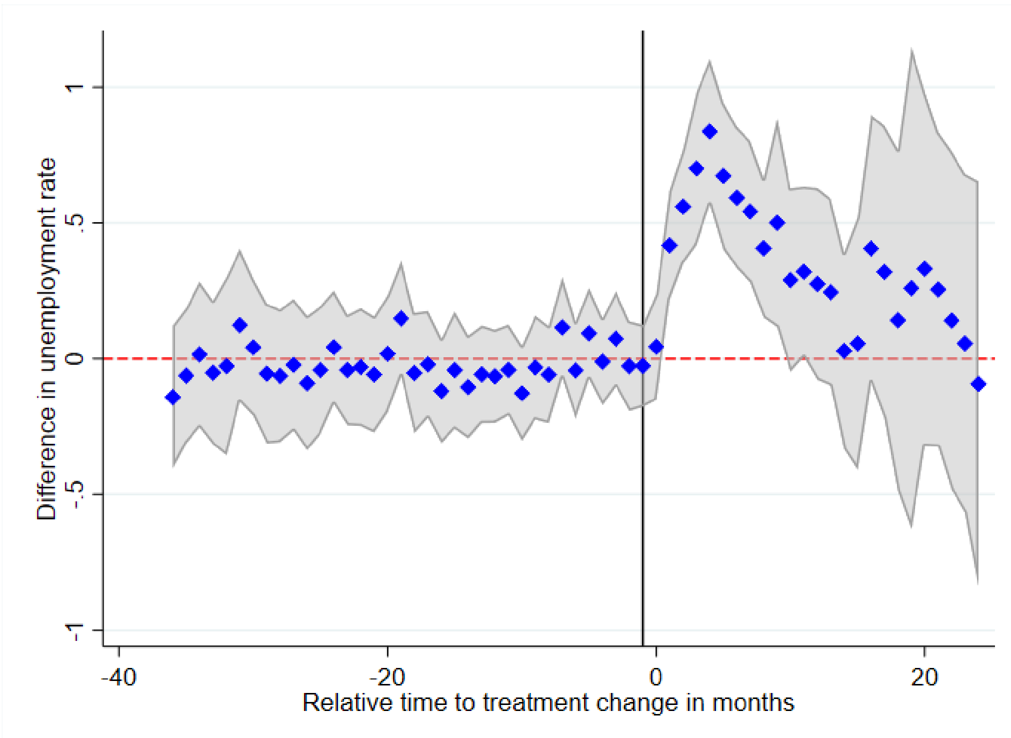

Figure 8. SDID Event Analysis Estimates for Unemployment Rate

5.4 Wages and Earnings

Table 4 reports the estimated effects of closures on average weekly wages from QCEW and individual average monthly earnings from QWI. Panel A shows little evidence of systematic changes in average weekly wages after the closure.

Table 4. SDID ATT Estimates for Average Wage and Earnings

	Logs	Levels
A. Wage		
Average weekly wage	-0.020	-14.52
	(0.019)	(16.89)
Manufacturing average weekly wage	-0.056	-47.11
	(0.079)	(77.71)
Non-manufacturing weekly wage	0.006	2.15
	(0.009)	(8.92)
B. Earnings		
All	-0.015*	-50.44
	(0.009)	(34.03)
White	-0.015	-59.90*
	(0.009)	(35.17)
Hispanic	-0.093*	-152.19
	(0.048)	(167.92)
Black	0.025	165.55
	(0.041)	(134.26)
Asian	0.036	90.36
	(0.041)	(194.58)

Notes: Estimate in top row, SE in parentheses below. The sample includes all counties with non-missing values in Midwest. Standard errors are bootstrapped. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

Panel B turns to individual monthly earnings and reveals clearer distributional effects. Overall, average earnings decline by about 1.5 percent. The decline is especially large for Hispanic workers, who see average earnings fall by 9.3 percent, consistent with the disproportionate employment losses documented above. By contrast, estimates for Black and Asian workers are not significantly different from zero.

The event-study results provide further insight into these dynamics. Figure 9 shows the path of manufacturing average weekly wages around closure events. Average wages rise briefly at the time of closure before entering a persistent decline. The short-run increase likely reflects a compositional effect, as lower-paid workers disproportionately lose their jobs, temporarily raising the average among those who remain employed. Over the following quarters, however, average weekly wages trend downward. This is consistent with the standard labor market model that as labor demand decreases, the new equilibrium wage will be lower.

