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**ABSTRACT**

We present new evidence on the labor market effects of large and permanent minimum wage increases by examining the policy changes implemented by Minneapolis and announced by Saint Paul in 2018. Beginning with synthetic difference-in-differences methods, we find that the increase in the minimum wage substantially decreased employment in restaurants, retail, and health, even after accounting for potential confounding effects from the pandemic and civil unrest. Next, using variation in exposure to the minimum wage across establishments and workers within zip codes and industries of the Twin Cities, we find employment effects that are about half as large as those from the time series. We quantify an industry equilibrium model to rationalize our estimates and differentiate among competing economic mechanisms that determine how the minimum wage affects the labor market. Our model accounts quantitatively for the importance of reduced entry in generating a larger employment decline than implied by the cross-sectional estimates; for the employment decline from the announcement of a future minimum wage increase; and for the more negative employment effects of the minimum wage over time, relative to the size of the increase, and when the economy is in a recession.

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# 1 Introduction

Increasing the minimum wage is one of the most debated economic policies in the United States. Despite decades of academic research, both policymakers and economists are still debating the economic impacts of minimum wages on workers, establishments, and regions. Estimating the effects of the minimum wage is also important for understanding which classes of economic models better characterize labor markets.

We present new evidence from two minimum wage policies instituted recently in Minneapolis and Saint Paul that bears on this debate. Our paper differs in several ways from previous studies on the minimum wage. First, the minimum wage increase that we examine is local, large, permanent, and interacts with a recession for a subperiod of our sample. Second, we use a new administrative dataset that improves measurements relative to previous studies. Third, in terms of the research design, we use both time series and cross-sectional sources of variation to estimate the effects of the minimum wage and quantify an equilibrium model to rationalize our estimates and differentiate among competing economic mechanisms that determine the transmission of a minimum wage increase to the labor market. Finally, we present evidence of anticipation effects arising from the announcement of a future minimum wage change.

Minneapolis began implementing its minimum wage policy in 2018 with the aim of reaching the statutory minimum of 15 dollars per hour for all workers by 2024. Saint Paul introduced a similar policy in 2018 for implementation beginning in 2020. The changes in the minimum wage are permanent because the minimum wage is indexed to inflation. The changes are large by historical standards, with the minimum wage increasing by 53 percent in Minneapolis and by 42 percent in Saint Paul. Our analyses use a new administrative dataset on workers and establishments from Minnesota. The dataset merges worker-level Unemployment Insurance data with establishment-level Quarterly Census of Employment and Wages data to create a quarterly dataset between 2001(1) and 2023(4) on workers' hours and wages, as well as the establishments where they work by industry, zip code, and city. Our dataset improves measurement relative to that of previous studies, because we present estimates on hours worked, we include in our analyses firms with multiple establishments, and we leverage detailed physical location data to exploit within-city variation across establishments and workers.

We begin our analyses by using time series variation to compare outcomes in the Twin Cities with those of control cities from the rest of the state of Minnesota. For this comparison, we adopt the synthetic control method proposed by Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2015) and augment it with fixed effects, following Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021). We find wage gains in most low-wage industries in Minneapolis and in some industries in Saint Paul. However, the minimum wage policy is associated with employment declines in various industries. Employment in restaurants begins to decline before the pandemic, with the decline significantly accelerating during the first year of the pandemic. Despite rebounding in 2021, employment in restaurants declines by around 25 percent by the end of 2023. In addition to restaurants, we also estimate employment declines in retail and in health. Industries with lower initial wages experience larger wage gains and larger employment and earnings losses.

One interpretation for the decline in restaurant employment is that the pandemic recession interacted with the minimum wage to accelerate the employment losses. However, the post-pandemic results could plausibly reflect a differential sensitivity to the pandemic recession for the synthetic control relative to that of Minneapolis and Saint Paul. Additionally, the Twin Cities experienced idiosyncratic shocks, such as civil unrest in the second quarter of 2020, that may not be differenced out in the post-treatment period.

We overcome these challenges for the interpretation of our results in two ways. First, as potential control units, we use other U.S. cities that also faced lockdowns and civil unrest to some extent, but did not experience increases in their minimum wage. Using the sample of other U.S. cities, we continue to find jobs declines in restaurants, in retail, and in health. However, these declines are smaller in magnitude than the ones we estimated using variation from within Minnesota, plausibly because they difference out other factors affecting larger cities during and after the pandemic. When we directly adjust jobs for the impact of the pandemic and civil unrest using cell phone mobility and protest data, we continue to find similar in magnitude employment declines. While the Twin Cities are more exposed to pandemic restrictions and civil unrest than the typical other U.S. city, their observed jobs declines are outliers relative to the declines predicted by pandemic and civil unrest conditions.

The second solution is to use variation from the cross section of establishments within a zip code of a city. The cross-sectional estimates do not suffer from the concern that other factors confound the effects of the minimum wage, as long as the Twin Cities shocks are differenced out during a quarter across establishments that belong to the same industry and zip code. We demonstrate that establishments with larger exposure of their labor costs to the minimum wage experienced larger increases in their wage and larger declines in their jobs, hours, and wage bill. The ratio of employment to wage changes induced by exposure to the minimum wage policy is about $-1$. Reassuringly for our research design, which attempts to difference out common factors at the zip code and industry level, we find that the response of all variables to an exposure to the minimum wage is remarkably stable between 2019 and 2020. Additionally, we document that the responsiveness of all establishment variables to changes in their labor costs differs before and after the minimum wage increase and that these responses do not exhibit secular trends before the minimum wage increase. Finally, we show that the responses at the establishment level tend to become larger over longer horizons.

The estimates that use variation across establishments are not necessarily informative about worker outcomes, because workers may have reallocated from exposed to non-exposed establishments or found jobs outside of their zip code. For this reason, we also analyze the cross section of workers whose jobs we can track everywhere within Minnesota. For the first three to four years after the minimum wage change, we find that workers who are more exposed to the minimum wage experience significantly larger employment and earnings losses than workers who are less exposed to the minimum wage. However, at horizons greater than four years, we do not detect employment and earnings losses, which implies an important role for worker reallocation over longer horizons.

To summarize our various estimates for the jobs effects, the time series analysis shows that the minimum wage increase was associated with an average jobs decline of roughly 3 percent in the Twin Cities. The jobs losses appear in the restaurant, retail, and health industries, which account for roughly 30 percent of total jobs in the Twin Cities. The analysis using variation from the cross section leads to estimates of jobs losses around half as large as the estimates from the time series.

In the last part of the paper, we quantify a dynamic, industry equilibrium model with four goals. First, we explore which economic mechanisms are consistent with our empirical results and contrast these with mechanisms highlighted in the literature. Second, we reconcile our estimates from the cross section with those from the time series. Despite our efforts to difference out other shocks, the Twin Cities may have experienced idiosyncratic shocks or had a differential response to an aggregate shock that cannot be differenced out using other cities during the post-treatment period. Time series effects of the minimum wage on employment sum up employment effects at the intensive margin, effects arising from the exit of establishments, and effects arising from the lack of entry of new establishments. By design, the estimates from the cross section do not account for the effects of entry, because they use establishments and workers that exist for at least one period. At the same time, estimates from the cross section do not account for equilibrium adjustments of the aggregate price and wage that affect all establishments and workers simultaneously, a problem often referred to as the "missing intercept." Third, through the lens of the model we study anticipation effects arising from announcement of a future minimum wage increase, such as the one in Saint Paul. Finally, the structure of the model allows us to estimate parameters that may be portable to other settings and determine product and input substitution, the degree of product and input market competition, and dispersion in establishments' productivity and workers' amenities.

The model features entry and exit dynamics, heterogeneity in both productivity and amenities across establishments, and imperfect competition in both product and labor market. A main result from the model is that it is plausible to reconcile the time series estimates with those from the cross section by appealing to entry dynamics that are omitted from the analysis of the cross section. When we quantify the model to reproduce the establishment responses that we observe in the cross section alongside various micro-level statistics before the minimum wage increase, we find that the industry-level employment decline generated by the model comes closer in magnitude to the one that we estimated in the time series of restaurants. This result highlights the potential of endogenous entry to account for the difference between employment effects in the time series and the cross section, because we estimate deeper parameters of the model independently of our time series treatment effects.

To more directly test whether missing entry is an important factor for reconciling the different estimates, we decompose the employment losses in the data between losses that occur at continuing establishments, losses arising from exiting establishments, and losses arising from non-entering establishments. Quantitatively, we find that entry plays the most important role.

Our results suggest that the cross-sectional estimates plausibly reflect a lower bound of employment losses, whereas the time-series estimates plausibly reflect an upper bound of employment losses. We cannot rely on a single source of variation to estimate the labor market effects of the minimum wage, because cross-sectional estimates miss the entry margin and time-series estimates may be contaminated by confounders. An important lesson from the model is that it is fruitful to use both sources of variation simultaneously.[1]

We highlight four additional results from the model. First, we do not find an important role for industry equilibrium adjustments that take place through the aggregate price and wage. Intuitively, the equilibrium adjustment in the price would make entry unimportant for job losses and the equilibrium adjustment in the wage would spillover in a counterfactual way to establishments that are not affected by the minimum wage directly. We thus favor parameter combinations that neutralize these equilibrium effects. Second, we show that the employment elasticity with respect to the minimum wage is increasing in the size of the minimum wage

[1] We draw a parallel between our approach and similar approaches recently advocated in the macroeconomics literature, such as the one in Wolf (2023), that argue that time series and cross-sectional variation should be used jointly.

increase, which allows us to rationalize our larger estimated job losses than in most of the literature. Third, we show that there is a significant interaction between the increase in the minimum wage and a "large recession" such as the Covid recession that, similar to the data, causes employment to fall sharply during the recession and to rebound after.

Finally, our model is qualitatively consistent with the observed decline in employment in Saint Paul upon announcement of a future minimum wage increase, without a corresponding change in the wage. The logic is that entry decisions are forward looking, and the reduced profitability of entry generates a lower employment at the industry level upon announcement of the future policy. However, quantitatively, the employment response in the model is significantly smaller than in the data. We show how a modified version of the model that allows firms to use a less labor-intensive technology upon entry accounts quantitatively for the announcement effects that we document in the data.

Some previous studies examining low-wage workers across industries (Cengiz, Dube, Lindner, and Zipperer, 2019; Dube and Lindner, 2021), do not detect significant employment effects. The comprehensive analysis of estimates for low-wage workers and low-wage industries in Neumark and Shirley (2021) reveals that roughly 80 percent of estimates are negative, with the average reported elasticity across studies being around $-0.15$. While we also fail to detect employment effects in some industries, we find negative effects for retail and health, and our estimated employment elasticity with respect to the minimum wage for restaurants is more negative than the typical estimate found in the literature. For restaurants, Dube, Lester, and Reich (2010) estimate nearly zero effects using minimum wage variation within contiguous-county pairs across state borders, but Jha, Neumark, and Rodriguez-Lopez (Forthcoming) find an elasticity of around $-0.25$ using variation within commuting zones across state borders.

Our estimated jobs elasticity with respect to the minimum wage for restaurants is $-0.3$ using the cross-sectional analysis and $-0.5$ using the time series analysis. The employment impacts that we document might be larger than those in the literature because the policy change we examine is larger, a prediction that is consistent quantitatively with our model.[2] An interpretation of our time series results, which is also borne out quantitatively by our model, is that the jobs elasticity is more negative when a higher minimum wage interacts with a recession. For example, the Seattle study by Jardim, Long, Plotnick, Van Inwegen, Vigdor, and Wething (2022) estimates an elasticity of $-0.3$ for restaurants. However, Seattle was booming during the implementation of their large minimum wage increase, whereas the Twin Cities were hit

[2]The roughly 50 percent increases in the Twin Cities minimum wages by 2023 are significantly larger than the policy changes classified as "large minimum wage increases" by Clemens and Strain (2021), which range between 20 and 25 percent.

by a recession.[3] Finally, our estimated job losses increase over time both in our empirical analyses and in the model, a finding which is consistent with the larger long-run effects than the contemporaneous effects documented by Meer and West (2016) and Jha, Neumark, and Rodriguez-Lopez (Forthcoming).

Relative to recent quantitative work on the minimum wage, such as Berger, Herkenhoff, and Mongey (2025) and Hurst, Kehoe, Pastorino, and Winberry (Forthcoming), our model features establishment entry and exit dynamics. Our model departs from canonical models of industry equilibrium such as Hopenhyan (1992) and Melitz (2003), because we consider equilibrium adjustments both in the product and the labor market, an outside good that disciplines the strength of industry equilibrium effects, and multiple sources of heterogeneity across establishments. Similar to Sorkin (2015) and Aaronson, French, Sorkin, and To (2018), we also use a putty-clay technology, but we show that this technology is essential for generating large negative employment effects from an announcement of a minimum wage policy, as opposed to an implementation of a minimum wage policy. An important difference relative to Aaronson, French, Sorkin, and To (2018) is that the increase in the aggregate price level does not affect establishment decisions in the baseline parameterization of the model, reflecting our finding in the data that entry accounts for the majority of job losses. This is consistent with the findings of Rohlin (2011) who uses a border approach and documents negative impacts of the minimum wage on new business activity.

# 2 Policy Background and Data Sources

In this section, we detail the policy background underlying the minimum wage increases in the Twin Cities and describe our sources of data. The last minimum wage change in the state of Minnesota occurred in 2014, with the minimum wage reaching 7.75 dollars for small firms and 9.50 dollars for large firms by 2017 (see Appendix Table A.1). In 2018, Minneapolis increased the minimum wage for establishments that operate within the city. The increase was implemented in phases, with the goal of reaching 15 dollars per hour in 2022 for large firms and in 2024 for small firms (see Appendix Table A.2). In 2018, Saint Paul followed Minneapolis in adopting a 15 dollar minimum wage policy. Saint Paul also enacted a phased implementation that began increasing its minimum wage in 2020, with the goal of reaching 15 dollars for all

[3]The acceleration of jobs losses during the pandemic recession is consistent with earlier studies such as Addison, Blackburn, and Cotti (2013), who document the larger sensitivity during recessions, and more recent work such as Clemens and Wither (2019), who find an employment elasticity with respect to the minimum wage of $-1$ when analyzing the increase in federal minimum wage during the Great Recession.

firms by 2027. Both cities followed the statewide minimum wage policy regarding gratuities, which requires employers to pay their employees a wage equal at least to the minimum wage before tips and gratuities are applied.

We use two main sources of data on workers and establishments. Both sources are administrative and non-publicly-available data that were provided to us by Minnesota's Department of Employment and Economic Development (DEED). The first data source is individual-level data on workers from Unemployment Insurance (UI). Minnesota requires most employers to file unemployment wage detail reports quarterly for the purpose of estimating the amount of unemployment insurance tax they owe. These reports provide us with data on quarterly earnings and hours worked for each worker. We calculate the hourly wage for each worker by dividing total quarterly earnings by quarterly hours. Minnesota collects both of these variables for each employee of a firm at the level of the establishment where they work. This feature of the data is especially important in studying the minimum wage effects, as roughly 50 percent of employment is generated in multi-establishment firms.[4]

The UI data do not contain information on the physical location of establishments, which is necessary in order to identify which establishments are affected by the minimum wage increase. To overcome this problem, the UI data is merged with establishment-level data from the Quarterly Census of Employment and Wages (QCEW). The QCEW records jobs that account for roughly 97 percent of employment in Minnesota. From these data, we observe the six-digit NAICS code for the industry that the establishment operates in, the physical location of the workplace, and the firm to which the establishment belongs. The physical location data consist of both the city and the zip code in which the establishment operates.[5]

The merged data result in a quarterly dataset between 2001(1) and 2023(4) on workers' hours and wages, as well as their establishments of employment by industry, zip code, and city. Our geographic unit of analysis is a zip code within a city. This allows the same zip code to be affected differently by the minimum wage policy if it belongs to two different cities. It also allows for multiple treated units within a city that faces an increase in its minimum wage. For

[4]We exclude roughly 1 percent of observations with jobs that reported an hourly wage below the applicable youth minimum wage for Minnesota. For calculating the wage, we exclude the roughly 5 percent of observations that reported zero hours worked. We keep these observations for calculating other outcomes. While reporting is required at the establishment level, a few firms file reports under a single account. We have to exclude from our analysis multi-establishment firms that have at least one establishment in Minneapolis or Saint Paul and at least one establishment outside of Minneapolis or Saint Paul, but report the UI wage details of all their employees under a single account. These establishments constitute roughly 3 percent of all establishments and 6 percent of all wage records.

[5]The raw data do not have physical location information for roughly 4 percent of establishments. In addition, we exclude 2 percent of establishments for which the city name and zip codes are contradictory or the city name is invalid and the zip code alone does not identify the city boundary.

each industry, we calculate the average wage, aggregate number of jobs (sum of full-time and part-time jobs), aggregate hours, and aggregate earnings paid within geographic units for each quarter. For the wage, we calculate the average hourly wage per worker for workers below the 90th percentile within the industry and year and treatment or control groups.[6] Finally, we aggregate all units with less than 50 full-time equivalent jobs to one unit, separately for each industry and for treatment or control groups.

Our dataset improves measurement relative to that of the typical minimum wage study along three dimensions. First, using administrative sources, we provide estimates for the effects of a minimum wage increase on hours worked.[7] Second, Minnesota is unique in that it records employee hours worked at the establishment level within firms. This feature allows us to include in our analyses firms with multiple establishments across city borders.[8] Finally, we leverage physical location data at the zip code level to increase the precision of our estimates and conduct additional analyses at the establishment level that require within-city variation.

# 3 Evidence from the Time Series

We begin by laying out the econometric framework for analyzing the impact of the minimum wage increase using variation from the time series of cities. We then present our baseline estimates that use other Minnesota geographical units in the control group. Finally, we use U.S. cities from outside Minnesota in the control group.

## 3.1 Econometric Methodology: Time Series

We analyze the labor market effects of the increase in the minimum wage separately in Minneapolis and Saint Paul. We exclude Saint Paul from the control group in our analysis of Minneapolis. Similarly, we exclude Minneapolis from the control group in our analysis of Saint Paul. Our choice to analyze Minneapolis and Saint Paul in parallel, as opposed to merging

[6]We examined wage results without excluding the top of the wage distribution. This measure of the wage is too noisy because of outliers at the top of the wage distribution and, in many cases, leads to statistically insignificant results for the wage. We also examined results that trimmed workers at the 75th percentile and generally find similar wage effects as those in our baseline measures, which trim at the 90th percentile.