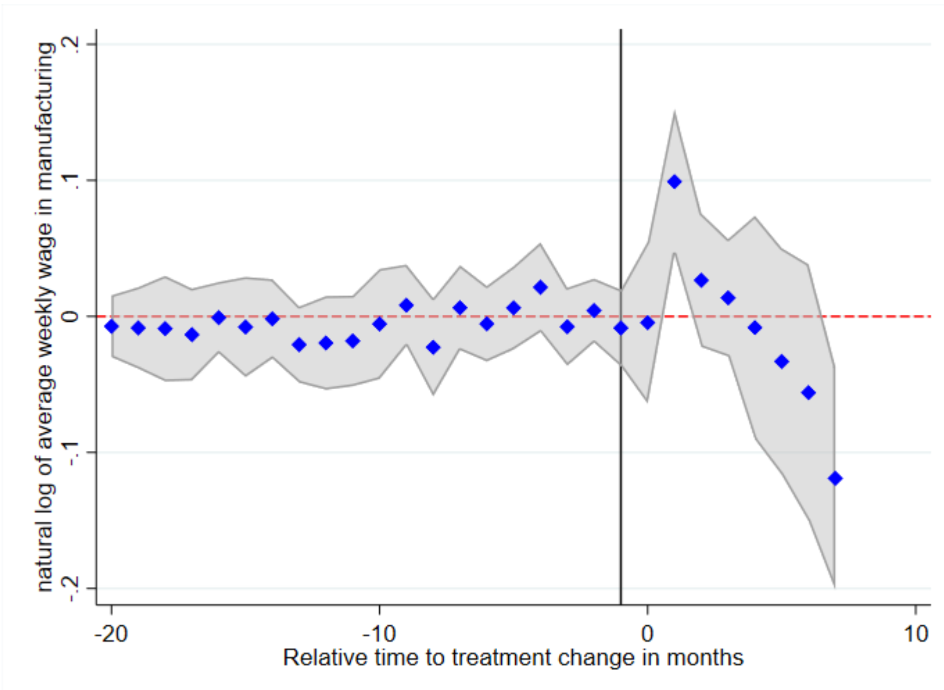

Figure 9. SDID Event Analysis Estimates for Natural Log of Wage in Manufacturing

Appendix Figure A8 presents the event-study estimates for weekly wages across all sectors. The figure shows a downward trend following closures, similar to the pattern for manufacturing wages in Figure 9, though without the temporary increase at the closure date. This broader decline suggests that wage effects extend beyond manufacturing, with a smaller magnitude than in the manufacturing sector.

5.5 Industry Spillovers

Table 5 summarizes the effects of closures on employment across selected industries. Beyond manufacturing, several local service industries, including construction, education and health services, and professional and business services, also show declines, consistent with spillover effects into sectors that depend on local demand.

Employment in animal production falls sharply in the few counties where detailed data are available, underscoring the upstream dependence of farm activity on food processing facilities. Although the estimates come from only three treated counties, the magnitude of the effect points to meaningful linkages between agriculture and downstream processing.

I also find evidence that closures reduce the number of local establishments. While the log specification yields a small and statistically insignificant effect, the level estimates indicate an average decline of more than 31 establishments per county. This suggests that closures are not only associated with job losses but also with broader contraction in the local business base. The shrink of the market mainly comes from industries other than manufacturing, as there is no significant decline in establishments in manufacturing.

Together, these results confirm that food manufacturing plant closures generate meaningful spillovers that extend into both local service industries and upstream agriculture, while also weakening the broader firm structure of local economies

5.6 Other Outcomes

I also examined several additional outcomes for broader impacts of plant closures. Appendix Figures A9–A10 present event-study estimates from QWI data on job losses and new hires. The results show a sharp spike in job losses at the time of closure, consistent with direct displacement, and little evidence of offsetting increases in new hires.

Beyond labor market flows, I explored outcomes related to local housing markets and social well-being. Using FHFA county-level housing price indices, I find no evidence that closures affect local housing values. Similarly, estimates for SNAP participation, mental health outcomes, and child poverty show no significant changes following closures.

Table 5. SDID ATT Estimates for Industry Spillovers

	Log	Levels
A. Employment		
Construction	-0.018	-24.85**
	(0.044)	(11.64)
Education and health services	-0.028	-36.32*
	(0.020)	(20.45)
Leisure and hospitality	-0.079	-36.01
	(0.050)	(34.10)
Natural resources and mining	-0.059	-11.70
	(0.043)	(6.27)
Professional and business services	-0.129*	-39.41*
	(0.067)	(21.29)
Trade, transportation, and utilities	-0.022	-28.76
	(0.018)	(20.89)
Animal production[a]	-0.682*	-66.24**
	(0.351)	(32.05)
B. Establishment		
Establishment	-0.032	-31.61***
	(0.021)	(11.66)
Manufacturing establishment	-0.035	-0.27
	(0.041)	(0.73)

Note: Estimate in top row, SE in parentheses below. The sample includes all counties with non-missing values in Midwest. Standard errors are bootstrapped. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.
[a] The estimate for this outcome is based on only 3 treated counties in primary group because of the confidentiality of detailed industry data.

6. **Robustness Checks**

To assess the robustness of the main findings, I conduct a series of sensitivity analyses. These exercises test whether the estimated effects are sensitive to anticipation effects, alternative timing assumptions, or sample composition.

6.1 Placebo Timing: Six Months Earlier

A first robustness check shifts the treatment start six months earlier than the actual closure. This test can check if I successfully identify the closure date, and it also serves as a check for anticipation effects. If the closure dates are not correct or if closures triggered early adjustments, I would observe significant changes during this placebo window.

Figure 10 plots the event-study estimates for total employment under this placebo timing. As expected, the first six months after the placebo treatment date show coefficients close to zero and statistically indistinguishable from zero. Beyond that window, the path of estimated employment losses converges closely to the baseline specification, with persistent and significant declines emerging after the actual closure date. This pattern reassures that the post-treatment effects documented in Section 5.1 are not artifacts or biased because of anticipation effects.

Full ATT comparisons for other outcomes are reported in Appendix Table A.4. The corresponding ATT is slightly attenuated when calculated from the placebo date, because the average incorporates six additional months in which no effect is present. For example, log employment falls by 7.5 percent under the placebo timing, compared to 8.1 percent in the baseline. Overall, the placebo results strengthen confidence in the identification strategy.

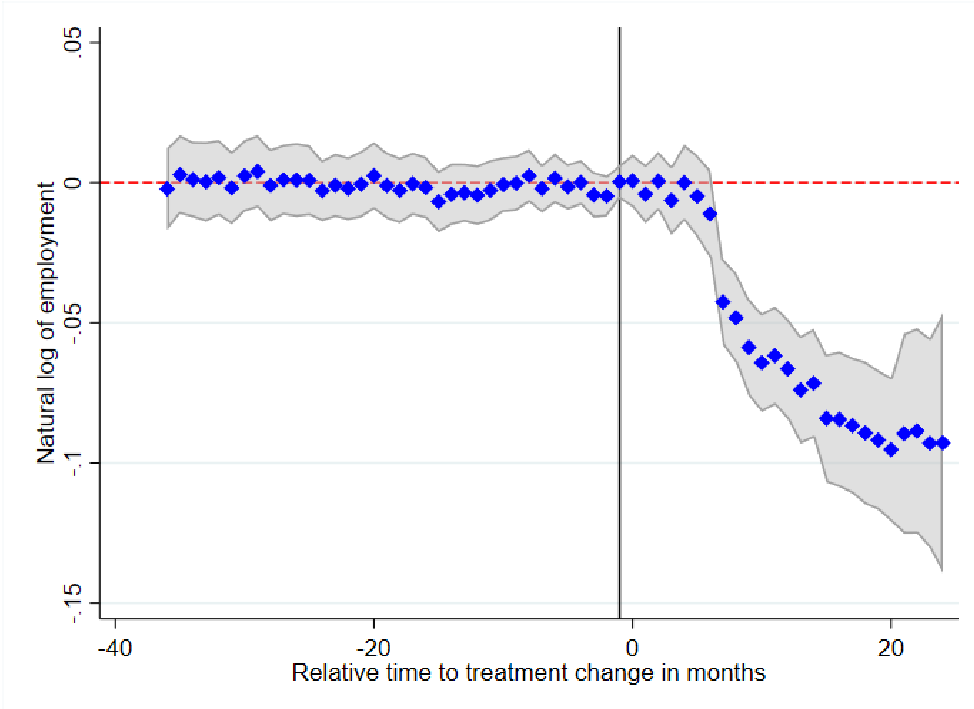

Figure 10. SDID Event Analysis Estimates for Total Employment with Placebo Timing

6.2 Notification Timing

As a second robustness check, I redefine treatment timing using the WARN Act notification date rather than the effective date. Because WARN requires firms to provide at least 60 days' notice before mass layoffs, this alternative specification allows us to test for anticipation effects, such as workers leaving jobs early or firms scaling down operations before the official closure.

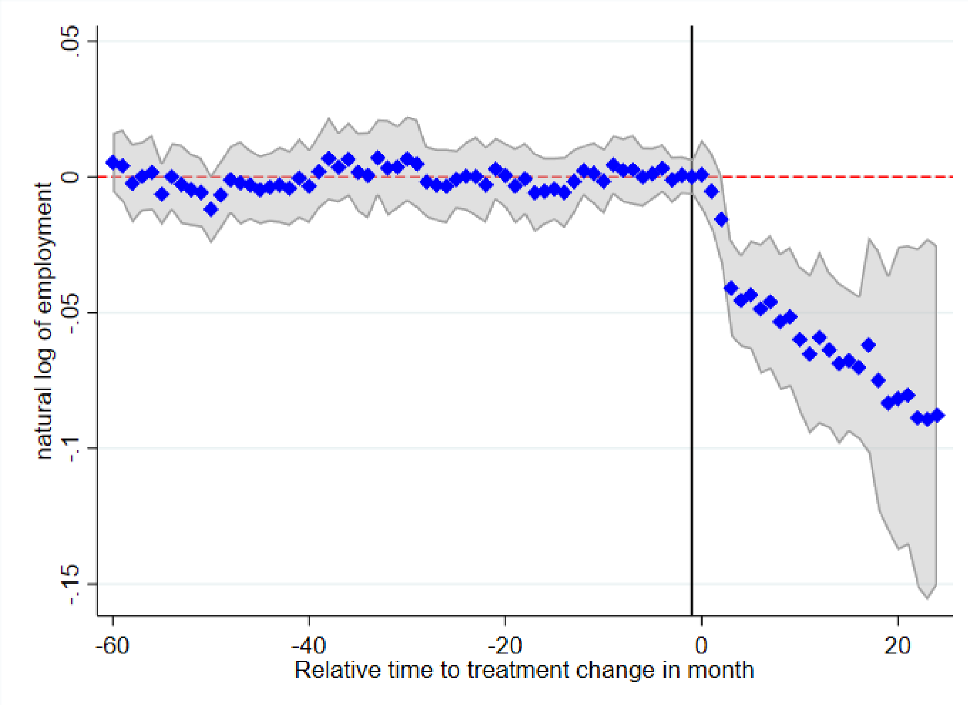

Figure 11. SDID Event Analysis Estimates for Total Employment Using Notification-Date Treatment

Figure 11 presents the event-study estimates under this specification. The trajectory closely mirrors the baseline. Employment in treated counties tracks the synthetic control in the pre-notice period, with no sign of anticipatory adjustment at the time of notification. The sharp and persistent decline begins only at the closure itself, roughly two months later, and the post-treatment path is nearly identical to the baseline.

This similarity indicates that the main results are not sensitive to the exact choice of treatment timing. The corresponding ATTs for employment are reported in Appendix Table A.5, which confirm the absence of anticipatory effects and show smaller but close estimates to the baseline specification.

6.3 Excluding Adjacent Counties from the Donor Pool

The third robustness check re-estimates the model after excluding counties adjacent to treated units from the donor pool. This addresses the concern that neighboring counties might themselves be affected by spillovers from plant closures. For example, neighboring counties can be affected through commuting or regional supply chains, which could bias the estimates toward zero if such counties are included as controls.

Table A.6 reports the results that are basically identical to the baseline specification. Total employment falls by about 8.1 percent, manufacturing by 23.2 percent, and non-manufacturing by 3.8 percent, all basically the same as the baseline estimates in Table 2. The similarity of these results to the baseline specification suggests that spatial spillovers into neighboring counties do not affect the main findings.

6.4 Excluding Metropolitan Counties and Larger Counties

Although the majority of treated counties are rural, four treated counties fall within metropolitan statistical areas (MSAs), and only Dallas County, Iowa, has a population exceeding 50,000. Because economic activity is more diversified in these places, the relative shock from a single plant closure is likely attenuated compared to rural counties. Including them should therefore, if anything, bias the estimated effects toward zero.

To assess this possibility, I conduct three robustness checks. Table A.7 reports estimates from a specification that excludes Dallas County, the largest and most urbanized treated county. The results show employment losses that are nearly identical to the baseline. Total employment declines by 8.2 percent, corresponding to an average loss of 519 jobs. Manufacturing employment falls by 22.2 percent, or 359 jobs, while non-manufacturing employment falls by 3.8 percent, or 161 jobs. All estimates are close to the baseline estimates in Table 2.