[7]Some studies examining effects on hours worked (Zavodny, 2000; Couch and Wittenburg, 2001; Neumark, Schweitzer, and Wascher, 2004) have largely used reported usual weekly hours from the Current Population Survey. This measure has been documented to contain significant measurement errors (Bound, Brown, and Mathiowetz, 2001). There are only four states in the U.S. that collect hours worked in the matched employer-employee administrative data, the other three being Oregon, Rhode Island, and Washington. Minnesota Statute (Section 268.044) requires employers to report total number of paid hours for the purpose of UI administration.

[8]For example, this crucial subsample of firms, accounting for roughly 40 percent of jobs, was missing from the administrative data used in the evaluation of the minimum wage increase in Seattle by Jardim, Long, Plotnick, Van Inwegen, Vigdor, and Wething (2022).

them in one treated unit, is appropriate because the Minneapolis ordinance was implemented in 2018, whereas the Saint Paul ordinance was implemented in 2020. We choose to treat both cities with an indicator of a minimum wage increase after 2018. Our logic for treating both cities in 2018 is that Saint Paul credibly committed to a minimum wage policy immediately after Minneapolis passed its ordinance in 2017 and Saint Paul passed its ordinance in 2018 for implementation in 2020. Our logic for adopting a treatment indicator that covers the entire period after 2018 is that both cities announced the entire schedule of minimum wage increases at once and not in increments.

### 3.1.1 Synthetic Difference-in-Differences

We have a balanced panel of $N$ geographic units for $T$ periods. The outcome for unit $i$ in period $t$ is $Y_{it}$. The treatment of a minimum wage increase is $W_{it} \in \{0, 1\}$, where $W_{it} = 0$ denotes that unit $i$ did not experience a minimum wage increase in period $t$ and $W_{it} = 1$ denotes that it did. We order units so that the first $N_{\text{co}}$ units are never exposed to the treatment, while the last $N_{\text{tr}} = N - N_{\text{co}}$ units are exposed to the treatment after time $T_{\text{pre}}$. In our specifications that use DEED data from Minnesota, we have multiple treated units because the unit of analysis is a zip code within a city.

We wish to estimate the average treatment effect in period $t$, $\tau_t = \frac{1}{N_{\text{tr}}} \sum_{i=N_{\text{co}}+1}^{N} (Y_{it}^1 - Y_{it}^0)$, and the average treatment effect across all periods, $\tau = \frac{1}{T - T_{\text{pre}}} \sum_{t=T_{\text{pre}}+1}^{T} \tau_t$, where $Y_{it}^1$ is the outcome under a minimum wage increase and $Y_{it}^0$ is the counterfactual outcome in the absence of the minimum wage increase. Since the seminal study of Card and Krueger (1994) on the minimum wage increase in New Jersey, a popular method has been to find a control group of non-treated units and use its post-treatment outcomes to estimate the counterfactual $Y_{it}^0$ for treated units. With multiple units and time periods in the sample, this amounts to a two-way fixed effects regression

$$Y_{it} = \alpha_i + \beta_t + \tau W_{it} + u_{it}, \tag{1}$$

where $\alpha_i$ is a unit fixed effect, $\beta_t$ is a time fixed effect, and $u_{it}$ is the error term. The specification in equation (1) assumes that outcomes of treated and non-treated units are equal (up to a constant) in the post-treatment period in the absence of the minimum wage increase. Typically, the plausibility of parallel trends is assessed by evaluating whether trends are parallel during the pre-treatment period.

A concern with the difference-in-differences specification is that there might not exist a control group with pre-treatment outcomes that resemble those of treated units. Synthetic control methods, such as those in Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2015), aim to overcome this problem by finding a vector of weights $\hat{\omega}$ that forces pre-treatment trends for non-treated units to align with those for treated units. More explicitly, the goal is to find weights such that $\sum_{i=1}^{N_{\text{co}}} \hat{\omega}_i Y_{it} \approx N_{\text{tr}}^{-1} \sum_{i=N_{\text{co}+1}}^{N} Y_{it}$ for each time period before the treatment $t = 1, \ldots, T_{\text{pre}}$.

Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021) propose a synthetic difference-in-differences methodology, which uses estimating equation (1) and, additionally, weights observations with $\omega_i$ so that treated and non-treated units are as close as possible in terms of pre-treatment outcomes. The weights are estimated as [9]

$$(\hat{\omega}_0, \hat{\omega}) = \arg \min_{\omega_0 \in \mathbb{R}, \omega \in \Omega} \sum_{t=1}^{T_{\text{pre}}} \left( \omega_0 + \sum_{i=1}^{N_{\text{co}}} \omega_i Y_{it} - \frac{1}{N_{\text{tr}}} \sum_{i=N_{\text{co}}+1}^{N} Y_{it} \right)^2 + \zeta^2 T_{\text{pre}} ||\omega||_2^2, \tag{2}$$

$$\Omega = \left\{ \omega \in \mathbb{R}_+^N : \sum_{i=1}^{N_{\text{co}}} \omega_i = 1, \omega_i = N_{\text{tr}}^{-1} \text{ for all } i = N_{\text{co}} + 1, \ldots, N \right\}.$$

If we use the estimated $\hat{\omega}$ from equation (2) as weights in the estimating equation (1), the synthetic difference-in-differences treatment effect $\hat{\tau}$ is

$$\left(\hat{\tau}, \hat{\alpha}, \hat{\beta}\right) = \arg \min_{\tau, \alpha, \beta} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \alpha_i - \beta_t - \tau W_{it}\right)^2 \hat{\omega}_i \right\}. \tag{3}$$

Removing the estimated weights $\hat{\omega}_i$ from the least-squared problem in equation (3) leads to the standard difference-in-differences specification. Removing the unit fixed effects $\alpha_i$ from equation (3) and $\omega_0$ from equation (2) leads to the standard synthetic control specification.

### 3.1.2 Growth Specification of Synthetic Difference-in-Differences

We express outcome variables $Y_{it}$ in equation (3) in growth rates. We prefer a specification in growth rates to a specification in levels.[10] The unit fixed effect $\alpha_i$ in a growth specification allows average growth to be correlated with the policy of increasing the minimum wage. If one uses a levels specification and the Twin Cities are growing at a different rate than other cities,

[9] Following these authors, we allow for a shifter $\omega_0$ that aligns the pre-treatment trends for the synthetic control and the treated units up to a constant, which is differenced out by the fixed effect. The regularization parameter $\zeta$ penalizes non-zero weights to ensure the minimization problem has a unique solution. We find that a small penalty of $\zeta = 10^{-6}$ works well in terms of minimizing the weight on control units with dissimilar pre-trends to treated units.

[10] Another popular specification in the minimum wage literature is to add unit-specific linear time trends to equation (1). However, pre-treatment trends could be non-linear. Meer and West (2016) critique the practice of using unit-specific time trends in levels specifications and argue in favor of specifications that use growth rates of employment as the dependent variable. In our context, an example of non-linearity is retail jobs in Minneapolis which decline in the 2000s, are stable in the first part of the 2010s, and increase after 2015. See Appendix Figures A.2 to A.17 for the time series in the other low-wage industries that are included in our analyses.

as we find in several industries, that would introduce a correlation between the assignment of the treatment and the level of outcomes.[11] Additionally, using yearly growth rates allows us to remove quarterly seasonal variation, thus improving the efficiency of our estimates.

If $y_{it}$ is a time series in levels, we take year-over-year differences in logs and define

$$Y_{it} \equiv \log y_{it} - \log y_{i,t-4}, \forall i = 1, ..., N_{\text{co}}, \quad Y_{it} \equiv (\log y_{it} - \log y_{i,t-4})\, \bar{\nu}_i, \forall i = N_{\text{co}} + 1, ...., N. \quad (4)$$

In equation (4), we weight zip codes of the treated cities with their share $\bar{\nu}_i$ of the corresponding variable in the three years before the minimum wage increase, so that the treatment effect pertains to the city as a whole as opposed to the average zip code within a city.[12] Holding $\bar{\nu}_i$ constant over time allows us to interpret the treatment effects as counterfactual outcomes that the Twin Cities would have experienced in the absence of the minimum wage increase, holding the spatial distribution of economic activity constant at the same levels observed just before the policy change.[13]

### 3.1.3 Discussion of Methodology

Before presenting our results, we pause to discuss the performance of the synthetic control method. A concern with the method arises when only few controls receive positive weight, because it raises the possibility that the results may be too sensitive to omitting or adding few units in the donor pool. For example, in Abadie and Gardeazabal (2003) only two regions receive positive weights and in Abadie, Diamond, and Hainmueller (2015) only five countries receive positive weights. In our application, we almost always have more than ten units in the donor pool which receive a positive weight. Across 64 combinations of industries, variables, and cities, the median top weight is only 0.18, with an interquartile range of 0.12 to 0.23. We conjecture that our weights are more dispersed than in a typical application of synthetic controls, because our unit of observation is a zip code within a city and outcome variables are in growth rates. Thus, it is difficult to find only a few units that replicate well the pre-treatment

[11] Ferman and Pinto (2021) show that the synthetic control estimator is biased if treatment assignment is correlated with the factor structure underlying the dynamics of outcome variables, even when the number of pre-treatment periods goes to infinity. This bias arises for a fixed the number of control units, but with a growing number of control units the bias vanishes (Arkhangelsky, Athey, Hirshberg, Imbens, and Wager, 2021).

[12] The exception is the wage, for which we do not use any weights. The reason is that we are interested in the effects of the minimum wage increase on the wage of the average worker. For the control units, we do not weight the growth rates of zip codes, because these weights enter multiplicatively with $\omega_i$ in equation (3).

[13] Working with the outcome variable in equation (4) means that $\tau$ is the effect of the minimum wage policy on the average yearly growth rate of the variable over the entire post-treatment period, $T - T_{\text{pre}}$. We transform the growth effect into a cumulative effect up to final period $T$ on the (log) variable with the formula $g_T \equiv \mathbb{E}\big(\log y^1_{i,T} - \log y^0_{i,T}\big) = \frac{(T - T_{\text{pre}})\tau}{4}$, where 4 appears in the formula because $\tau$ is a yearly, as opposed to a quarterly, growth rate.

path of outcomes.[14]

To assess the fit of the synthetic control method, Appendix Table A.5 reports R-squared coefficients from regressions of variables' growth in Minneapolis or Saint Paul on the growth of the synthetic control calculated using the weights $\hat{\omega}_i$. The regressions are performed only during the pre-treatment period. We find that for five out of the six low-wage industries included in our time series analyses and separately for restaurants, the synthetic control accounts for a substantial fraction of the variation of growth of Minneapolis and Saint Paul before the minimum wage increase. To give an example from a key industry that we elaborate upon below, for full-service restaurants the synthetic control accounts for 88 percent of the time series variation of jobs growth in Minneapolis and 76 percent of that in Saint Paul. Despite the overall success in accounting for a substantial variation of the pre-treatment growth, the synthetic control does not perform equally well in all industries. The most notable lack of fit is for the arts, entertainment, and recreation and, thus, we discount the results for this industry.

While these R-squared statistics are informative, we do not rely solely on them to assess the appropriateness of the synthetic difference-in-differences methodology. Recent research by Ferman and Pinto (2021) has documented biases when the pre-treatment fit is less than perfect. We alleviate these concerns by using a specification in growth rates with a fixed effect instead of a levels specification. Additionally, following Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021), below we add time weights that balance the pre-treatment and the post-treatment outcomes for the control group. Finally, assuming that the data generating process is a linear factor model, we perform Monte Carlo simulations to assess the size of the bias in the presence of imperfect fit and generally conclude that the bias in our context is small.

## 3.2 Evidence from Minnesota Cities

We focus on the two-digit industries in which 30 percent or more of workers earn below 15 dollars per hour in 2017 (see Appendix Table A.6 for the detailed estimates). The six industries that satisfy this criterion are retail trade (44); administrative services (56); health care and social assistance (62); arts, entertainment, and recreation (71); accommodation and food services (72); and other services (81), which consists of repair and maintenance shops, personal and laundry services, and various civic, professional, and religious organizations. In addition, we separately analyze full-service (722511) and limited-service (722513) restaurants, which have a high fraction of potentially impacted workers and have been studied extensively in the literature.

[14] See Appendix Table A.3 for the weights that control zip codes receive, separately by two-sector industry, variable, and city, Appendix Table A.4 for the weights for restaurants, and Appendix Figure A.1 for a map with

Table 1: Minimum Wage Effects, Time Series of Minnesota Cities

| Minneapolis | Wage | Jobs | Hours | Earnings |
|---|---|---|---|---|
| Retail Trade (44) | 10.4 | −28.3 | −38.0 | −9.8 |
| | (0.0) | (3.0) | (0.0) | (35.4) |
| Administration and Support (56) | 9.7 | 31.3 | 27.3 | 29.5 |
| | (0.0) | (7.8) | (15.8) | (10.0) |
| Health Care and Social Assistance (62) | −9.6 | −22.1 | −33.1 | −25.2 |
| | (0.0) | (1.4) | (0.4) | (2.0) |
| Arts, Entertainment and Recreation (71) | −11.0 | 11.0 | 15.4 | 9.3 |
| | (0.0) | (37.8) | (8.8) | (82.7) |
| Accommodation and Food Services (72) | 4.8 | −18.4 | −18.9 | −6.3 |
| | (0.2) | (1.4) | (2.8) | (52.9) |
| Other Services (81) | 8.5 | −1.3 | −11.7 | 4.2 |
| | (0.0) | (84.7) | (22.2) | (51.7) |
| Full-Service Restaurants (722511) | 8.2 | −44.5 | −56.9 | −52.7 |
| | (0.0) | (0.0) | (0.0) | (0.0) |
| Limited-Service Restaurants (722513) | 8.0 | −43.1 | −29.8 | −20.1 |
| | (0.0) | (0.0) | (1.6) | (7.2) |

| Saint Paul | Wage | Jobs | Hours | Earnings |
|---|---|---|---|---|
| Retail Trade (44) | 9.2 | −15.0 | −28.0 | −31.1 |
| | (0.0) | (15.8) | (0.6) | (1.0) |
| Administration and Support (56) | 9.4 | −8.8 | 0.5 | −39.9 |
| | (0.4) | (43.8) | (72.5) | (1.8) |
| Health Care and Social Assistance (62) | −0.9 | 2.3 | 11.5 | 0.8 |
| | (45.2) | (73.5) | (19.0) | (81.3) |
| Arts, Entertainment and Recreation (71) | −0.5 | 9.0 | −5.4 | −12.4 |
| | (78.9) | (34.4) | (51.3) | (3.2) |
| Accommodation and Food Services (72) | 4.9 | −17.0 | −36.6 | −15.5 |
| | (0.0) | (1.4) | (0.0) | (9.2) |
| Other Services (81) | −3.2 | 22.1 | −2.2 | 3.1 |
| | (1.4) | (0.0) | (99.9) | (49.2) |
| Full-Service Restaurants (722511) | 1.9 | −22.2 | −18.0 | −19.1 |
| | (18.2) | (2.8) | (12.0) | (11.0) |
| Limited-Service Restaurants (722513) | 0.6 | −37.6 | −35.2 | −46.9 |
| | (76.3) | (0.4) | (0.8) | (0.0) |

Notes: The estimates are in log points, multiplied by 100. Entries in parentheses are $p$-values, multiplied by 100, using the placebo method.

Table 1 presents our results. Entries are multiplied by 100 and equal the log point change in outcomes in 2023(4) due to the minimum wage increase. The columns present different outcome variables. For example, the first row shows that the increase in the minimum wage in Minneapolis caused a 10.4 log points (roughly 11 percent) increase in the retail wage and a 28.3 log points (roughly 25 percent) decrease in retail jobs. Each entry in parentheses is the $p$-value (multiplied by 100) associated with the estimated treatment effect, which is the probability of obtaining a treatment effect as extreme as the point estimate under the null hypothesis that the treatment effect is zero. Continuing the example, the $p$-value is 0 for the wage and 3 percent for jobs, and thus we conclude that the effects can be statistically distinguished from zero at conventional levels of significance.[15]

In Minneapolis, we estimate wage increases with $p$-values below 5 percent for retail; administrative and support services; accommodation and food services; other services; and restaurants.[16] Among industries with statistically significant wage increases, we document increases that range between 5 and 10 log points. In Saint Paul, we estimate statistically significant wage increases for retail; administrative and support services; and accommodation and food services. The wage increases for these industries in Saint Paul range between 5 and 9 log points. We find the magnitudes of our estimated wage gains reasonable. Holding worker hours constant at their 2017 level, the average establishment in the Twin Cities would experience a 9 percent increase in its labor cost if all its workers were paid a minimum of 15 dollars per hour. Weighted with employment, the increase in labor costs is 6 percent. The mechanical effect of the minimum wage on labor costs falls comfortably in the range of wage gains that we estimate.

Turning to the second and third columns, in Minneapolis we find negative and statistically significant jobs and total hours effects in 2023(4) for retail; health care and social assistance;

all estimated weights for jobs in the restaurants of the Twin Cities.

[15] To infer the statistical significance of the estimated effects, we use the "placebo method" as described by Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021). The method estimates placebo treatment effects in samples of subsets of non-treated units. Since we should be estimating a zero treatment effect in the absence of a treatment, the distribution of treatment effects under the placebo method gives us the distribution of noise inherent in the data. In our application, we have multiple treated units, as our geographic unit of analysis is a zip code within a city. Thus, we construct placebo estimates by assigning a treatment status to 999 random subsamples of zip codes, with each subsample having a size equal to the number of treated units in Minneapolis or Saint Paul. We use the formula $p = 2\min\{p_H, p_L\}$ to calculate the $p$-value for a point estimate, where $p_H$ is the fraction of placebo samples with point estimates that are higher than the estimate of Minneapolis or Saint Paul in 2023(4) and $p_L$ is the fraction of placebo samples with point estimates that are lower than the estimate of Minneapolis or Saint Paul in 2023(4).