Table A.8 reports estimates after excluding all four treated counties located within MSAs. The results again remain close to the baseline. Total employment falls by 8.9 percent, equal to 538 jobs. Manufacturing employment declines by 23.2 percent, or 387 jobs, and non-manufacturing employment declines by 4.0 percent, or 157 jobs. These findings confirm that the baseline estimates are not sensitive when dropping metro counties. Including metro counties does not attenuate the effects of closure much.

Finally, Table A.9 reports results when restricting the analysis to counties with fewer than 50,000 residents. In this smaller and more rural sample, closures reduce total employment by 8.2 percent, equal to 511 jobs. Manufacturing employment falls by 22.3 percent, or 335 jobs, and non-manufacturing employment falls by 3.9 percent, or 153 jobs. The results demonstrate that the main findings are robust to excluding larger counties and remain highly consistent with the baseline specification.

Together, these robustness checks confirm that the estimated impacts are not affected by including metro counties. The substantial employment losses documented in Section 5 hold across different sample definitions, underscoring the robustness of the main results.

7. Conclusion

This paper provides the first systematic evidence on the local economic impacts of food manufacturing plant closures across Midwestern counties. Using the synthetic difference-in-differences method, I find that closures lead to substantial and persistent employment losses. Total county employment falls by about 8 percent, equivalent to an average loss of 528 jobs compared with an average layoff size of 418 workers. Within manufacturing, employment drops immediately by more than 23 percent, while non-manufacturing employment erodes more gradually in the following months. Consistent with these dynamics, the unemployment rate spikes sharply at the closure date and remains elevated for several months before showing signs of decline.

The consequences are not evenly distributed. Hispanic and Black workers bear larger proportional employment losses compared to White workers, and these groups also experience local population decline, pointing to selective out-migration. Event-study estimates reveal that these losses emerge quickly at the closure date and continue to accumulate in subsequent periods, underscoring both the immediacy of direct displacement and the slower adjustments in broader local labor markets.

Taken together, these findings demonstrate that food manufacturing plant closures impose costs that extend well beyond the directly displaced workers, resulting in broad and unequal disruptions to rural and small-town economies. Future research could extend this analysis to other regions of the United States, explore the conditions under which recovery is possible, and assess the role of place-based policies in supporting resilience and reducing inequality.

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Appendix A

Table A.1: Summary Statistics for Food Manufacturing Plant Closures in Treated Counties, Midwest, 2010–2024

	(1) Mean	(2) Standard deviation	(3) Min	(4) Max
A. Total treatment group				
Number of workers affected	200.0	219.4	20	1513
Number of closures per treated county	2.17	1.66	1	7
Relative layoff size	1.50%	3.23%	0.00014%	22.31%
Treatment year	2018.8	3.8	2012	2024
B. Primary treatment group				
Number of workers affected	549.2	442.6	92	1513
Relative layoff size	6.15%	5.32%	3.04%	22.31%
Treatment year	2022.3	2.8	2015	2024

Note: Source: WARN.

Table A2. SDID ATT Estimates for Employment in Primary and Moderate treatment groups

	Primary treatment	Moderate treatment
Total employment	-0.081***	0.039
	(0.015)	(0.034)
Manufacturing	-0.232***	-0.049*
	(0.043)	(0.029)
Non-manufacturing	-0.037***	0.059
	(0.011)	(0.040)

Note: Estimate in top row, SE in parentheses below. The sample includes all counties with non-missing values in Midwest. Standard errors are bootstrapped. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

Table A.3 SDID ATT Estimates for Population by Age Group

	Logs	Levels
Age 0-14	0.002	66.12*
	(0.009)	(39.79)
Age 15-24	-0.027	-29.21
	(0.023)	(87.44)
Age 25-54	-0.008	-200.78***
	(0.006)	(58.98)
Age 55-64	0.018	10.57
	(0.013)	(26.67)
Age 65+	-0.023**	-59.82*
	(0.010)	(33.05)

Note: Estimate in top row, SE in parentheses below. The sample includes all counties with non-missing values in Midwest. Standard errors are bootstrapped. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

Table A.4. SDID ATT Estimates for Employment with 6-month-early treatment

	Log	Levels
Total employment	-0.075***	-399.27***
	(0.016)	(127.90)
Manufacturing	-0.218***	-343.14***
	(0.041)	(82.89)
Non-manufacturing	-0.034***	-75.01
	(0.013)	(131.47)

Note: Estimate in top row, SE in parentheses below. The sample includes all counties with non-missing values in Midwest. Standard errors are bootstrapped. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

Table A.5. SDID ATT Estimates for Employment with Notification-Date Treatment

	Log	Levels
Total employment	-0.080***	-479.11***
	(0.016)	(121.52)
Manufacturing	-0.224***	-365.33***
	(0.038)	(100.58)
Non-manufacturing	-0.038***	-107.24
	(0.014)	(107.11)

Note: Estimate in top row, SE in parentheses below. The sample includes all counties with non-missing values in Midwest. Standard errors are bootstrapped. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

Table A.6 SDID ATT Estimates for Employment Excluding Adjacent Counties from Donor Pool

	Log	Levels
Total employment	-0.081***	-531.95***
	(0.015)	(114.69)
Manufacturing	-0.232***	-375.96***
	(0.042)	(115.15)
Non-manufacturing	-0.038***	-157.19***
	(0.011)	(41.15)

Note: Estimate in top row, SE in parentheses below. The sample includes all counties with non-missing values in Midwest. Standard errors are bootstrapped. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

Table A.7 SDID ATT Estimates for Employment Excluding Dallas County

	Logs	Levels
Total employment	-0.082***	-519.31***
	(0.014)	(110.20)
Manufacturing	-0.222***	-359.41***
	(0.040)	(105.67)
Non-manufacturing	-0.038***	-160.93***
	(0.011)	(38.77)