[16] A seemingly counterintuitive result is obtained for health in Minneapolis, which exhibits a negative wage effect alongside negative jobs and hours effects. We investigated this case and concluded that the decline in both the wage and employment reflects the exit of two large establishments that were paying above average wages. Contrary to health, arts, entertainment, and recreation has a notable lack of fit in the pre-treatment period, so we interpret the results for this industry with caution.

and accommodation and food services. Within accommodation and food services, we find large declines for both full-service and limited-service restaurants. The outlier in Minneapolis is administrative and support services that exhibits large, but imprecisely estimated, gains. In Saint Paul, we find negative and statistically significant effects for hours in retail; for both jobs and hours in accommodation and food services; for jobs in full-service restaurants; and for both jobs and hours in limited-service restaurants. The outlier in Saint Paul is other services, which exhibits large gains in terms of jobs, but without a noticeable change in total hours.[17]

The last column of the table presents results for worker earnings. Given the modest wage gains for most industries and the significant employment losses for some industries, it is not surprising that we never detect a statistically significant increase in worker earnings. In Minneapolis, we detect statistically significant declines in worker earnings for health care and social assistance and full-service restaurants. In Saint Paul, we detect statistically significant declines in worker earnings for retail; administrative and support services; arts, entertainment, and recreation; and limited-service restaurants.[18]

Figure 1 helps to understand the heterogeneity in wage and employment responses across industries. The figure plots the wage, jobs, hours, and earnings responses of each industry in Table 1 against each industry's median wage before the minimum wage increase, which proxies for the intensity of the minimum wage treatment. We find that industries with a lower median wage experience more positive wage responses and more negative jobs, hours, and earnings responses. We find this result sensible and acknowledge that the heterogeneity in responses across sectors could reflect factors other than the intensity of the treatment, such as the product and labor market structure of each industry. We discuss these factors in more detail through the lens of our model in Section 6.

Next, we examine the time variation of the estimated effects for restaurants (see Appendix Figures A.18, A.19, and A.20 for other industries). The top panels of Figure 2 plot the cumulative wage effects of the minimum wage increase.[19] Along with the estimated effects, we plot

[17] We investigated the growth of jobs in other services in Saint Paul and it reflects the entry of a large establishment and the significant growth of an incumbent establishment.

[18] We find a large decline in earnings for administration and support in Saint Paul that it is difficult to reconcile with its wage and hours changes. We investigated the time series of earnings and concluded that the estimated effect on earnings entirely reflects an extreme increase in reported earnings for some establishments just before 2018. This increase is not reflected in the wage because we trimmed the wage at the 90th percentile. When we also trim earnings at the 90th percentile, the decline in earnings in this industry is statistically indistinguishable from zero.

[19] We run the regression $Y_{it} = \alpha_i + \beta_t + \sum_{h=T_{\text{pre}+1}}^{T} \tau(h) W_{it}(h) + u_{it}$ using weights $\hat{\omega}_i$, where $h = T_{\text{pre}+1}, ..., T$ denotes the quarter of the treatment. For each quarter $h$ shown in the figure, its cumulative effect equals the sum of the growth effects, $100 \cdot \sum_{j=T_{\text{pre}+1}}^{h} \hat{\tau}(j)/4$, where 4 appears in the formula because $\tau(h)$ is a yearly, as opposed to a quarterly, growth rate.

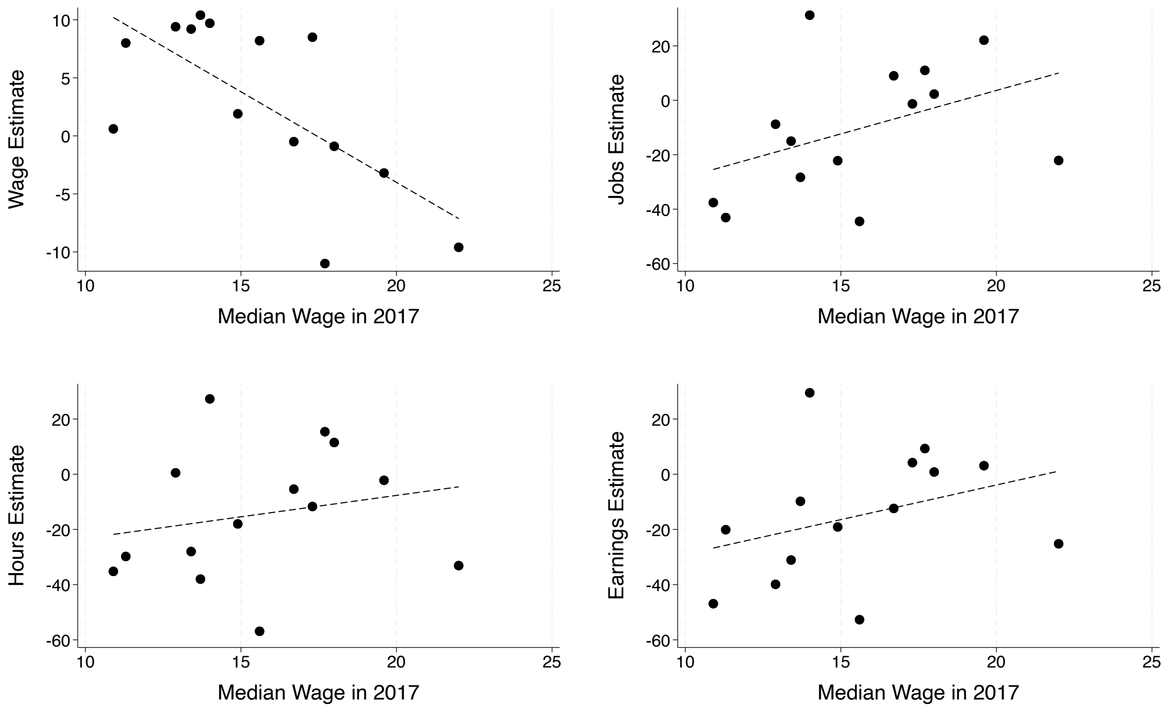
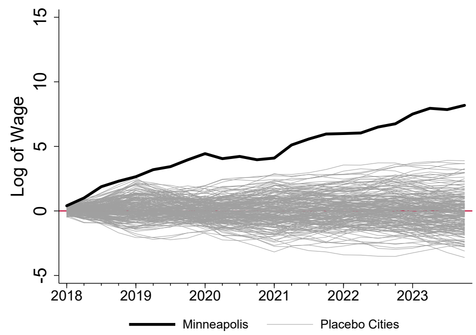



Figure 1: Wage and Employment Responses Across Industries and Cities

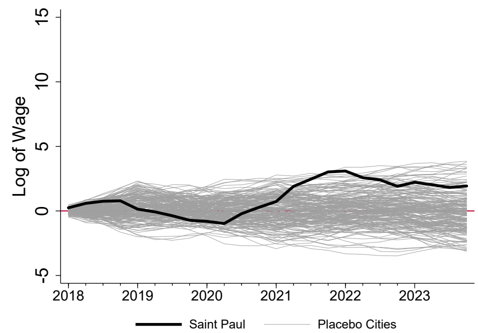
placebo effects for 200 collections of units that were not subject to the minimum wage increase. The left panels of the figure show that the wage for restaurants in Minneapolis increased soon after the minimum wage ordinance went into effect. By contrast, in Saint Paul there is no statistically significant increase in the wage for full-service restaurants until the second half of 2021. For limited-service restaurants, wages increase in the end of 2019. We find the difference in the response of the wage between Minneapolis and Saint Paul intuitive, because Saint Paul implemented the policy two years after Minneapolis.

The bottom panels of Figure 2 plot the cumulative jobs effects of the minimum wage increase for restaurants in the Twin Cities, from which we draw three conclusions. First, in contrast to the wage, jobs in Saint Paul declined before the implementation of the minimum wage and the pandemic in 2020. To the extent that establishments face entry costs or adjustment costs of changing their labor inputs or production techniques, we expect them to react upon the announcement of the schedule. This evidence of advance notice is consistent with our cross-sectional results below, which also show jobs declines before 2020 in Saint Paul.[20] Second,

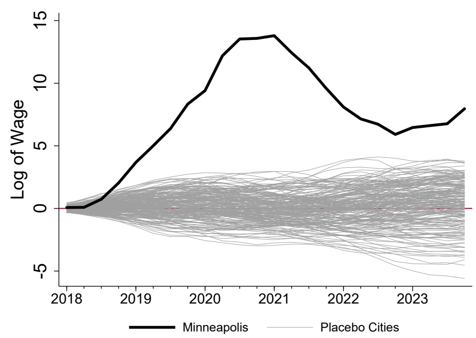
[20]For some other recent evidence on announcement effects see Jha, Neumark, and Rodriguez-Lopez (Forthcoming) and Kudlyak, Tasci, and Tuzemen (2025). We also examined advance notice in Minneapolis by backdating the treatment of the minimum wage to 2016 and 2017. We failed to detect significant effects in Minneapolis. The difference with Saint Paul is explained by the greater uncertainty during 2016 and 2017 about whether the Minneapolis minimum wage ordinance would pass, whereas in Saint Paul the ordinance was passed in 2018 but



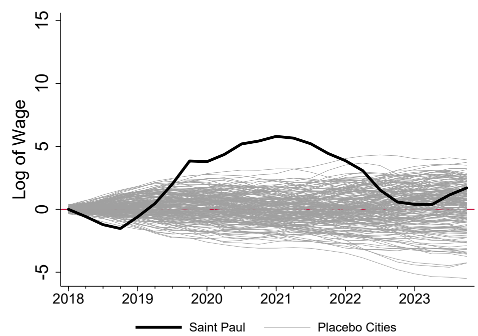

(a) Full-service restaurants, MPLS



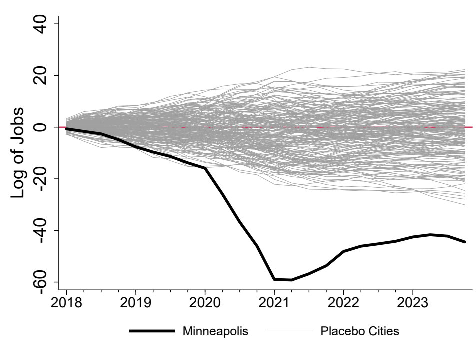

(b) Full-service restaurants, SP



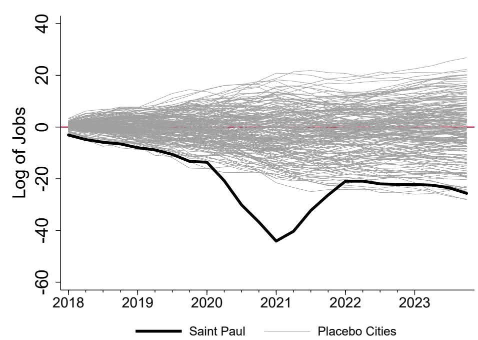

(c) Limited-service restaurants, MPLS



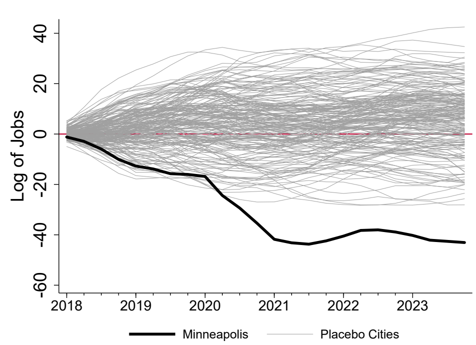

(d) Limited-service restaurants, SP



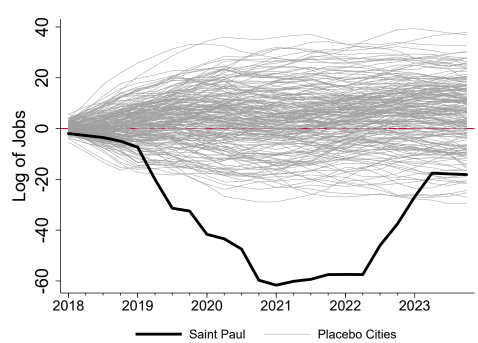

(e) Full-service restaurants, MPLS




(f) Full-service restaurants, SP




(g) Limited-service restaurants, MPLS




(h) Limited-service restaurants, SP

Figure 2: Time-Varying Wage and Jobs Effects in Restaurants

while in most cases we observe significant declines before the pandemic, there is a significant acceleration of the job losses between 2020 and 2021. Finally, some of the excess job losses during the first pandemic year were reversed in 2021. By the end of 2023, with the exception of limited-service restaurants in Saint Paul, jobs in restaurants of the Twin Cities extend the negative trend observed before the pandemic.

We conclude this section by discussing three robustness checks. Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021) also propose adding time weights $\lambda_t$ to equation (3), with the goal of balancing outcomes for the control group between the pre-treatment and the post-treatment period. Appendix Table A.7 shows that, when we re-weight the data using time weights, the results are quite similar to the baseline results, with the exception of limited-service restaurants. We prefer the estimates without the time weights, because these weights change significantly as additional quarters of data become available. By contrast, the estimated weights $\hat{\omega}_t$ do not change as more data become available, which implies that the estimated treatment effects for prior quarters do not change with the addition of new data.

Our second robustness check repeats our estimates in a sample of cities that excludes cities bordering Minneapolis and Saint Paul. It is conceivable that the implementation of a higher minimum wage reallocated jobs from the Twin Cities to neighboring cities. From the perspective of a city that implements a minimum wage increase, the policy-relevant statistic is its change in jobs, irrespective of whether these jobs disappeared or were reallocated to neighboring cities. Therefore, we do not merge neighboring cities with the Twin Cities in estimating the effects of the minimum wage change. However, to the extent that jobs were reallocated to neighboring cities and these cities receive positive weights, we could be double-counting the effects of the minimum wage because cities in the synthetic control experience jobs growth. Appendix Table A.8 shows that, with the exception of restaurant wages in Saint Paul, this is not the case, because our estimates do not change significantly when we exclude bordering cities from the sample of cities that form the synthetic control.

The usual practice in synthetic control methods with multiple outcomes is to estimate weights separately for each outcome. Sun, Ben-Michael, and Feller (2025) propose estimating common weights across outcomes. The idea is that when multiple outcomes are related to a common underlying factors, using common weights may reduce bias due to less than perfect pre-treatment fit as well as reduce concerns of overfitting the pre-treatment data. In Appendix

implemented in 2020. The Minneapolis City Council passed the minimum wage ordinance on June 30, 2017 to take effect January 1, 2018. The legality of the legislation was challenged shortly after and the District Court decided on February 27, 2018 that cities in Minnesota have the legal authority to set local minimum wages at levels higher than the state minimum wage.

Table A.9 we present estimates based on common weights for the wage and jobs. The estimates based on common weights are generally similar to the baseline results, with some attenuation of the effects especially for wages and a larger imprecision of some of the point estimates. We favor our baseline specification relative to the specification with common weights, because in our context wages and jobs are related through a more complicated data generating process than the one Sun, Ben-Michael, and Feller (2025) have in mind. An ideal situation for estimating common weights is when outcomes are multiple noisy measures of the same outcome, such as different test scores that proxy for the ability of a student. Here, the outcomes are wages and jobs, which do not correspond to multiple measures of the same outcome, and allowing for different weights places less restrictions on their data generating process.

## 3.3 Evidence from Other U.S. Cities

While some of our estimated negative jobs effects following the minimum wage increase in the Twin Cities become apparent by the end of 2019, the largest yearly decline in jobs for full-service restaurants is observed during 2020, the year when the pandemic recession began. By design, the synthetic control aims to fit pre-treatment series of Minneapolis and Saint Paul in both expansions and downturns. However, we acknowledge that the pandemic recession is quite atypical relative to other downturns observed in our sample. A potential threat to identification would arise if in 2020 the sensitivity to aggregate shocks changed for the control group relative to that of Minneapolis and Saint Paul. For example, the enforcement and economic impact of lockdowns may have been more significant in larger, more densely populated cities than in the smaller cities that compose our control group. Additionally, as with any research design that uses time series variation, it may still be the case that the Twin Cities experienced idiosyncratic shocks that are not being differenced out in the post-treatment period. An example of such an idiosyncratic shock is the civil unrest in the second quarter of 2020, which impacted the Twin Cities differently from other cities in Minnesota.

To address these concerns, we now use other U.S. cities of similar size to Minneapolis and Saint Paul in the control group. These cities are also dense, also faced severe lockdowns, and some of them also experienced civil unrest. Using these cities in the control group also allows us to hold constant nationwide changes in economic conditions that were plausibly more prevalent in larger cities. Examples of such changes are the substitution of services prone to virus transmission with online shopping, the rise of gig work, and labor shortages.

We use publicly available data from the Quarterly Census of Employment and Wages

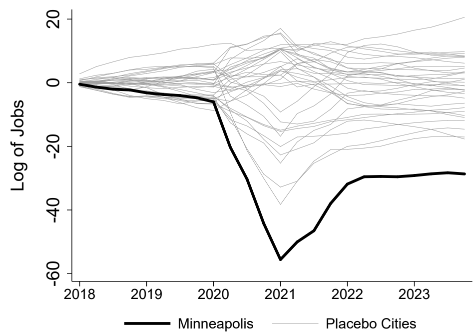
(QCEW) produced by the U.S. Bureau of Labor Statistics.[21] The measure of employment refers to the number of workers who worked during or received pay for a pay period that includes the 12th of the month, as reported by establishments covered under the unemployment insurance program. We note two differences between the research design using the QCEW data and that of our previous analyses using the DEED data. First, the QCEW does not have a measure of hours, and the wage measure differs from that in the DEED. Thus, we analyze only jobs and not hours or wages. Second, the unit of analysis in the QCEW data is other U.S. cities of similar size to Minneapolis and Saint Paul, whereas in the DEED data we used zip code within a city as our unit of analysis.

Figure 3 presents our synthetic difference-in-differences estimates from the QCEW for restaurants, health, and retail.[22] The estimates from the QCEW tend to be less precise than those from the DEED, which is not surprising given that the QCEW sample includes a smaller number of control cities and we only have one treated unit. We estimate negative jobs effects in the QCEW, but the effects are smaller than in the DEED. For example, by the end of 2023, we estimate jobs declines of 22 log points for full-service restaurants in the Twin cities in the QCEW as opposed to 28 log points in the DEED. For limited-service restaurants, the declines are 10 log points in the QCEW as opposed to 33 log points in the DEED. For retail, the declines are 9 log points in the QCEW as opposed to 19 log points in the DEED. For health and social assistance, the declines are 8 log points in the QCEW as opposed to 9 log points in the DEED. Averaged across the four industries, the job losses found in the QCEW are roughly 60 percent of the job losses found in the DEED. We find this difference intuitive, because using variation from other U.S. cities of similar size to Minneapolis and Saint Paul might difference out more credibly other factors affecting jobs that are contemporaneous to the minimum wage change.