Note: ATT estimates are in the top row, bootstrapped standard errors are in parentheses. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

Table A.8 SDID ATT Estimates for Employment Excluding Treated MSA Counties

	Logs	Levels
Total employment	-0.089***	-538.08***
	(0.016)	(135.68)
Manufacturing	-0.232***	-387.29***
	(0.043)	(134.03)
Non-manufacturing	-0.040***	-157.20***
	(0.013)	(39.97)

Note: ATT estimates are in the top row, bootstrapped standard errors are in parentheses. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

Table A.9 SDID ATT Estimates for Employment Excluding Metro Counties

	Logs	Levels
Total employment	-0.082***	-510.87***
	(0.015)	(115.52)
Manufacturing	-0.223***	-334.80***
	(0.040)	(113.09)
Non-manufacturing	-0.039***	-153.21***
	(0.012)	(37.05)

Note: ATT estimates are in the top row, bootstrapped standard errors are in parentheses. *Significantly different from zero at the ten percent level. **Significant at five percent level. ***Significant at one percent level.

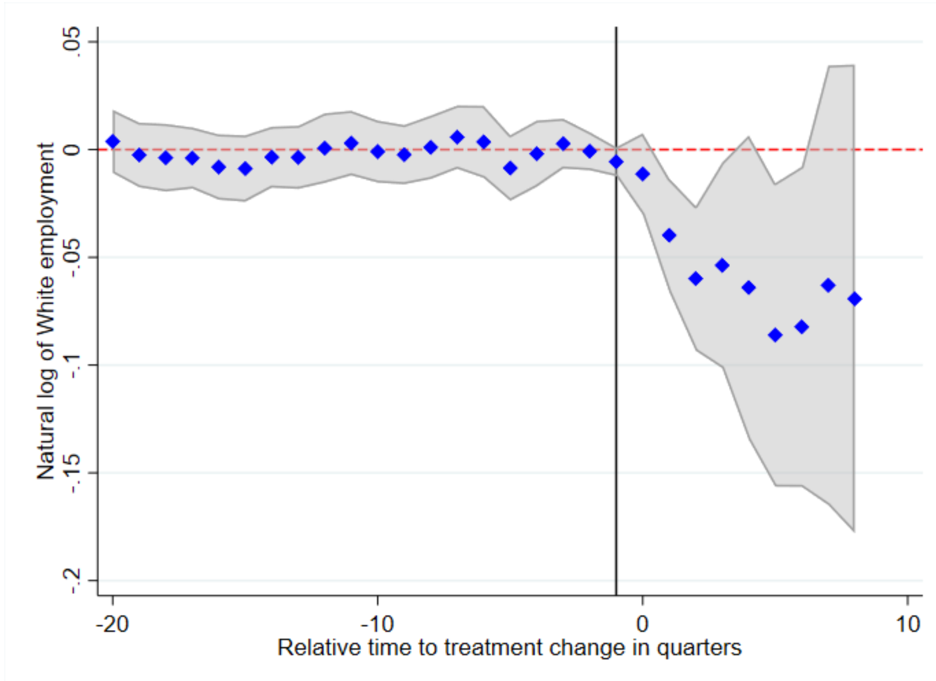

Figure A.1. SDID Event Analysis Estimates for Natural Log of White Employment

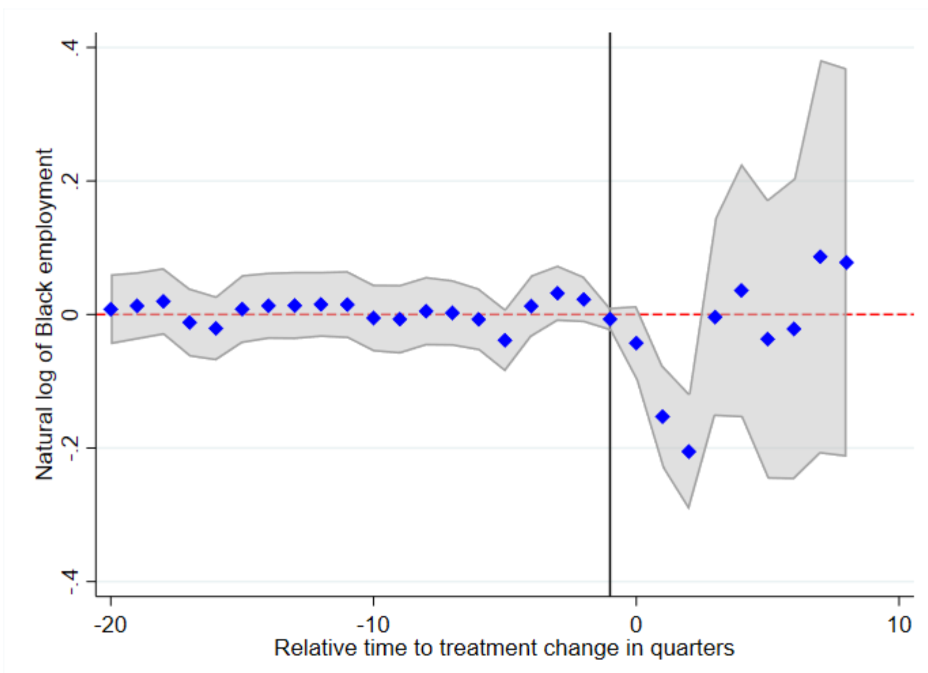

Figure A.2. SDID Event Analysis Estimates for Natural Log of Black Employment

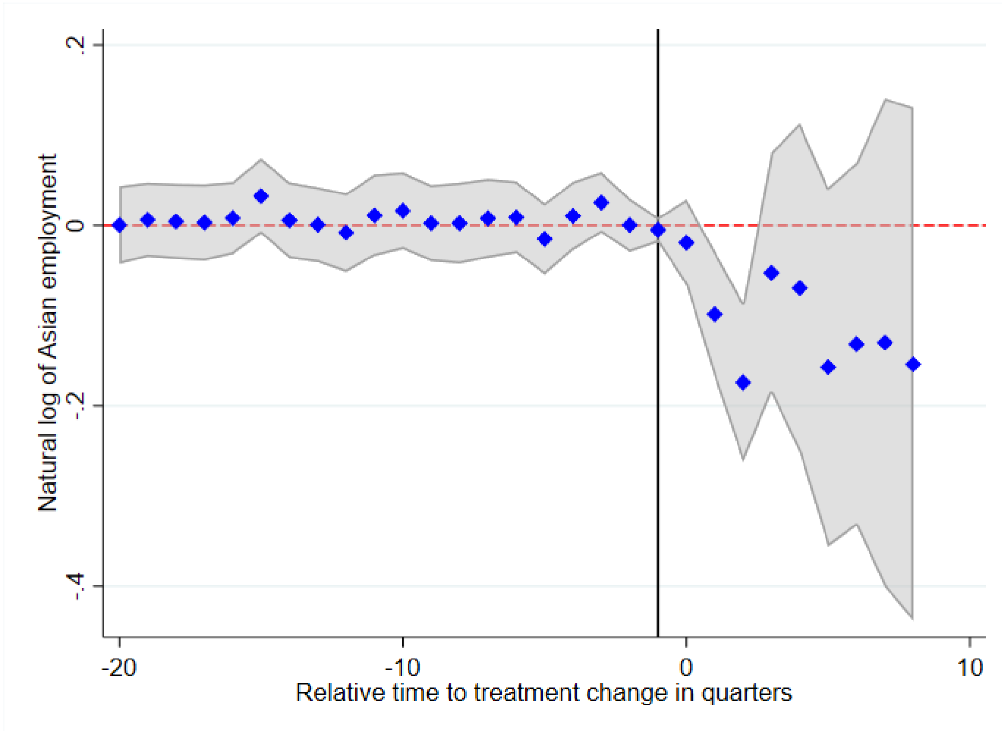

Figure A.3. SDID Event Analysis Estimates for Natural Log of Asian Employment

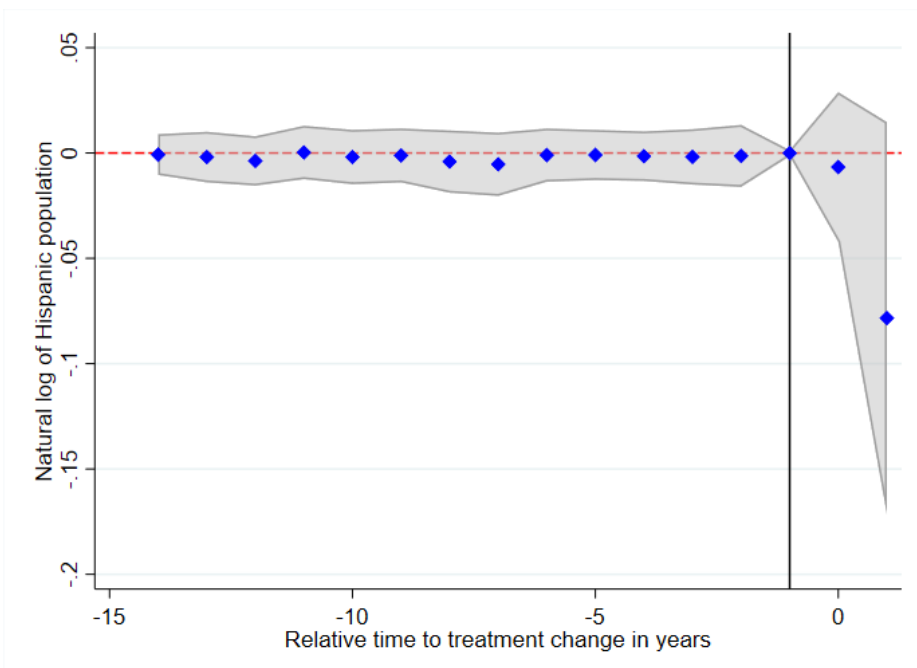

Figure A.4. SDID Event Analysis Estimates for Natural Log Hispanic Population

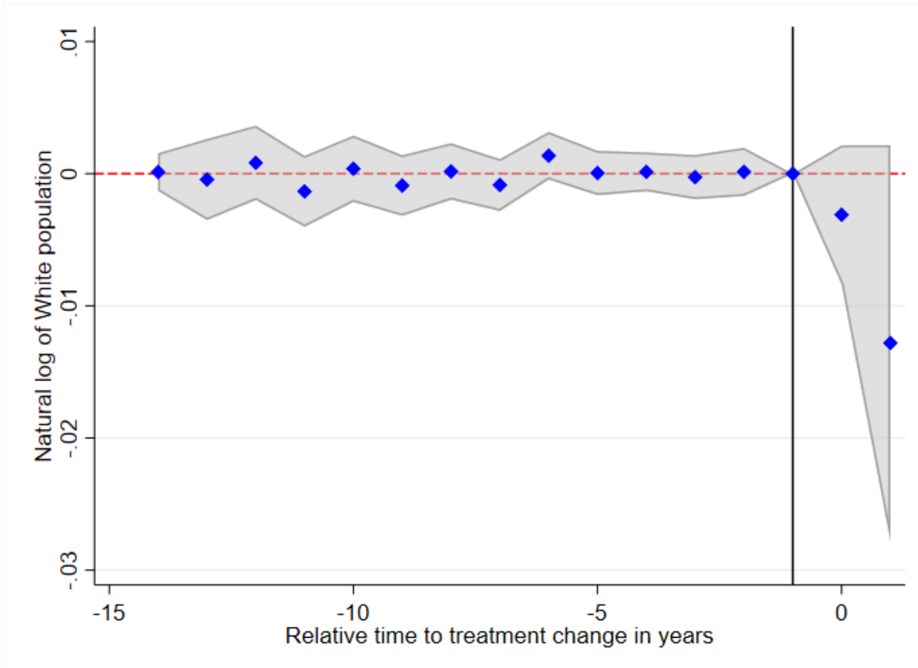

Figure A.5. SDID Event Analysis Estimates for Natural Log White Population

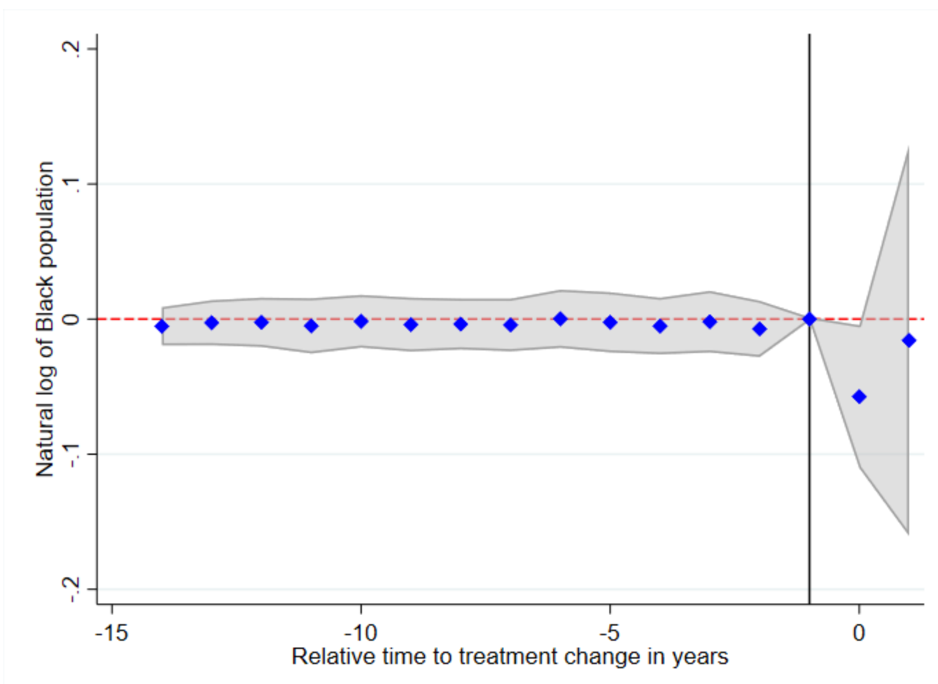

Figure A.6. SDID Event Analysis Estimates for Natural Log Black Population

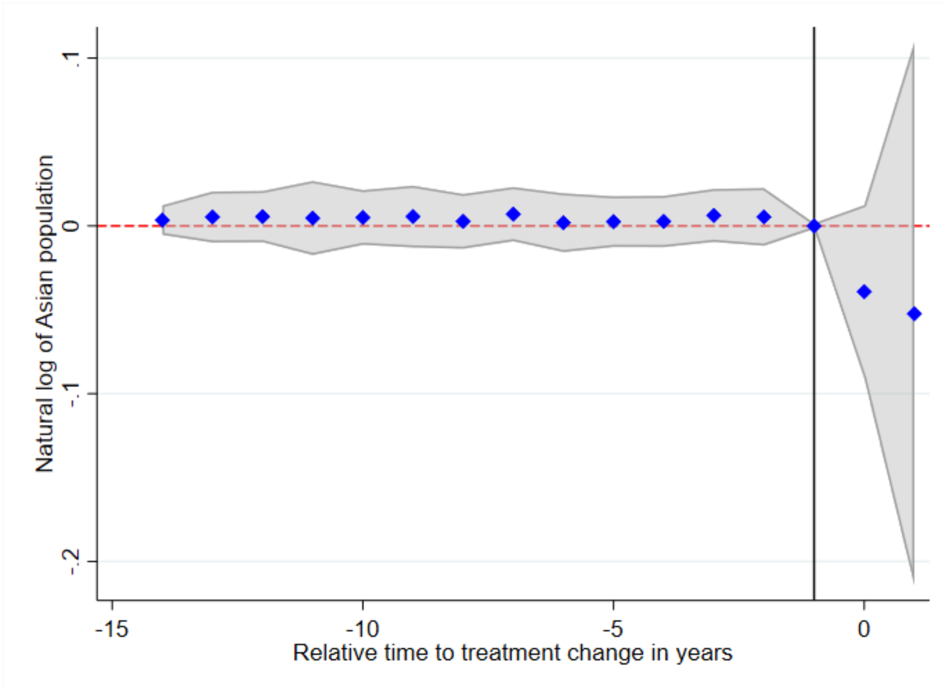