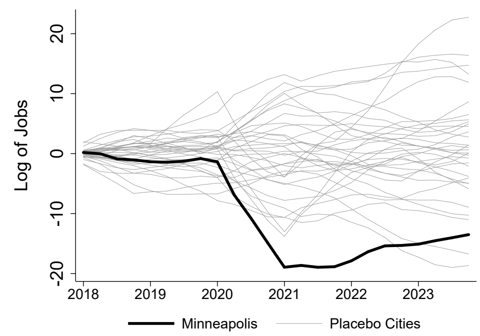
To examine more formally by how much these other factors affect our estimates, we now extend our methodology to directly adjust our estimates for pandemic and civil unrest conditions in the sample of other U.S. cities. We use four indicators of pandemic and civil unrest conditions. The first two come from Chetty, Friedman, Stepner, and The Opportunity Insights

[21] Before the minimum wage increases, Minneapolis employment is roughly 280,000 and Saint Paul employment is roughly 150,000. We include in the control group only cities without a minimum wage change between 2017 and 2019 and employment between half and double of that of either Minneapolis or Saint Paul. This restriction results in a sample of 33 cities for the Minneapolis control group and of 42 cities for the Saint Paul control group. Appendix Table A.10 shows the U.S. cities included in the control groups.

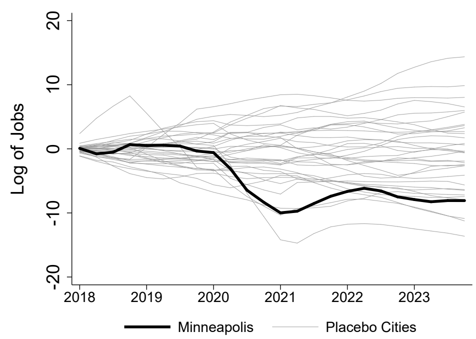
[22] In Figure 3, we present results for the four industries for which we previously documented jobs declines in the DEED data. For all other low-wage industries we find statistically insignificant jobs effects. Figure A.21 shows the stability of our results when adding time weights $\lambda_t$ to the specification underlying the analysis of Figure 3, which uses only $\hat{\omega}_i$ weights. Table A.11 presents Monte Carlo simulations from a linear factor model and shows that the bias of the synthetic difference-in-differences estimator is generally small.



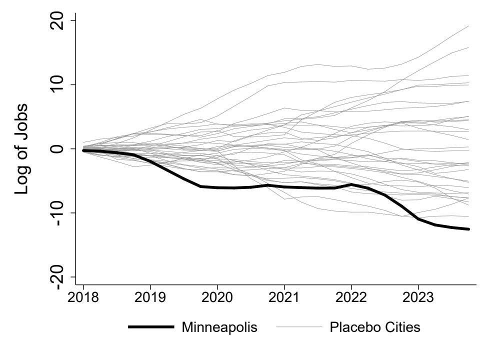

(a) Full-service restaurants, MPLS



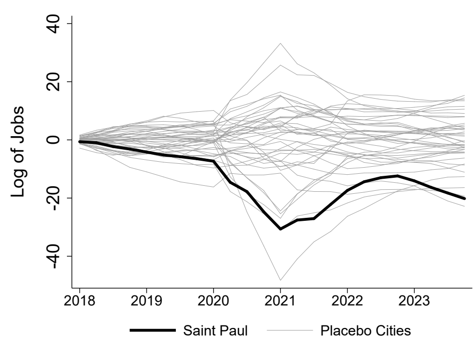

(b) Ltd-service restaurants, MPLS



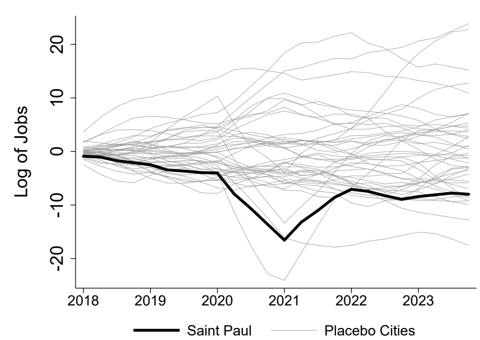

(c) Retail trade, MPLS



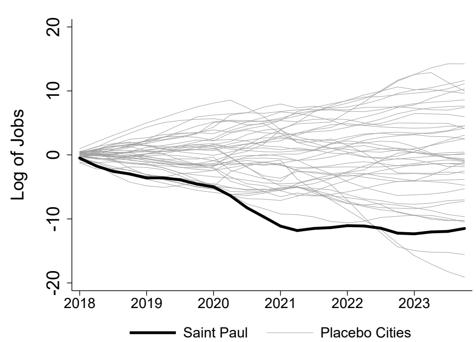

(d) Health and social, MPLS



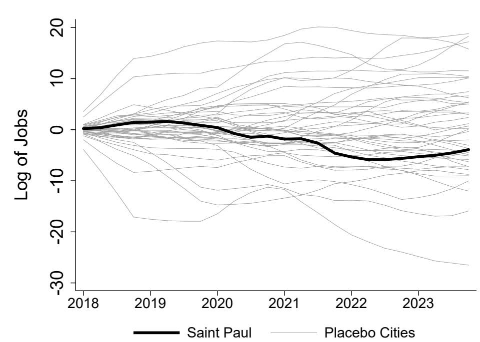

(e) Full-service restaurants, SP




(f) Ltd-service restaurants, SP




(g) Retail trade, SP




(h) Health and social, SP

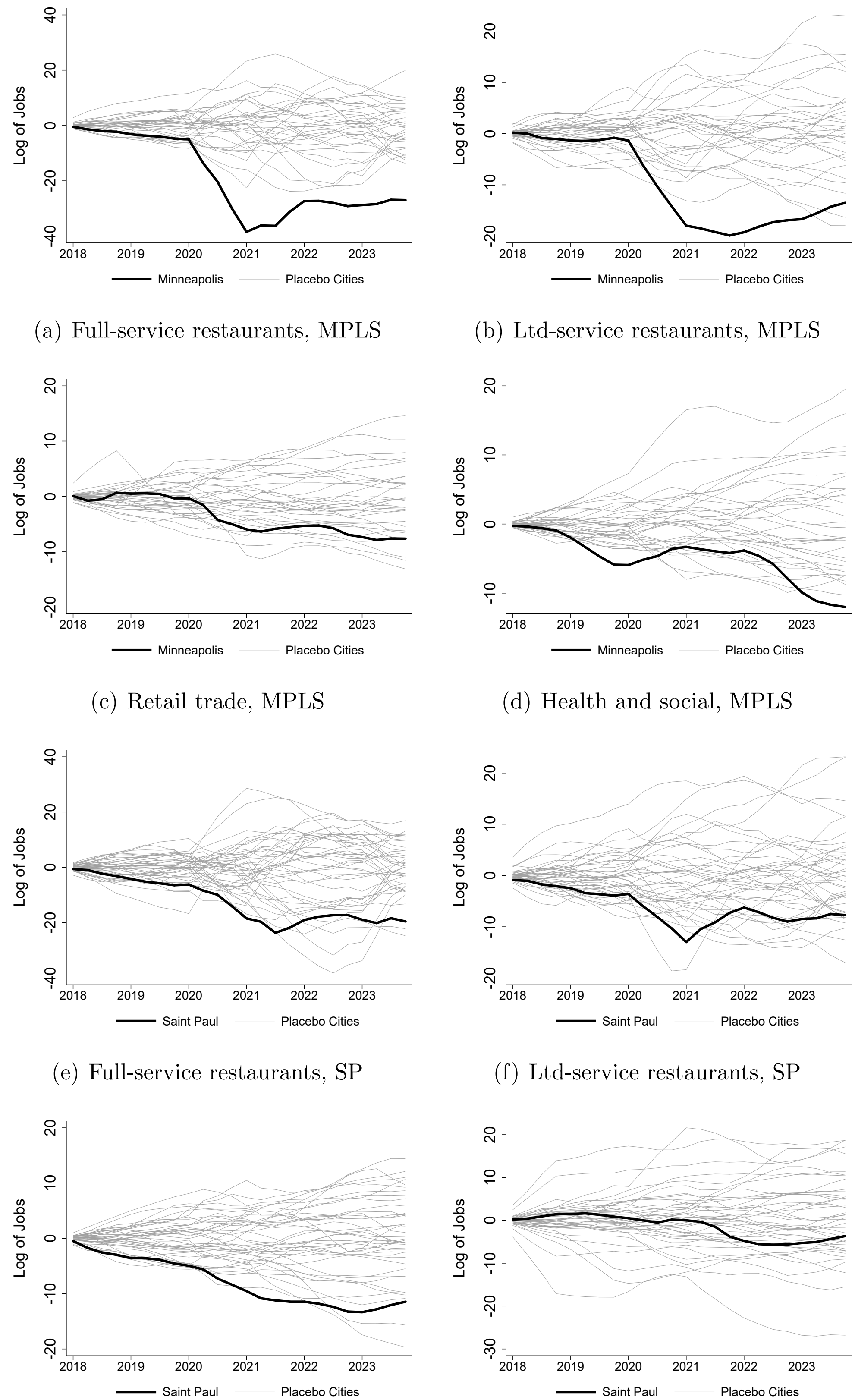
Figure 3: Time-Varying Jobs Effects, Time Series of U.S. Cities

Team (2023) who develop a database tracking economic activity in the United States at a granular level. From this database, we use Google's COVID-19 Community Mobility Reports to measure mobility in retail and recreation and in workplaces between 2020 and 2022. These two mobility indicators likely capture both pandemic and civil unrest conditions. The next two indicators capture only civil unrest conditions and come from the Armed Conflict Location & Event Data Project that collects information on the dates, actors, locations, and types of all reported protest events across U.S. cities. We use violent protests and total protests where Black Lives Matter was listed an affiliated actor because we wish to adjust for civil unrest conditions similar to those in the Twin Cities during 2020.

Our methodology of adjusting for pandemic and civil unrest conditions proceeds in three steps. We denote by $Z_{it}$ the variable we wish to adjust for, where depending on the application $Z_{it}$ denotes either changes in retail and recreation mobility, or changes in workplace mobility, or violent protests, or total protests. The first step is to project outcomes $Y_{it}$ on $Z_{it}$ in the sample of non-treated units, $i = 1, ..., N_{\text{co}}$, during the post-pandemic period, $t = 2020, ....$ From this step, we obtain the effect of $Z_{it}$ on $Y_{it}$ which we denote by $\hat{\beta}_Z$. The second step is to residualize outcome variables for both treated and non-treated units, $\hat{Y}_{it} = Y_{it} - \hat{\beta}_Z Z_{it}$. The final step is to repeat our synthetic difference-in-differences methodology using the residualized outcomes $\hat{Y}_{it}$ and the original weights $\hat{\omega}_i$ that are not affected by the adjustments. Thus, our methodology allows us to examine the sensitivity of our estimates in the case that jobs for all cities, including the Twin Cities, are adjusted for pandemic and civil unrest conditions as predicted by the cross-sectional relationship between jobs and these conditions in the sample of non-treated units during the period with pandemic and civil unrest.[23]

Figure 4 presents our estimates in the sample of other U.S. cities when adjusting jobs for the effects of changes in retail and recreation mobility. The estimates for all industries and cities are very similar to the ones shown previously in Figure 3. Why does adjusting for pandemic and civil unrest conditions makes little difference for the estimated effects of the minimum wage on jobs? While the Twin Cities are more exposed to pandemic restrictions and civil unrest than the synthetic control, their observed jobs declines are outliers relative to the jobs declines predicted by the cross-sectional relationship between jobs and pandemic restrictions and civil

[23]This procedure is not equivalent to controlling directly for $Z_{it}$ in the synthetic difference-in-differences regressions, because the projections that yield $\hat{\beta}_Z$ exclude the Twin Cities from the sample. This is appropriate because the Twin Cities experience both the effects of $Z_{it}$ and the effects of the minimum wage. We perform these projections separately for each industry and separately for the control cities of Minneapolis and of Saint Paul. For violent and total protests, we use only 2020 data since most civil unrest took place during this year. For changes in retail and recreation mobility and workplace mobility we pool data across years, but using only 2020 data to estimate $\hat{\beta}_Z$ does not alter significantly our results.




(a) Full-service restaurants, MPLS

(b) Ltd-service restaurants, MPLS

(c) Retail trade, MPLS

(d) Health and social, MPLS

(e) Full-service restaurants, SP

(f) Ltd-service restaurants, SP

(g) Retail trade, SP

(h) Health and social, SP

Figure 4: Time-Varying Jobs Effects, Adjusted for Retail and Recreation Mobility

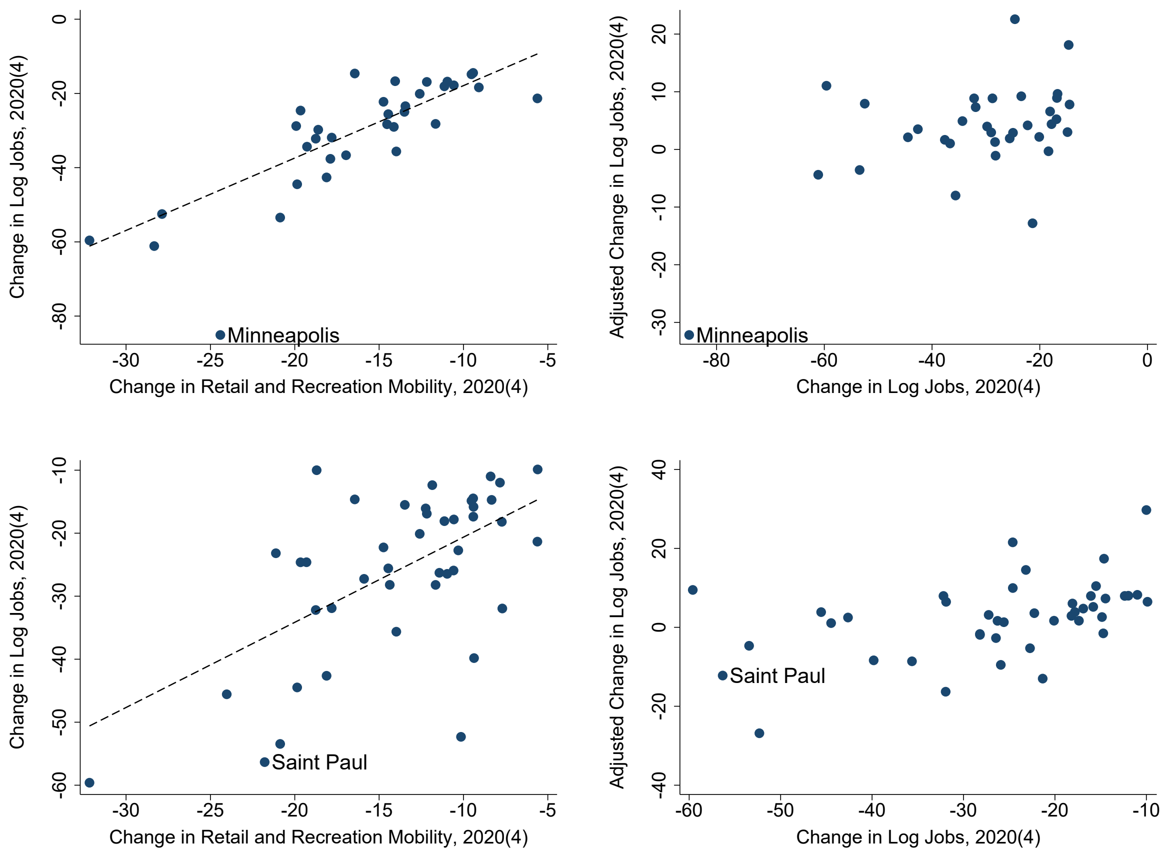



Figure 5: Adjustments for Retail and Recreation Mobility

unrest in the sample of control cities. We illustrate this in Figure 5 that uses as an example the case of full-service restaurants in 2020. The left panels display the relationship between changes in log jobs and changes in retail and recreational mobility in the cross-section of U.S. cities. The estimates are economically reasonable, with a 10 percentage points drop in mobility being associated with a roughly 10 to 15 log points drop in jobs. However, both Minneapolis and Saint Paul are outliers relative to the predicted relationship between these two variables, because they experience larger declines in jobs relative to the declines we would expect based on their reduced mobility. The right panels formalize this by plotting that residualized jobs declines $\hat{Y}_{it}$ against the observed jobs declines $Y_{it}$. Even after adjusting for pandemic and civil unrest conditions, the jobs declines are among the largest in the cross-section of U.S. cities.[24]

[24] Appendix Figures A.22, A.23, and A.24 also show the stability of our results when adjusting our estimates for workplace mobility, violent protests, and total protests. Appendix Figures A.25, A.26, and A.27 illustrate that the same intuition underlies the stability of our results when using the other three indicators to adjust for pandemic and civil unrest conditions.

# 4 Evidence from the Cross Section

The adjustments in the time series methodology aim to difference out pandemic and civil unrest conditions that may have impacted Twin Cities differently from other cities. However, one might still be concerned that Twin Cities are somehow special and either experienced other, unobserved, idiosyncratic shocks or were affected differently by pandemic and civil unrest conditions than other cities. We now estimate the effects of the minimum wage increase using variation from the cross sections of establishments and workers within the Twin Cities, which allows us to difference out Twin Cities shocks common to establishments and workers in the same industry and zip code.

## 4.1 Econometric Methodology: Cross Section

Our starting point is a local projection

$$Y_{jszt}(h) = \gamma_{szt} + \tau_t(h) \cdot \mathrm{GAP}_{jszt-h} + u_{jszt}(h), \tag{5}$$

where $t$ is calendar time, $h$ is the horizon of the projection, and $t-h$ denotes the initial period. For example, when $t = 2018$ and $h = 1$, we examine the effects of the minimum wage on outcomes between 2017 and 2018, whereas when $t = 2021$ and $h = 4$, we examine the effects of the minimum wage between 2017 and 2021. Variable $Y_{jszt}(h)$ denotes an outcome for establishment $j$ over horizon $h$ in industry $s$, zip code $z$, and period $t$. The outcome variables are the arc percent change of $y_{jszt}$ over a horizon of $h$ years

$$Y_{jszt}(h) = \frac{y_{jszt} - y_{jszt-h}}{(1/2)(y_{jszt} + y_{jszt-h})},$$

where $y_{jszt}$ is the level of the wage, jobs, hours, and worker earnings for an establishment. We adopt the arc percent change transformation of growth rates to capture potential changes in the propensity of establishments to exit in response to the minimum wage increase. The lowest value of $Y_{jszt}(h)$ is $-2$, which we obtain for jobs, hours, and earnings when an establishment exists in period $t-h$ and exits in period $t$. The establishments we include in this regression are located only within Minneapolis or Saint Paul and have to exist in the sample in period $t-h$.[25]

In regression (5), the fixed effect $\gamma_{szt}$ absorbs the common growth in period $t$ of all establishments that belong to the same industry $s$ and zip code $z$ of the Twin Cities. For example,

[25] Different from our analysis from the time series that focuses on industries with a high share of affected workers, here we include all industries in our sample. This is appropriate because, even within industries that are relatively less exposed to the minimum wage, there exist establishments and workers with high exposure to the minimum wage.

among other things, the fixed effect could capture the common effect arising from the pandemic recession or civil unrest in the second quarter of 2020.