Figure A.7. SDID Event Analysis Estimates for Natural Log Asian Population

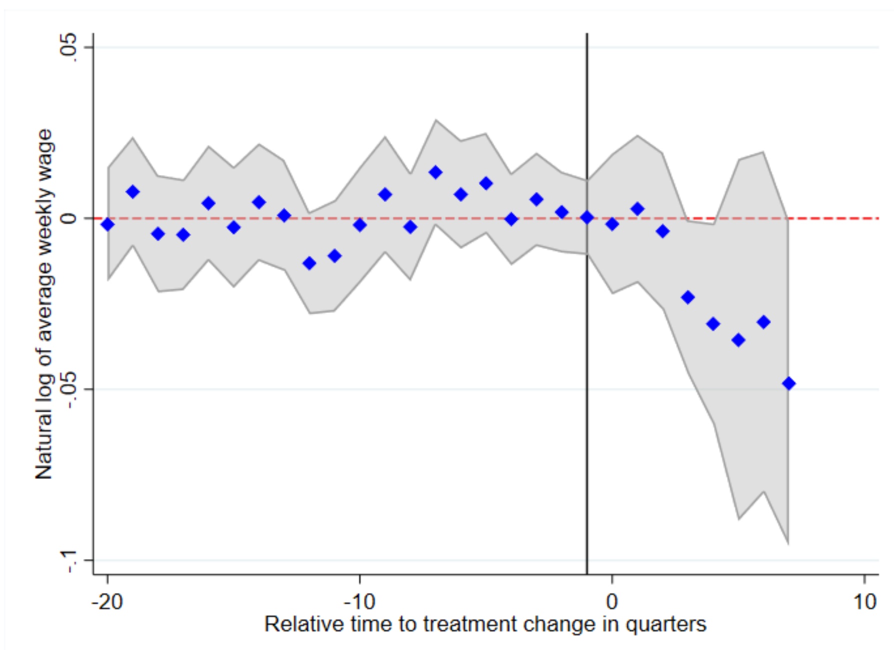

Figure A8. SDID Event Analysis Estimates for Natural Log of Average Weekly Wage

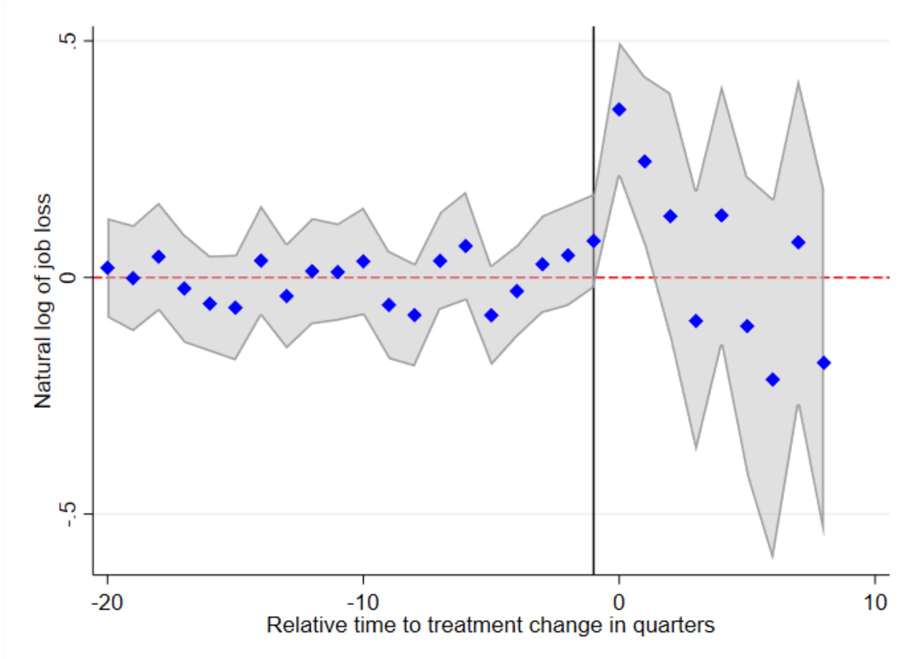

Figure A9. SDID Event Analysis Estimates for Natural Log of Job Losses

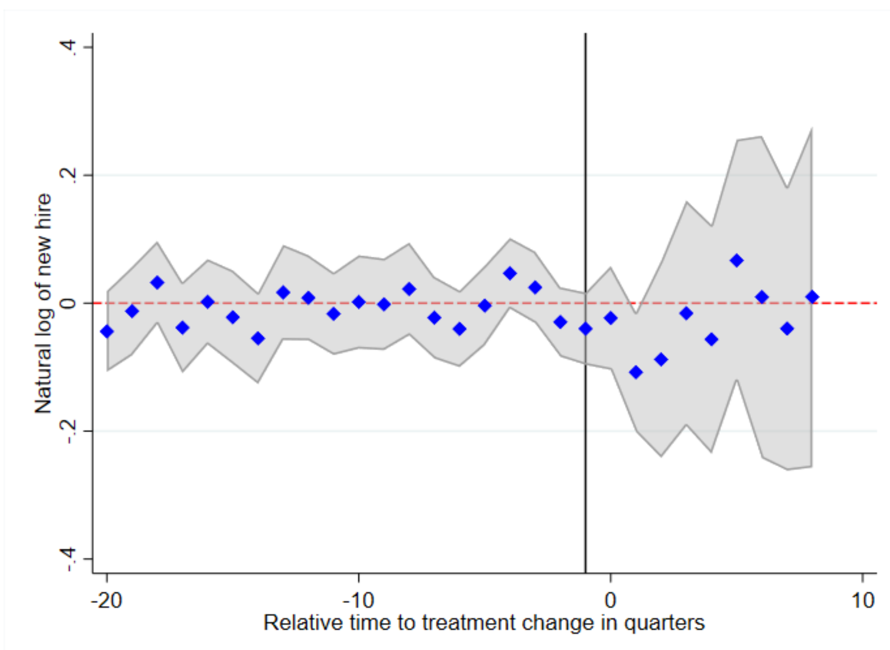

Figure A10. SDID Event Analysis Estimates for Natural Log of New Hires

Appendix B. Calculating Average WARN Layoffs Consistent with SDID

To align WARN layoff counts with the SDID framework, I compute a period-weighted average layoff size, where counties with longer observed post-treatment horizons contribute proportionally more. Let L_i denote the number of WARN layoffs in treated county i, and let T_i denote the number of post-treatment months observed for that county through December 2024. The weighted average layoff size is

$$\bar{L} = \frac{\sum_{i=1}^{N} L_i \cdot T_i}{\sum_{i=1}^{N} T_i}$$

Using this approach, the average closure in the sample corresponds to approximately 418 workers. This estimate is close to, though somewhat larger than, the SDID estimate of realized county-level job losses (≈374), reflecting that not all announced layoffs result in sustained employment declines.

Appendix C. Additional Data Source

To capture broader aspects of community well-being, I use annual county-level indicators from the County Health Rankings & Roadmaps program, including measures of health behaviors and social determinants. In addition, I include county-level Supplemental Nutrition Assistance Program (SNAP) participation, available at bi-annual frequency from USDA Food and Nutrition Service (FNS) administrative records, as a proxy for household economic distress.