The key variable of interest in regression (5) is the gap in labor costs evaluated in the initial period $t-h$

$$\text{GAP}_{jszt-h} = \frac{\sum_{i\in j} \max(15/(1+\pi_{t,2017}) - w_{ijszt-h}, 0) h_{ijszt-h}}{\sum_{i\in j} w_{ijszt-h} h_{ijszt-h}}. \tag{6}$$

The numerator of the GAP variable is the additional costs incurred by establishment $j$ when its workers $i$ earn wages in period $t-h$ that are below the projected level of the minimum wage. The denominator of the GAP variable denotes the wage bill of the establishment. Therefore, the GAP variable captures the exposure of an establishment to the minimum wage increase, where exposure is the fraction of the wage bill that is subject to additional labor costs. In equation (6), we adjust the projected level of the minimum wage in each period with the metro-level CPI deflator $\pi_{t,2017}$, where $\pi_{2017,2017} = 1$. As an example, if an establishment pays all of its workers above 15 dollars per hour in 2017, its GAP measure equals zero.[26]

One might be tempted to interpret the coefficients $\tau_t(h)$ as the difference in establishment outcomes arising from differences in their exposure to the minimum wage increase, after differencing out any common time effect that these establishments share with other establishments in the same zip code and industry. These coefficients, however, do not only capture differences in exposure to the minimum wage, because typical establishment dynamics unrelated to exposure introduce a spurious correlation between exposure and various outcomes. Smaller establishments pay lower wages and thus have larger gaps. At the same time, smaller establishments tend to exit at faster rate, which may generate a negative $\tau_t(h)$ for jobs, hours, and earnings. The wage regressions include only establishments that exist in both period $t$ and period $t-h$. We expect smaller establishments that survived to experience higher wage growth, which may generate a positive $\tau_t(h)$ for the wage.

To address this concern, we augment the sample used in the regression to include calendar years between 2010 and 2017, which is a period before the minimum wage change. The final specification is

$$Y_{jszt}(h) = \gamma_{szt} + \tau_t(h) \cdot \text{GAP}_{jszt-h} \cdot \mathbb{I}(t \geq 2018) + \tau_0 \text{GAP}_{jszt-h} + u_{jszt}(h), \tag{7}$$

where $\tau_0$ controls for any correlation between GAP and outcomes due to typical establishment dynamics unrelated to the minimum wage increase.[27]

[26]Previous studies that also used the GAP measure of exposure to the minimum wage include Card and Krueger (1994), Draca, Machin, and Van Reenen (2011), Harasztosi and Lindner (2019), and Dustmann, Lindner, Schonberg, Umkehrer, and vom Berge (2022).

[27]We run our regression with quarterly data but estimate one coefficient common to all quarters within a

Table 2: Minimum Wage Effects, Cross Section of Twin Cities Establishments

| | Minneapolis | | | | Saint Paul | | | |
|---|---|---|---|---|---|---|---|---|
| Change Since 2017 | Wage | Jobs | Hours | Earnings | Wage | Jobs | Hours | Earnings |
| 2017 – 2018 | 6.6 | −5.1 | −4.2 | −1.9 | 0.6 | −17.5 | −17.6 | −10.7 |
| | (0.1) | (21.2) | (32.9) | (67.7) | (80.1) | (0.1) | (0.2) | (7.8) |
| 2017 – 2019 | 7.4 | −3.3 | −3.2 | −1.0 | 4.9 | −18.6 | −19.4 | −13.5 |
| | (0.7) | (51.8) | (54.3) | (86.3) | (19.3) | (0.4) | (0.4) | (6.9) |
| 2017 – 2020 | 11.1 | −13.2 | −12.0 | −14.0 | 2.7 | −22.3 | −21.0 | −20.5 |
| | (0.0) | (1.4) | (2.7) | (2.6) | (54.6) | (0.1) | (0.2) | (0.9) |
| 2017 – 2021 | 14.6 | −15.5 | −15.1 | −18.1 | 6.6 | −11.2 | −11.0 | −7.3 |
| | (0.0) | (0.6) | (0.9) | (0.8) | (17.9) | (11.6) | (13.3) | (39.5) |
| 2017 – 2022 | 15.4 | −19.5 | −17.8 | −21.5 | 9.1 | −21.7 | −18.6 | −18.6 |
| | (0.0) | (0.1) | (0.3) | (0.3) | (5.5) | (0.4) | (1.5) | (4.4) |
| 2017 – 2023 | 19.2 | −15.3 | −14.9 | −17.5 | 10.2 | −27.6 | −25.5 | −27.2 |
| | (0.0) | (2.4) | (2.7) | (3.8) | (8.4) | (0.1) | (0.3) | (1.0) |
| Three-Year Changes | Wage | Jobs | Hours | Earnings | Wage | Jobs | Hours | Earnings |
| 2015 – 2018 | 6.6 | −9.3 | −11.3 | −8.5 | 3.0 | −11.8 | −12.4 | −12.4 |
| | (2.0) | (4.3) | (1.5) | (11.4) | (41.8) | (6.3) | (5.3) | (8.7) |
| 2016 – 2019 | 9.4 | −14.7 | −15.4 | −12.9 | 3.1 | −22.9 | −20.9 | −23.1 |
| | (0.3) | (0.6) | (0.5) | (3.9) | (48.4) | (0.1) | (0.4) | (0.5) |
| 2017 – 2020 | 11.1 | −13.2 | −12.0 | −14.0 | 2.7 | −22.3 | −21.0 | −20.5 |
| | (0.0) | (1.4) | (2.7) | (2.6) | (54.6) | (0.1) | (0.2) | (0.9) |

Notes: The estimates are in percent, multiplied by 100. Entries in parentheses are $p$-values, multiplied by 100, using standard errors clustered at the establishment level.

## 4.2 Evidence from the Cross Section of Establishments

The upper panel of Table 2 presents estimates of the coefficients $\tau_t(h)$ from specification (7) applied to the wage, jobs, hours, and earnings, separately by each city. We begin our analysis by fixing the initial year to 2017 and varying the horizon from one to six years after the minimum wage increase. Entries are multiplied by 100 and are interpreted as the percent change in establishments' outcomes when the GAP in 2017 changes from 0, which is the value for an establishment that is not exposed to the minimum wage, to 1, which is the value for an establishment that experiences 100 percent increase in its wage bill due to the minimum wage.[28] Entries in parentheses are $p$-values in percent associated with each coefficient. We

year. To improve the readability, we have suppressed the notation of the quarters from regression.

[28]Our sample includes many establishments with a zero GAP. The average outcome of these establishments estimates the constant $\gamma_{szt}$. We believe it is appropriate to include non-exposed establishments in the regression, because they are a valid control group for exposed establishments within a zip code and industry. To examine how sensitive our results are to the linear specification adopted in regression (7), we have repeated our regressions

cluster standard errors at the establishment level.

Beginning with the wage effects in Minneapolis, we estimate wage growth of around 7 percent in the first two years after the minimum wage increase. Wage gains for establishments exposed to the minimum wage increase over time and reach between 15 and 20 percent at horizons of four to six years. By contrast, we fail to detect statistically significant wage increases in Saint Paul establishments until 2022. This result echoes the result using time series variation, which showed stronger wage responses in Minneapolis implementing a minimum wage ordinance in 2018 than in Saint Paul implementing it in 2020.

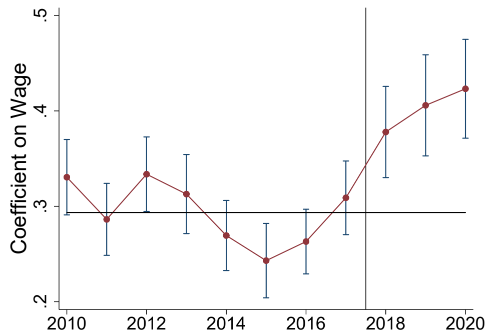
Turning to the employment responses, we estimate declines of jobs and hours that range between 12 and 20 percent in Minneapolis establishments three years after the implementation of the minimum wage policy. The employment effects in Minneapolis tend to increase over time. We estimate even larger employment declines in Saint Paul establishments, with the largest effects exceeding 25 percent. Different from Minneapolis, in Saint Paul the employment declines are also detected before 2020. The employment declines in Saint Paul establishments before the implementation of the policy, without a corresponding increase in the wage, are consistent with our time series results. Finally, in both cities, we estimate negative relationships between exposure to the minimum wage and earnings at the establishment level, with the effects becoming larger and more precise beginning three years after the implementation of the policy.[29]

A reasonable concern about our cross-sectional results in 2020 is whether our strategy identifies establishments' sensitivity to the minimum wage or whether it identifies an excess sensitivity of smaller establishments that happen to have a larger GAP to the pandemic recession or civil unrest. In the bottom panel of Table 2, we fix the horizon to $h = 3$ years and vary the initial period over which the response is calculated. The estimated coefficients for all variables and cities are remarkably stable between 2019 and 2020. This reassures us that our identification strategy isolates establishments' differential exposure to the minimum wage rather than a heterogeneous effect of the pandemic or civil unrest on establishments.

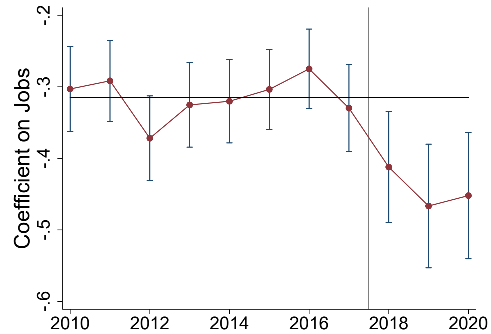
The responses of the wage, jobs, hours, and earnings are above and beyond those generated by typical establishment dynamics because regression (7) includes the GAP measure in the period before the minimum wage increase. However, it could still be the case that there is a

by excluding establishments with a zero GAP. We find no significant differences in our results.

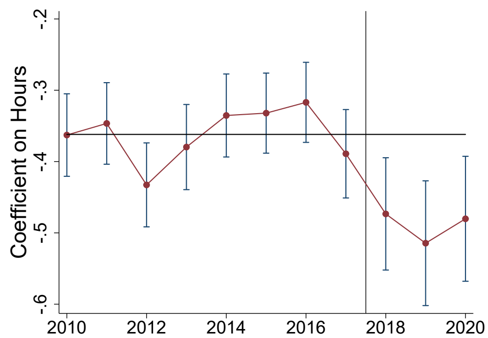
[29] Appendix Table A.12 presents estimated coefficients $\tau_t(h)$ in a specification in which we add lags of the dependent variable into the local projection. Our estimated coefficients do not change much, with the exception of the wage effects in Minneapolis establishments, which decrease somewhat in magnitude. We have also examined the robustness of our results to including calendar years between 2007 and 2017, instead of 2010 to 2017, with no difference in our results. Appendix Table A.13 also adds a size fixed effect interacted with industry, quarter, and zip code, that differentiates establishments below from above 100 employees prior to the minimum wage change. The results are also very similar to the baseline results.



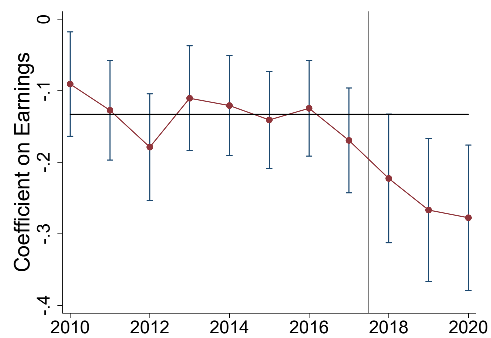

(a) Minneapolis



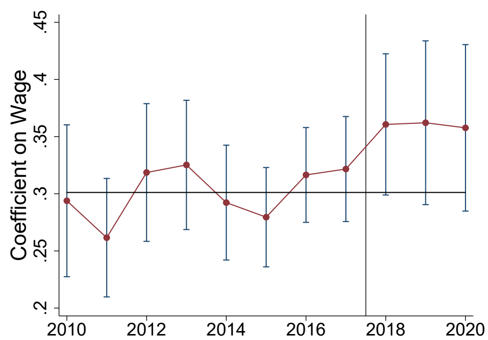

(b) Minneapolis



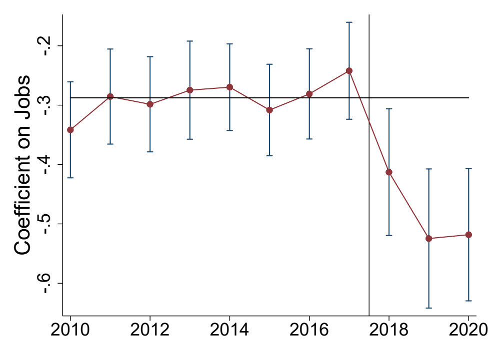

(c) Minneapolis



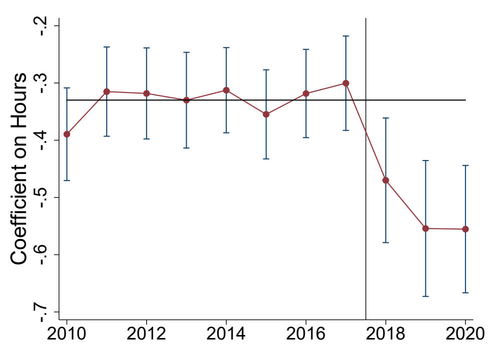

(d) Minneapolis



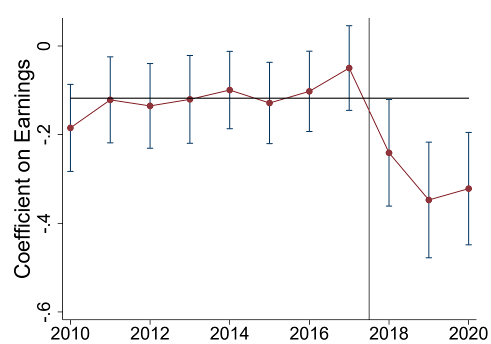

(e) Saint Paul




(f) Saint Paul




(g) Saint Paul




(h) Saint Paul

Figure 6: Cross-Sectional Establishment Responses Over Time

Notes: The figure shows estimates for $\tau_t(3)$ from regressions $Y_{jszt}(3) = \gamma_{szt} + \tau_t(3) \cdot \text{GAP}_{jszt-3} + u_{jszt}(3)$, together with 95 percent confident intervals. The horizontal line represents the average of the estimated $\tau_t(3)$ between 2010 and 2017.

trend in establishment dynamics that increases over time these coefficients in absolute value, irrespective of the minimum wage policy change. To examine this possibility, we again fix the horizon to $h = 3$ years and estimate regression (5) for different calendar years starting in $t = 2010$. We end these regressions in $t = 2020$, so that none of our regressions mix outcomes for the periods before and after the minimum wage policy change. Figure 6 shows that the largest absolute values of the coefficients for wages, jobs, hours, and earnings in both cities are estimated during the minimum wage increase and, with the exception of wages in Saint Paul, that these coefficients are statistically different from the average coefficient before the minimum wage increase in 2018, indicated by the horizontal line. It also shows that there is no noticeable trend in these estimated coefficients before the minimum wage increase.

### 4.3 Evidence from the Cross Section of Workers

While our estimates speak to the outcomes of establishments that were located in the Twin Cities before the minimum wage increase, they may not necessarily be informative about worker outcomes, because workers may have reallocated from exposed to non-exposed establishments or found jobs outside of their zip code. Additionally, there may be spillovers from high to low GAP establishments that make the interpretation of our results from the cross section of establishments more nuanced. To give an example, if workers reallocated from high to low GAP establishments within the same zip code and industry, then we would be double-counting the effects of the minimum wage increase on establishments' employment.

We now present specifications from the cross section of workers, whose outcomes we can track everywhere in the state of Minnesota, irrespective of whether they reallocated to other establishments within or outside of the Twin Cities. Our specification is

$$Y_{it}(h) = \sum_{s} \gamma_{st} X_{ist} + \tau_t(h)\overline{\text{GAP}}_{it-h} \cdot \mathbb{I}(t \geq 2018) + \tau_0 \overline{\text{GAP}}_{it-h} + \rho Y_{it-1}(h) + u_{it}(h), \tag{8}$$

where the wage gap relative to the initial period $t - h$ is

$$\overline{\text{GAP}}_{it-h} = \frac{1}{\#J_t(i)} \sum_{j \in J_t(i)} \text{GAP}_{jt-h}, \tag{9}$$

$\#J_t(i)$ denotes the number of establishments that worker $i$ worked in during period $t$, and $\text{GAP}_{jt-h}$ is establishment's $j$ gap in labor costs defined in equation (6). Thus, we treat workers with their establishments' gaps to capture their exposure to the minimum wage. This specification allows us to track workers' outcomes over time, as workers reallocate to other establishments both in and outside of the Twin Cities. However, the treatment is defined at

Table 3: Minimum Wage Effects, Cross Section of Twin Cities Workers

| | Minneapolis | | | Saint Paul | | |
|---|---|---|---|---|---|---|
| | Wage | Hours | Earnings | Wage | Hours | Earnings |
| 2017 – 2018 | 1.4 | −7.8 | −8.4 | −2.1 | −7.7 | −8.1 |
| | (0.2) | (1.1) | (0.8) | (8.0) | (5.2) | (4.2) |
| 2017 – 2019 | 4.4 | −10.4 | −8.3 | 0.9 | −3.5 | 0.4 |
| | (0.0) | (0.0) | (0.8) | (52.6) | (34.3) | (92.7) |
| 2017 – 2020 | −1.3 | −11.8 | −9.7 | 0.9 | −7.8 | −3.6 |
| | (0.4) | (0.0) | (0.2) | (56.3) | (3.4) | (34.8) |
| 2017 – 2021 | 9.8 | −6.9 | −3.6 | 4.5 | −7.7 | −6.2 |
| | (0.0) | (1.8) | (24.6) | (0.9) | (3.6) | (10.9) |
| 2017 – 2022 | 15.6 | 1.7 | 9.0 | 11.7 | 2.0 | 10.5 |
| | (0.0) | (55.7) | (0.4) | (0.0) | (58.3) | (0.6) |
| 2017 – 2023 | −8.5 | 3.8 | −5.1 | 7.1 | −7.8 | −5.8 |
| | (0.0) | (19.7) | (10.7) | (0.0) | (3.3) | (13.2) |

Notes: The estimates are in percent, multiplied by 100. Entries in parentheses are $p$-values, multiplied by 100, using standard errors clustered at the worker level.

the establishment level, thus alleviating the concern that low-wage workers' difficulty finding jobs in 2020 is because of the pandemic or civil unrest.[30] The fixed effect $\gamma_{st}$ absorbs time and industry effects. Workers may work in more than one industry in a year, so the variable $X_{ist}$ denotes the share of worker $i$'s employment in industry $s$. The $\tau_t(h)$ coefficients are the percent change in worker outcomes resulting from a higher exposure to the minimum wage for workers with the same growth rate $Y_{it-1}(h)$ in the previous period, after differencing out the common effect that workers in the same industry experience, $\gamma_{st}$, and any effects we would detect due to typical worker dynamics, captured by the coefficient $\tau_0$.

Table 3 presents the estimated coefficients from regression (8). Workers in exposed establishments experience wage gains beginning in 2018 in Minneapolis and in 2021 in Saint Paul. Workers in exposed establishments experience hours losses starting in 2018 in both cities, with some of these losses being similar in magnitude to the losses we documented from the cross section of establishments in Minneapolis. However, the losses in hours tend to reverse after 2022, suggesting that workers may have reallocated to other cities. This can also explain the negative wage estimate that we find for Minneapolis in 2023. We also detect statistically significant declines in worker earnings until 2020 for Minneapolis and in 2018 for Saint Paul, but

[30]This is the reduced-form coefficient of a two-stage instrumental variable procedure, in which we instrument workers' gaps with their establishments' gaps. The first stage coefficient is around 1.5 with a F-value above 40,000.

Table 4: Jobs Effects of Minimum Wage Increases: Summary of Estimates

| Jobs (2023, percent) | Time Series | Cross Section | Ratio |
|---|---|---|---|
| Minneapolis Average | −4.4 | −0.8 | 0.18 |
| Minneapolis Most Negative | −28.2 | −15.0 | 0.53 |
| Saint Paul Average | −2.2 | −1.4 | 0.63 |
| Saint Paul Most Negative | −19.3 | −19.5 | 1.01 |
| Average | | | **0.58** |

Notes: Average from the time series includes all two-digit industries and averages between the DEED and the QCEW. Most Negative from the time series uses the estimates for the restaurant industries. The estimates for the cross section multiplies the jobs coefficient from the establishments' regressions between horizon 3 and 6 with the weighted average and maximum GAP and then averages across horizons.

these declines reverse or even become gains in 2022.[31]

# 5 Summary of Estimates

Table 4 summarizes our estimates using variation from the time series of cities and the cross sections of establishments. In the first row, we present the average jobs losses in Minneapolis in 2023. The time series estimate of the jobs losses is 4.4 percent. We calculate this number as the average jobs losses across all two-digit industries, where losses are weighted with the employment of the corresponding industry in total Minneapolis employment before the minimum wage increase. We average our estimates between the DEED and the QCEW data sources. The estimate of jobs losses using variation from the cross section is 0.8 percent. We calculate this number by multiplying the jobs coefficient from the establishments' regressions for horizons three to six years with the weighted-average GAP and then averaging across horizons. Similar calculations in Saint Paul lead to estimated jobs losses of 2.2 percent from the time series and 1.4 percent from the cross section.

The second and fourth rows summarize our most negative jobs estimates. For the time series, we use the estimates for restaurants and conclude that the most negative jobs effects are 28 percent in Minneapolis and 19 percent in Saint Paul. For the cross section, we multiply each jobs coefficient from the establishments' regressions with the maximum GAP and then average across horizons. We use the maximum GAP so that we can get a comparable estimate of the

[31] Dustmann, Lindner, Schonberg, Umkehrer, and vom Berge (2022) document the reallocation of low-wage workers from smaller, lower-paying, and less productive establishments to larger, higher-paying, and more productive establishments following the introduction of a national minimum wage in Germany in 2015.

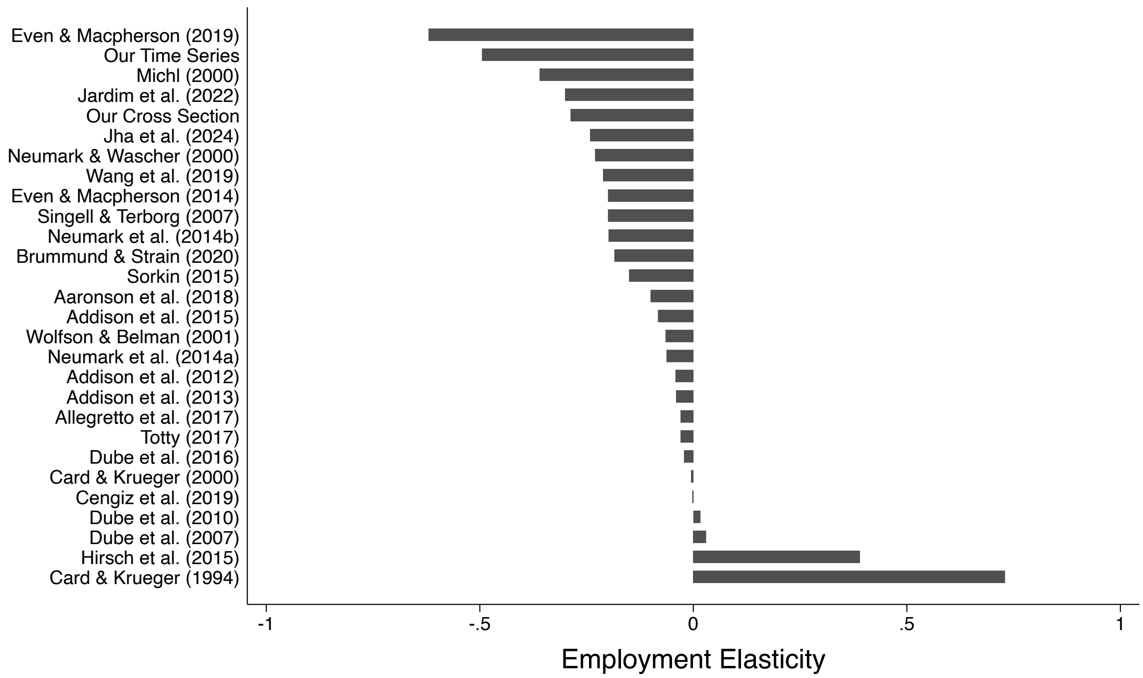



Figure 7: Comparison of Restaurant Employment Elasticity to the Literature

most negative jobs effects. This yields estimated jobs losses of 15 percent in Minneapolis and 20 percent in Saint Paul.

Figure 7 compares our estimated elasticity of restaurant employment with respect to the minimum wage to the elasticities found in other studies.[32] The elasticity of jobs with respect to the minimum wage in Minneapolis is found by dividing $-28.2$ percent in Table 4 for restaurants with the 53 percent increase in the minimum wage between 2018 and 2023. The corresponding elasticity for Saint Paul is $-0.46$. Averaging across the two estimates, our time series elasticity of employment with respect to the minimum wage is $-0.5$. For the elasticity using variation from the cross section, we multiply the elasticity from the time series with 0.58, which Table 4 shows to be the average ratio of estimates from the cross section to those from the time series. This yields an elasticity of employment with respect to the minimum wage of $-0.3$. As seen in the figure, our employment elasticities are more negative than most of those found in the literature, which average around $-0.1$.

There are several reasons why our employment elasticities with respect to the minimum

[32] We include papers published after the study of Card and Krueger (1994) and for which we could obtain an estimated elasticity with respect to the minimum wage for the U.S. restaurant industry. Our estimate is the jobs elasticity, because the analysis using other U.S. cities from the QCEW has only jobs and not hours. However, we showed that in most cases the results using hours are similar to those using jobs. Other papers mainly report jobs elasticities, but we also include few papers with hours elasticities such as Michl (2000) and Jardim, Long, Plotnick, Van Inwegen, Vigdor, and Wething (2022).

wage might be larger than those found in the literature. First, our policy change is at the local level. Product substitution elasticities are larger at the local level than the state or national level. For example, consumers might be substituting more expensive Twin Cities restaurants or shops with cheaper establishments in surrounding suburbs. But we would not expect consumers to substitute that much between Minnesota establishments and establishments in other states, had the minimum wage policy been enacted at the state level.

Additionally, the policy variation we examine is significantly larger than the typical variation found in the literature. The changes in the minimum wage of the Twin Cities are large even relative to the ones classified as large in the analysis of Clemens and Strain (2021), who estimate an elasticity of $-0.5$ for low-skilled employment during "large minimum wage increases," which are about 20 to 25 percent after three years and 30 to 40 percent after five years. The Seattle study by Jardim, Long, Plotnick, Van Inwegen, Vigdor, and Wething (2022) examines a policy change as large as the one in the Twin Cities and estimates a $-0.3$ elasticity of employment with respect to the minimum wage for restaurants. The difference in their elasticity with the one that we estimate for the Twin Cities could reflect that Seattle was booming during the implementation of its large minimum wage increase. Our model in Section 6 rationalizes a larger elasticity, when the minimum wage change is larger and when the economy is in a recession.

# 6 Model

In this section, we quantify a dynamic, equilibrium model of establishments that are subjected to a change in the minimum wage policy.

## 6.1 Environment

The economy consists of a representative household who demands goods and supplies labor, establishments that produce output in a sector that is subject to a minimum wage policy, and a sector that provides an outside good which serves as the numeraire. We think of the outside good as encompassing goods that are substitutable to restaurant services, such as grocery stores and home production of food.

*Household.* The household chooses consumption of the outside good, $C_t$, consumption of differentiated varieties of restaurants $y_{it}$, and differentiated varieties of labor supplied to restaurants

$\ell_{it}$ to maximize

$$\max_{C_t, y_{it}, \ell_{it}} U = \sum_{t=0}^{\infty} \beta^t \left( C_t + \psi^{\frac{1}{\gamma}} \frac{Y_t^{1-\frac{1}{\gamma}} - 1}{1 - 1/\gamma} - \frac{L_t^{1+\frac{1}{\xi}}}{1 + 1/\xi} \right), \tag{10}$$

where $\beta \in (0,1)$ is the discount factor, $\psi$ is a preference shifter for restaurant goods, parameter $\gamma > 0$ disciplines the curvature of utility with respect to restaurant goods, and parameter $\xi > 0$ is the elasticity of aggregate labor supply with respect to the aggregate wage. Utility is linear in the consumption of outside goods, which simplifies the model as the outside good absorbs all wealth effects. This assumption is realistic, because restaurants represent a small share of economic activity.

Differentiated varieties of restaurant services aggregate through a CES function

$$Y_t = \left( \sum_i y_{it}^{\frac{\varepsilon - 1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon - 1}}, \tag{11}$$

where parameter $\varepsilon > 1$ is the elasticity of substitution across varieties in product demand. Similarly, differentiated varieties of labor supplied to each restaurant aggregate through a CES function

$$L_t = \left( \sum_i \chi_i^{-1} \ell_{it}^{\frac{1+\theta}{\theta}} \right)^{\frac{\theta}{1+\theta}}, \tag{12}$$

where parameter $\theta > 0$ is the elasticity of substitution across varieties in labor supply and $\chi_i$ denotes the amenity value (or the inverse disutility) of the household for working in a particular variety.

The household maximizes its utility subject to the budget constraint

$$C_t + \sum_i p_{it} y_{it} = Z_t + \sum_i w_{it} \ell_{it} + \sum_i \pi_{it} - K_t. \tag{13}$$

The household derives resources from the endowment of the outside good, $Z_t$, from labor supplied at a wage $w_{it}$ to each operating restaurant, and from profits $\pi_{it}$ by ownership of restaurants. The household pays for the entry costs, $K_t$, occurred by establishments in the restaurant industry.

*Outside good.* The endowment of the outside good $Z_t$ is used for four purposes

$$Z_t = C_t + K_t + \sum_i f + \sum_i m_{it}, \tag{14}$$

where $f$ is the fixed cost of operation for restaurants and $m_{it}$ is all variable inputs except for labor used in the production of restaurant goods.

*Restaurant industry.* There is a large mass of potential entrants to the industry, $\bar{I}$, that produce differentiated varieties. We denote a potential entrant by $\iota$ and an establishment that operates in equilibrium by $i$. The industry is imperfectly competitive both in its product and its labor market. The timing of events is as follows.

1. Potential entrants decide whether to enter. Entering costs $\kappa_\iota$ units of the outside good. Upon entry, an establishment draws a vector $(\chi_\iota, a_\iota)$ that is fixed over time, where $\chi_\iota$ is the amenity value for working in the establishment and $a_\iota$ is its productivity.
2. New entrants and incumbents decide whether to operate by paying the fixed operating cost, $f$, or to exit.
3. Establishments draw an i.i.d. idiosyncratic destruction shock, $\delta_{\iota t} \in \{0, 1\}$. Fraction $\delta$ of establishments is destroyed exogenously.
4. Surviving establishments become operating and choose price, production, wage, and inputs.

Establishments are ex-ante heterogeneous in three dimensions. First, they have heterogeneous entry costs $\kappa_\iota$. We need heterogeneous entry costs in order to generate an interesting entry decision, as establishments compare the entry costs to the present discounted value of expected profits from entry, which do not vary by establishment. Establishments are heterogeneous in both amenities $\chi_\iota$ and productivity $a_\iota$. We need these two sources of heterogeneity in order to account for the relatively low correlation between wages and establishment size that we observe in the data. All sources of heterogeneity are uncorrelated to each other and with the idiosyncratic destruction shock, $\delta_{\iota t}$. Except for the idiosyncratic destruction shock, all other sources of heterogeneity are drawn from log normal distributions.

We begin by describing the problem of an establishment that has already entered, decided to operate, and survived the exogenous destruction shock. The establishment has a CES production function

$$y_{it} = a_i \left( \phi m_{it}^{\frac{\sigma-1}{\sigma}} + (1-\phi)\ell_{it}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{15}$$

where parameter $\phi \in [0, 1]$ is a distribution factor and parameter $\sigma \geq 0$ is the elasticity of substitution between all other inputs, $m_{it}$, and labor, $\ell_{it}$.

Establishments are imperfectly competitive in product markets, meaning that they internalize that their product demand depends on their price $p_{it}$. Product demand for variety $i$ comes from the first-order conditions for optimality of household consumption

$$p_{it} = \psi^{\frac{1}{\varepsilon}} P_t^{\frac{\varepsilon-\gamma}{\varepsilon}} y_{it}^{-\frac{1}{\varepsilon}}, \tag{16}$$

where $P_t = \left(\sum_i p_{it}^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$ is the aggregate price index. Product demand has an elasticity $-\varepsilon$ with respect to its own price. Industry equilibrium effects appear through the aggregate price index $P_t$. A higher $P_t$ tends to increase product demand for variety $i$, because all other varieties in the industry become more expensive. The strength of this effect is disciplined by the elasticity of substitution within the industry, $\varepsilon$. A higher $P_t$ tends to decrease product demand for variety $i$, because it makes the industry as a whole more expensive relative to the outside good. The strength of this effect is disciplined by the elasticity of substitution across goods, $\gamma$.

Establishments are also imperfectly competitive in labor markets, meaning that they internalize that their labor supply depends on their wage $w_{it}$. Labor supply for variety $i$ comes from the first-order conditions for optimality of household labor

$$w_{it} = \chi_i^{-1} W_t^{\frac{\theta-\xi}{\theta}} \ell_{it}^{\frac{1}{\theta}}, \tag{17}$$

where $W_t = \left(\sum_i \chi_{it}^{\theta} w_{it}^{1+\theta}\right)^{\frac{1}{1+\theta}}$ is the aggregate wage index. Labor supply has an elasticity $\theta$ with respect to its own wage. Industry equilibrium effects appear through the aggregate wage index $W_t$. A higher $W_t$ tends to decrease labor supplied to variety $i$, because it becomes more profitable to work for other varieties in the industry. The strength of this effect is disciplined by the elasticity of substitution within the industry, $\theta$. A higher $W_t$ tends to increase labor supply for variety $i$, because it increases the return of providing labor to the industry relative to consuming goods. The strength of this effect is disciplined by the elasticity of aggregate labor supply, $\xi$.

Profits of an incumbent or a new entrant $\iota$ are

$$\pi_{\iota t} = \max\{\max_{m_{\iota t}, \ell_{\iota t}} p(y_{\iota t}) \cdot y_{\iota t} - m_{\iota t} - \max(\bar{w}_t, w(\ell_{\iota t})) \cdot \ell_{it} - f, 0\}, \tag{18}$$

subject to the production function (15), the establishment product demand (16), and the establishment labor supply (17). An establishment faces a binding minimum wage $\bar{w}_t$, when its unconstrained equilibrium wage $w_{\iota t}$ falls below $\bar{w}_t$. An establishment exits if the fixed cost of operation $f$ exceeds its revenues net of factor payments, and so profits cannot be negative.

A potential entrant $\iota$ that has not already entered in period $t$, compares the costs of entry to the present discounted value of expected profits from entry. The establishment enters if

$$\sum_{t=s}^{\infty} \left(\beta(1-\delta)\right)^{t-s+1} \mathbb{E}\pi_t \geq \kappa_\iota. \tag{19}$$

The expectation of profits in equation (19) is taken over all possible draws of sources of heterogeneity, $(\chi_\iota, a_\iota)$, which incorporates that profits cannot be negative because of exit. The discount factor relevant for the entry decision depends both on the household discount factor $\beta$ and the probability of destruction $\delta$.

## 6.2 Equilibrium

Given a minimum wage policy, $\bar{w}_t$, and an initial number of operating establishments, $I_0$, an equilibrium is sequences of aggregate consumption of the outside good $C_t$, aggregate consumption of restaurants $Y_t$ and price $P_t$, aggregate labor $L_t$ and wage $W_t$, establishment-level output, $y_{\iota t}$, price $p_{\iota t}$, labor $\ell_{\iota t}$, wage $w_{\iota t}$, other inputs $m_{\iota t}$, number of entrants $E_t$, number of exits $X_t$, and number of operating firms, $I_t$, such that: (i) the representative household maximizes its utility subject to the budget constraint; (ii) operating establishments maximize their profits subject to the production function, the establishment product demand, and the establishment labor supply; (iii) potential entrants enter if the present discounted value of expected profits exceeds their entry cost; (iv) incumbents exit if they are hit by the destruction shock or their variable profits fall below the fixed operating cost; (v) product markets clear; (vi) labor markets clear; (vii) the market for the outside good clears.

We describe the equilibrium as a system of $8 + 5 \times \bar{I}$ equations in $8 + 5 \times \bar{I}$ unknowns. Consumption of the outside good $C_t$ is pinned down residually from market clearing in equation (14). Aggregate restaurant consumption $Y_t$ is given by equation (11) and the price index by $P_t = \left(\sum_i p_{it}^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$. Aggregate restaurant labor $L_t$ is given by equation (12) and the wage index by $W_t = \left(\sum_i \chi_{it}^{\theta} w_{it}^{1+\theta}\right)^{\frac{1}{1+\theta}}$.

In the restaurant industry, we need to compute the solution for output, inputs, prices, wages, and profits for all potential entrants $\iota$, before determining which establishments $i$ will operate in equilibrium. The reason is that establishments do not know their draws of amenities $\chi_\iota$ and productivity $a_\iota$ before entry and, thus, expected profits that determine entry in equation (19) depend on the distribution of outcomes for all potential entrants. The wage and labor at the establishment level is determined by the equalization of supply of labor to a restaurant, $\ell_{\iota t} = \chi_\iota^{\theta} w_{\iota t}^{\theta} W_t^{\xi-\theta}$, to labor demand,

$$\ell_{\iota t} = \psi(1-\phi)^{\varepsilon} P_t^{\varepsilon-\gamma} a_\iota^{\varepsilon-1} \left( \phi \left( \frac{\phi}{1-\phi} \mu_w w_{\iota t} \right)^{\sigma-1} + (1-\phi) \right)^{\frac{\varepsilon-\sigma}{\sigma-1}} (\mu_p \mu_w w_{\iota t})^{-\varepsilon}, \tag{20}$$

where we define the price markup as $\mu_p = \frac{\varepsilon}{\varepsilon-1}$ and the wage markup as $\mu_w = \frac{\theta+1}{\theta}$. Equation (20) is applicable only when the equilibrium wage $w_{\iota t}$ exceeds the minimum wage $\bar{w}_t$. Otherwise, equilibrium wage is $w_{\iota t} = \bar{w}_t$ and equilibrium labor is given by

$$\ell_{\iota t} = \psi(1-\phi)^{\varepsilon} P_t^{\varepsilon-\gamma} a_\iota^{\varepsilon-1} \left( \phi \left( \frac{\phi}{1-\phi} \bar{w}_t \right)^{\sigma-1} + (1-\phi) \right)^{\frac{\varepsilon-\sigma}{\sigma-1}} (\mu_p \bar{w}_t)^{-\varepsilon}. \tag{21}$$

The effects of the minimum wage on establishments' labor demand can be understood by comparing unconstrained labor demand in equation (20) to labor demand with a binding minimum wage in equation (21). In the absence of labor market power, $\mu_w = 1$, labor demand unambiguously falls for establishments for which the minimum wage $\bar{w}_t$ exceeds their competitive wage $w_{\iota t}$. This is a movement along the labor demand curve, with the elasticity of labor demand governing the magnitude of reduction in labor.[33] With labor market power, $\mu_w > 1$, the employment effect of the minimum wage is theoretically ambiguous. A binding minimum wage removes labor market power, because establishments perceive an infinite elasticity of labor supply for all labor units below the minimum wage. When $\mu_w w_\iota$ exceeds $\bar{w}_t$, a higher minimum wage increases equilibrium labor.

The optimal demand for other inputs is given by $m_{\iota t} = \ell_{\iota t}\left(\frac{\phi}{1-\phi}\mu_w w_{\iota t}\right)^\sigma$ when $w_{\iota t} > \bar{w}_t$ and by $m_{\iota t} = \ell_{\iota t}\left(\frac{\phi}{1-\phi}\bar{w}\right)^\sigma$ otherwise. Finally, the price and output of an establishment is determined by the equalization of the demand for an establishment's product, $y_{\iota t} = \psi p_{\iota t}^{-\varepsilon} P_t^{\varepsilon-\gamma}$, to the supply for an establishment's product, $y_{\iota t} = a_\iota\left(\phi m_{\iota t}^{\frac{\sigma-1}{\sigma}} + (1-\phi)\ell_{\iota t}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$.

The mass of establishments that exit, $X_t$, is determined by the rate of exogenous destruction $\delta$ and the condition that the fixed cost of operation exceeds revenues minus payments to factors of production, $f > \max_{m_{\iota t},\ell_{\iota t}}\{p(y_{\iota t})\cdot y_{\iota t} - m_{\iota t} - \max(\bar{w}_t, w(\ell_{\iota t}))\cdot \ell_{\iota t}\}$. The mass of establishments that enter, $E_t$, is determined by the entry condition in equation (19). Finally, the evolution of the number of operating establishments is given by $I_t = I_{t-1} + E_t - X_t$. Appendix B describes the computation of the model.

## 6.3 Quantification

Table 5 summarizes our parameterization, which is such that the stationary equilibrium of the model reproduces statistics of the restaurant industry in Minneapolis for the three years prior to the minimum wage change, 2015 to 2017. In the top panel, we present parameters that are set before solving the model. In each simulation of the model, there are $\bar{I} = 20,000$ potential entrants.[34] We use the initial minimum wage applicable to establishments from the state of Minnesota, $\bar{w} = 9$. The mean of establishment productivity, $\mu_a$, is normalized to one and the aggregate demand shifter $\psi$ is such that the equilibrium price index equals one. We pick $\delta = 0.13$, such that, in the initial stationary equilibrium of the model, the entry rate matches the average entry rate observed in the restaurant industry. Given our estimate of $\delta = 0.13$

[33] As in Hamermesh (1993), we calculate the total elasticity of labor demand (in absolute value) $\eta_{\iota t} = (1 - \alpha_{\iota t})\varepsilon + \alpha_{\iota t}\sigma$, which is a weighted average of the elasticity $\varepsilon$, which captures the reduction in scale as the marginal cost and price increase, and the elasticity $\sigma$, which captures substitution between factors. Weights $\alpha_{\iota t} = \frac{\left(\frac{\phi}{1-\phi}\right)^\sigma (\mu_w w_{\iota t})^{\sigma-1}}{1+\left(\frac{\phi}{1-\phi}\right)^\sigma (\mu_w w_{\iota t})^{\sigma-1}}$ equal $\phi$ in the limiting case of a Cobb-Douglas production function with $\sigma = 1$.

[34] Our quantitative results presented below average across 600 simulations, where every simulation corresponds to a different draw of the sources of heterogeneity.

Table 5: Baseline Parameters

| Parameter | Value | Comments |
|---|---|---|
| Number of potential firms, $\bar{I}$ | $20,000$ | |
| Initial minimum wage, $\bar{w}$ | 9 | Minnesota minimum wage |
| Mean productivity, $\mu_a$ | 1 | normalization |
| Aggregate demand shifter, $\psi$ | $6.32 * 10^{11}$ | $P = 1$ |
| Exit probability, $\delta$ | 0.13 | entry rate, 0.13 |
| Discount factor, $\beta$ | 0.85 | profit margin, 0.16 |
| Labor substitutability, $\theta$ | 7 | markdown, 0.13 |
| Standard deviation of entry cost, $\sigma_\kappa$ | $0.53\mu_\kappa$ | coefficient variation, $(\sigma_\chi/\mu_\chi)$ |
| Aggregate labor supply elasticity, $\xi$ | 7 | $= \theta$, neutralize GE feedback |
| Curvature of utility, $\gamma$ | 3.5 | $= \varepsilon$, neutralize GE feedback |
| **Parameter** | **Value** | **Targets** |
| Elasticity of product demand, $\varepsilon$ | 3.5 | labor share, 0.35 |
| Distribution factor, $\phi^\sigma$ | 0.65 | other inputs share, 0.32 |
| Elasticity of substitution in production, $\sigma$ | 0.05 | cross-sectional elasticity, $-1.08$ |
| Mean amenity value, $\mu_\chi$ | 0.47 | mean wage, 17.7 |
| Mean entry cost, $\mu_\kappa$ | $7 * 10^7$ | entry cost to revenue, 0.47 |
| Standard deviation amenities, $\sigma_\chi$ | $0.53\mu_\chi$ | standard deviation log wages, 0.36 |
| Standard deviation productivity, $\sigma_a$ | $0.75\mu_a$ | correlation wage-labor, 0.17 |
| Fixed operating cost, $f$ | $2.5 * 10^6$ | standard deviation log labor, 1.23 |

Notes: The top panel presents parameters that are set before solving the model. The bottom panel presents parameters that are calibrated such that the model reproduces empirical targets from Minneapolis restaurants between 2015 and 2017.

and our target for entry costs described below, a discount factor $\beta = 0.85$ generates an average profit margin of 0.16 for an entrant who is indifferent between entering and not entering.[35]

The remaining four parameters in the top panel of the table cannot be identified using only cross-sectional data. Here, we explain our logic for their baseline values, and discuss below how the comparative statics of our model are affected by different values of these parameters. We set $\theta = 7$, which generates a 13 percent markdown of wages, which is in the range of estimates reported in the literature, such as 5 to 17 percent in Azar, Marinescu, and Steinbaum (2022). The standard deviation of entry costs is also not identified from our cross-sectional statistics. We choose to set the standard deviation such that the coefficient of variation in entry costs,

[35] Our estimate of residual payments to profits and fixed operating costs is roughly one-third, as explained below. We allocate half of the residual payments to profits, which is consistent with margin estimates for publicly traded restaurants by Aswath Damodaran (https://shorturl.at/ePPsM). Using equation (19) in a stationary environment, we obtain $\beta = \frac{1}{1-\delta}\frac{\mathbb{E}(\kappa/py)/(\mathbb{E}\pi/py)}{1+\mathbb{E}(\kappa/py)/(\mathbb{E}\pi/py)}$.

$\sigma_\kappa/\mu_\kappa$, equals our calibrated coefficient of variation for the amenity value, $\sigma_\chi/\mu_\chi$. This is a conservative choice, because, if entry costs are less dispersed than amenity values, we obtain a larger drop of entry following the increase in the minimum wage. Finally, we begin our analysis by assuming that the two elasticities, $\gamma$ and $\xi$, take values equal to $\varepsilon$ and $\theta$ correspondingly. This parameterization implies that there is no equilibrium feedback from aggregate price and wage to establishment-level product demand in equation (16) and labor supply in equation (17). We defend this assumption below and discuss some counterintuitive implications of the model as we change the values of $\gamma$ and $\xi$.

The bottom panel of Table 5 presents parameters that are calibrated such that, in the initial stationary equilibrium, the model matches eight targets from the data. To some extent, all parameters affect all moments, but in the table we associate each parameter with the moment that most intuitively identifies the parameter (see Appendix Figure A.28 for a visualization of how parameters affect each targeted moment). Targeting a labor share of gross output of 0.35, we calibrate an elasticity of product demand equal to $\varepsilon = 3.5$ (so product market markups are roughly 40 percent). We target a 0.32 share of gross output accruing to other variable inputs, which allows us to pin down the value of the distribution parameter $\phi$ in the production function.[36] In conjunction with other parameters, a low elasticity of substitution between labor and other inputs, $\sigma = 0.05$, allows us to rationalize the cross-sectional elasticity of employment with respect to the wage, $\tau_\ell/\tau_w = -1.08$, found by dividing the jobs column with the wage column of the upper panel of Table 2 for horizons between three and six years. The mean value of amenities, $\mu_\chi$, is informative about average wages, which we estimate to be around 18 dollars before the minimum wage change.

We estimate the mean of entry costs, $\mu_\kappa$, such that the model generates a mean entry cost of 0.47 relative to mean revenues. We obtain the estimate of 0.47 as the average entry cost to sales for full-service and limited-service restaurants reported by the Independent Restaurant Cost to Open Survey (https://tinyurl.com/mwhu623h). The standard deviation of amenity values, $\sigma_\chi$, and productivity, $\sigma_a$, are calibrated such that the model matches the cross-sectional dispersion of wages across establishments and the correlation between wages and establishment size (labor) that we observe in the data. Intuitively, productivity variation leads to a positive correlation between wages and size, whereas amenity variation leads to a negative correlation.

[36] Surveys of the National Restaurant Association (https://tinyurl.com/3b9h9rk9) indicate a material share of 0.32. Consistent with this estimate and our estimate of the labor share, the industry tables of the Bureau of Economic Analysis show that the share of gross output that does not accrue to labor or materials is roughly 0.29 for arts, entertainment, recreation, accommodation, and food services (NAICS 72). For publicly listed companies, Aswath Damodaran (https://shorturl.at/ePPsM) calculates that the cost of goods sold equals 67 percent of sales, which is exactly equal to the sum of our labor share and other input share.

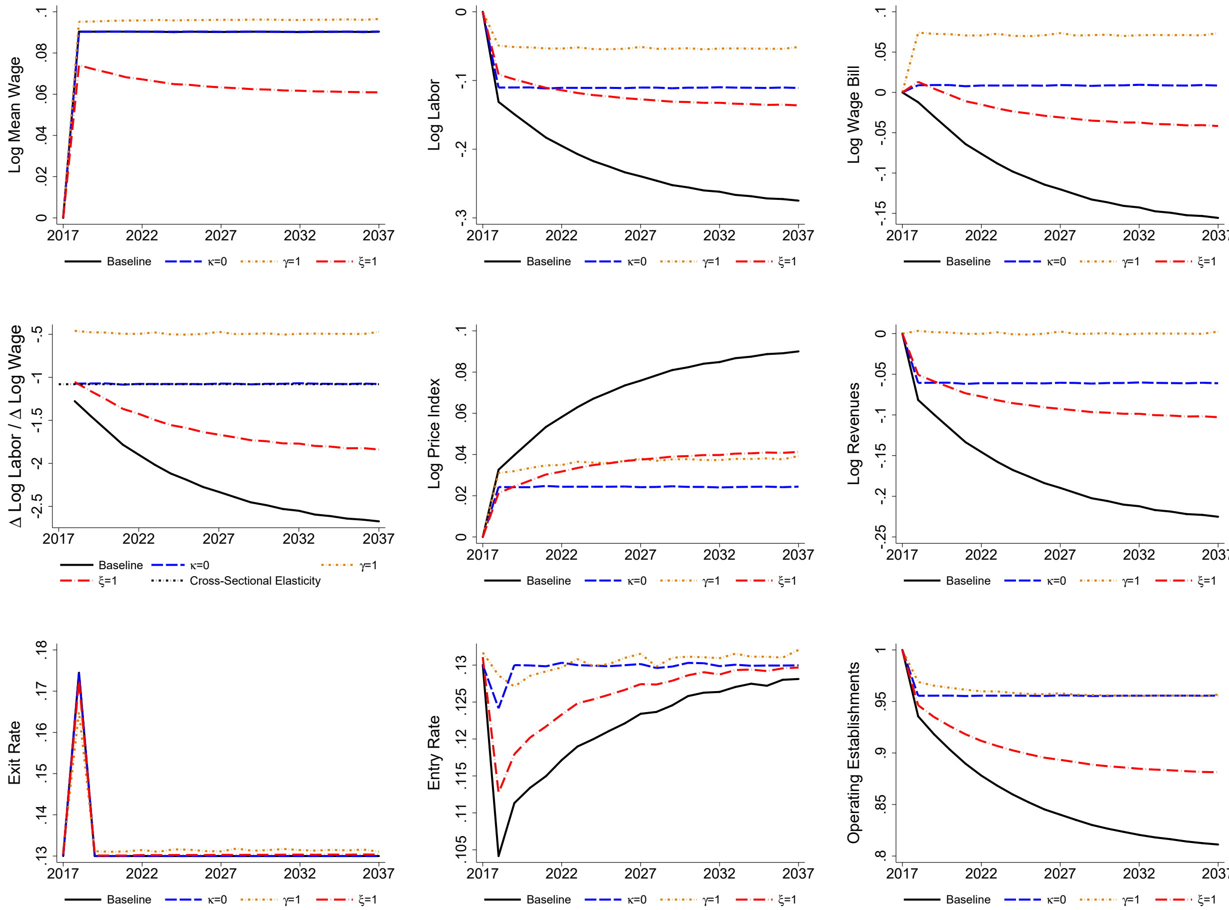



Figure 8: Model Responses to an Unexpected Increase in the Minimum Wage

Notes: The figure shows the transitional dynamics of the model economy in response to an unexpected and permanent change in the minimum wage in 2018 from 9 to 15 dollars. The black solid line shows the responses under the baseline parameterization and the other three lines show responses in nested versions of the model under no entry costs ($\kappa = 0$), lower substitutability across sectors ($\gamma = 1$), and lower elasticity of aggregate labor supply ($\xi = 1$).

The correlation in the data is positive but low, and so we need significant dispersion in both amenities and productivity. Finally, the level of the fixed cost $f$ affects the dispersion in firm size across establishments, with larger fixed costs leading to a lower dispersion. We find that $f$ is only 3 percent of revenues, because labor is significantly dispersed across establishments.

## 6.4 Unexpected Increase in the Minimum Wage

Figure 8 presents results from our first experiment, which is to introduce in 2018 an unexpected and permanent change in the minimum wage from 9 to 15 dollars.[37] The black solid line shows

[37] In both Minneapolis and Saint Paul, the minimum wage is indexed to inflation once the target level of 15 dollars per hour is reached. Thus, to the extent that firms and workers do not perceive further increases in the statewide minimum wage, the minimum wage increase is permanent. Sorkin (2015) explains why changes in the minimum wage that are indexed to inflation produce larger employment responses than changes that are not

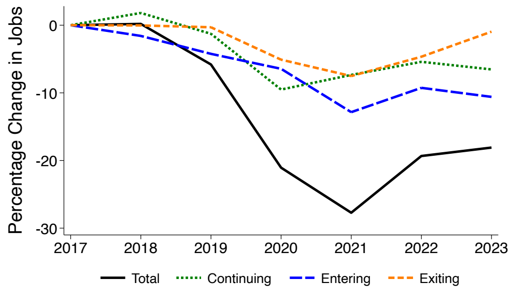
the responses under our baseline parameterization. Following the increase in the minimum wage, mean wages increase by roughly 9 log points, which is consistent with our empirical estimates of the wage effects in restaurants. By design, the model reproduces an elasticity of employment with respect to the wage of $-1.08$, as estimated from the cross-section of establishments. Had we used the cross-sectional elasticity to infer the employment effects of the minimum wage, we would have concluded that employment declines by roughly 10 log points. However, the second panel shows that the aggregate employment in the calibrated economy declines by more than 20 log points by 2023 and by roughly 30 log points in the new stationary equilibrium. Since employment changes by more than wages in absolute value, the wage bill in the industry also falls. The aggregate price index rises by almost 9 log points in the long run, but with $\gamma > 1$ the decline in quantity of restaurant services is larger in magnitude than the increase in the price and thus industry revenues fall significantly.

Why does aggregate employment in the model fall by more than one would have calculated using the cross-sectional estimates? The increase in the minimum wage puts a downward pressure on expected profits and, thus, limits the entry of new establishments. The effect of reduced entry on aggregate employment is not reflected in the cross-sectional elasticity because this elasticity uses information only from establishments which have already entered. The divergence between the cross-sectional and the time series elasticity is shown in the fourth panel, with the latter being roughly twice as large as the former in 2023. This result is quantitatively consistent with the divergence of our estimates from the time series and the cross section.

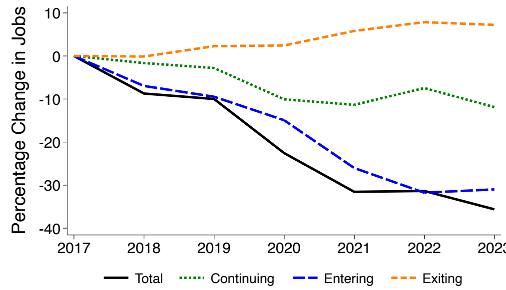
The last three panels show the dynamics of exit, entry, and number of operating firms. Exit temporarily spikes due to the reduced profitability and then falls back to its stationary level. Entry falls from roughly 13 percent to roughly 11 percent immediately after the increase in the minimum wage. Entry slowly returns to its stationary level and, thus, plays a significantly larger role than exit in accounting for the declining number of operating establishments. The number of establishments declines by roughly 15 percent in 2023 and by roughly 20 percent in the new stationary equilibrium of the model.

The similarity of the employment and wage responses between the model and the data is reassuring for the potential of endogenous entry to account for the difference between employment effects in the time series and in the cross section. We calibrated parameters to target cross-sectional moments and calibrated the entry cost independently of our time series treatment effects. To visualize the effects that entry plays on the dynamics of our economy, the blue dashed line in Figure 8 plots outcomes in a nested version of our model without entry costs,

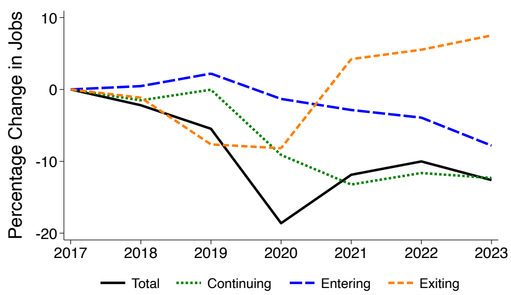
indexed to inflation.



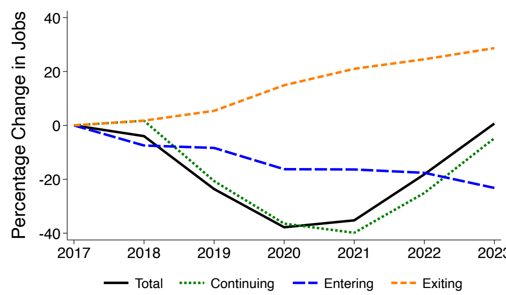

(a) Full-service restaurants, MPLS




(b) Ltd-service restaurants, MPLS




(c) Full-service restaurants, SP




(d) Ltd-service restaurants, SP

Figure 9: Decomposition of Job Losses in Restaurants

Notes: The figure presents the decomposition of changes in the net job creation rate ("Total") into changes from continuing establishments, changes from entering establishments, and changes from exiting establishments.

that is when $\kappa_\iota = 0$ for all firms. As the fourth panel shows, in that case the cross-sectional elasticity would be informative about the aggregate effects of the minimum wage increase, with the employment decline being roughly as large in magnitude as the increase in the wage.

Quantitatively consistent with the prediction of the model, the average entry rate for Minneapolis restaurants in the data fell from roughly 13 percent before the minimum wage increase to 11 percent after the minimum wage increase. To more directly test whether reduced entry is a plausible mechanism for reconciling the difference between the estimates from the cross section and those from the time series analysis, Figure 9 presents a decomposition of job losses in the data by comparing the Twin Cities to their synthetic controls.[38] Consistent with the prediction of the model, in Minneapolis entry plays the most important role and exit plays a minor

[38]Let $\ell_{it}$ be jobs in geographic unit $i$ in period $t$. We define the net job creation rate between period $t$ and period $t-h$ as $2(\ell_{it} - \ell_{it-h})/(\ell_{it} + \ell_{it-h})$. We then decompose the net job creation rate as job creation due to entering establishments plus net job creation due to continuing establishments minus job destruction due to exiting establishments. Entering establishments are establishments that did not have any employees in period $t-h$ but have in period $t$, and exiting establishments are establishments that had employees in period $t-h$ but do not in period $t$. The differences shown in Figure 9 are between the three components of net job creation in the treated cities and the corresponding statistics for the synthetic control, where for the synthetic control we use the estimated weights from the time series analyses. The decomposition is exact only for growth rates, so the numbers for the total differ somewhat from the ones in Section 3, which were in logs.

role in accounting for the decline in employment. Exit is also unimportant in Saint Paul. For full-service restaurants, reduced entry plays a smaller role in Saint Paul than in Minneapolis, especially before 2020. Appendix Figure A.29 presents decompositions for the other industries with job losses, and similarly shows a major role for entry.

The model generates a larger response of employment over time because entry returns slowly over time to its initial level. Thus, the number of operating establishments falls slowly over time. The magnification of the employment losses over time in the model is consistent with several of our empirical findings. In our time-series analyses, the employment declines are larger in 2023 relative to 2018 or 2019. In the cross-sectional analyses for establishments, the job losses also tend to become larger over time. Our findings are also consistent with the findings of Jha, Neumark, and Rodriguez-Lopez (Forthcoming), who document long-run negative employment effects that far exceed the contemporaneous effects of the minimum wage.

Figure 8 also presents two other nested versions of the model, that highlight how industry equilibrium effects affect our conclusions. Beginning with the case of $\gamma = 1$, we observe a significantly smaller response of labor than in the baseline. The response is even lower than the one predicted by the cross-sectional elasticity, and so the wage bill increases. Looking at the establishment-level product demand equation (16), with $\gamma < \varepsilon$, the rise in the aggregate price index $P_t$ tends to increase the marginal revenue product of labor. For incumbent firms, this generates an increase in their labor. For potential entrants, this generates an increase in the profitability of entry. We reject the model with $\gamma < \varepsilon$, both because it generates even smaller responses in the time series than in the cross section and because it fails to account for the observation that a declining entry rate accounts for a significant fraction of job losses.

Moving to the case with $\xi = 1$, we also observe a more muted response of labor than in the baseline, although the response is still larger in the long-run than the one implied by the cross-sectional elasticity. Looking at the establishment-level labor supply equation (17), with $\xi < \theta$, labor supplied to establishments increases as the aggregate wage index $W_t$ decreases. Thus, the fall in labor and the increase in the wage are smaller than in the baseline model with $\xi = \theta$. We reject the model with $\xi < \theta$, because the spillover through the aggregate wage index generates a counterfactual decline in wages for establishments that are not affected by the minimum wage.[39]

[39] In the figure, the first panel shows the mean wage which is more directly comparable to our empirical estimates of wage effects. The aggregate wage index $W_t$ is decreasing, because aggregate labor supply $L_t = W_t^{\xi}$ is upward sloping and total demand for labor is decreasing. We compared zero-GAP establishments in the Twin Cities to establishments outside of the Twin Cities that serve as controls. We did not find evidence that wage growth of non-affected establishments in the Twin Cities is economically different than wage growth in the controls.

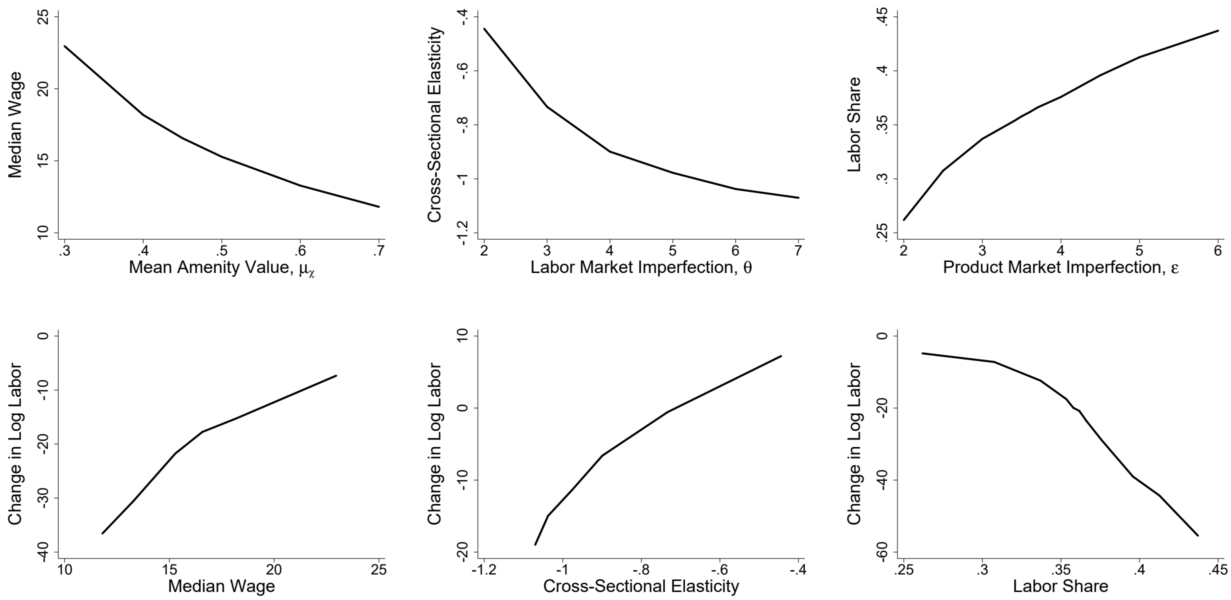



Figure 10: Comparative Statics of the Model Economy

Notes: The figure presents comparative statics of the model economy. The first column varies the mean amenity value ($\mu_\chi$), the second column varies the parameter related to the labor market imperfection ($\theta$), and the third column varies the parameter related to the product market imperfection ($\varepsilon$).

## 6.5 Heterogeneity in Responses

Figure 10 shows how parameters and, indirectly, targeted moments affect the decline in average employment between 2020 and 2023 in response to the increase in the minimum wage. The first column shows that the model is consistent, at least qualitatively, with the cross-industry relationship between jobs losses and exposure to the minimum wage shown previously in Figure 1. The interpretation is that industries with higher wages before the minimum wage increase, which corresponds to a lower amenity value of working for these industries, have a smaller share of workers affected by the minimum wage and, thus, experience a smaller drop in employment.

There is quite a bit of dispersion in job losses across industries that is not accounted for by exposure to the minimum wage. Our model can rationalize such dispersion if labor market or product market power varies across industries. In the second column, a higher labor market power, which corresponds to a lower value of $\theta$, lowers the cross-sectional elasticity of employment with respect to the wage, because some establishments experience employment increases alongside wage increases. Thus, the fall in employment is smaller in response to the minimum wage increase, and employment can even increase for sufficiently low values of $\theta$.[40] In the third

[40] While we do not have occupational data to perform an analysis similar to Azar, Marinescu, and Steinbaum (2022), from their work we map some of the occupations with the highest degree of labor market concentration, such as secretaries, telemarketers, and administrative services managers, to our administrative and support ser-

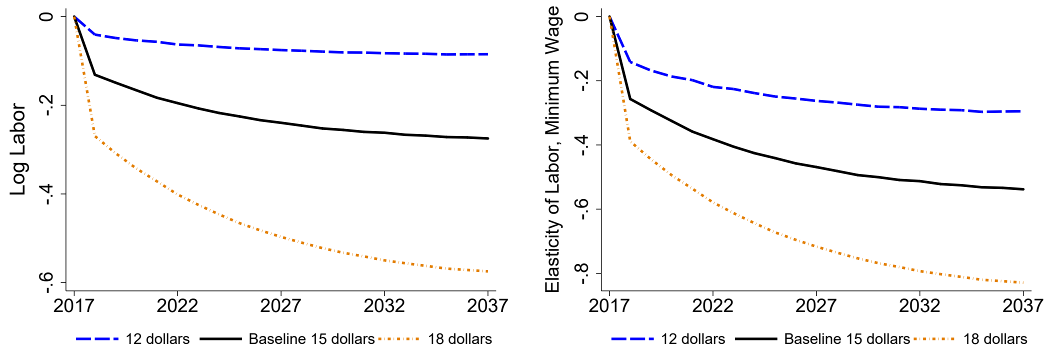



Figure 11: Model Responses and the Size of the Minimum Wage Increase

Notes: The figure shows the transitional dynamics of the model economy in response to an unexpected and permanent change in the minimum wage in 2018. The three lines present the responses when the minimum wage changes from 9 to 12, or to 15 (baseline), or the 18 dollars.

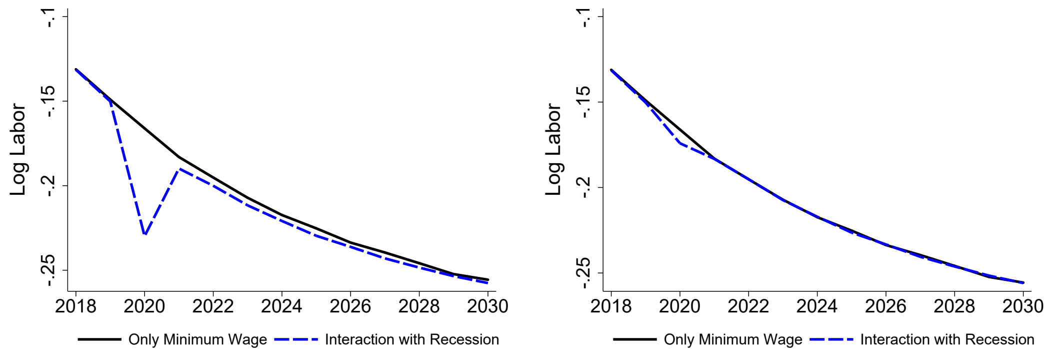
column, a higher product market power, which corresponds to a lower value of $\varepsilon$, increases profits and lowers the labor share. With a smaller share of revenues accruing to labor, the employment effects of the minimum wage become smaller.

It is worth highlighting that our results do not allow us to directly identify how competitive labor markets were in the Twin Cities before the introduction of the minimum wage. However, the model we reject is that labor markets are imperfectly competitive and that the increase in the minimum wage is sufficiently small to induce an equilibrium wage below the competitive level. This model generates positive employment effects in both the cross section and the time series, which are inconsistent with our estimates. In Appendix Figure A.30 we repeat our exercise of introducing a minimum wage increase under different values of $\theta$. We conclude that our results are compatible either with close to perfectly competitive labor markets or with an introduction of a minimum wage above the competitive level for establishments that may operate in labor markets with monopsony power.

## 6.6 Size of Minimum Wage Increase

One reason why our estimated jobs effects might be more negative than found in the literature is that the minimum wage increase that we examine is significantly larger than the typical increase examined the literature. Figure 11 shows the response of aggregate labor and the elasticity of aggregate labor with respect to the minimum wage as we vary the size of the minimum wage increase. The black solid lines repeat baseline results when the minimum wage increases from 9 to 15 dollars. The other two lines show the responses when the minimum wage increases to

vices industry (NAICS 56), which displays positive point estimates on jobs, hours, and earnings in Minneapolis.




(a) Large Recession

(b) Small Recession

Figure 12: Model Responses and the Interaction with a Recession

Notes: The figure shows the transitional dynamics of the model economy in response to an unexpected and permanent change in the minimum wage in 2018 from 9 to 15 dollars that is followed by an unanticipated one-time change in aggregate productivity in 2020. The black solid line shows the responses without the recession and the blue dashed line shows the responses when the minimum wage change is interacted with the recession.

12 dollars and 18 dollars respectively. We pick 12 dollars, because Clemens and Strain (2021) analyses show a differentiation between large and small minimum wage changes around that level. As the figure shows, under a smaller minimum wage increase, the model generates an elasticity of about $-0.2$, which is consistent with our analyses of published estimates shown previously in Figure 7. As the minimum wage increase becomes larger, so does the elasticity of employment, reaching an elasticity of about $-0.6$ in the medium run to about $-0.8$ in the long run for a minimum wage of 18 dollars. The model generates a non-linear response of aggregate labor with respect to the minimum wage, because around one-third of establishments pay wages between 12 to 18 dollars. Thus, as we increase the minimum wage, a disproportionate share of establishments is affected by the minimum wage.

## 6.7 Interaction with a Recession

Another reason why our estimated jobs effects might be more negative than found in the literature is that the minimum wage increase that we examine interacts with a large recession. Figure 12 shows how a recession affects the evolution of aggregate labor following the minimum wage increase. The black solid lines repeat the transitional dynamics of labor in our baseline economy without a recession. The blue dashed line shows the additional effect that the minimum wage exerts on aggregate labor in an economy with a recession. This additional effect is calculated as the difference between the path of aggregate labor when both the minimum wage and a recession are in effect minus the path of labor when only the recession is in effect. Thus, the difference between the black and the blue line quantifies the interaction between the minimum wage and a recession.

Beginning with the left panel, we introduce a large, unexpected aggregate productivity shock that reduces all $a_\iota$ proportionally in 2020. We then assume that productivity rebounds to its original value in 2021. We pick the decline in aggregate productivity to match the absolute decline in employment that we observe in the data.[41] The model generates a large interaction effect, with the path of aggregate labor mimicking the responses for restaurants that we documented before in the time series of cities, in the sense that the aggregate labor declines by more in 2020 relative to previous years and then rebounds in 2021. By contrast, the right panel shows that the interaction of a minimum wage increase with a moderate recession, such as the one following the Great Financial Crisis, is quantitatively insignificant. The logic of the interaction effect is that, in response to a productivity decline, wages have to adjust downward. In the presence of a minimum wage, however, the economy adjusts by reducing its labor. The larger is the recession, the more wages would have to fall in the absence of a minimum wage, and thus the larger is the employment effect of the minimum wage during a recession.

## 6.8 Anticipated Increase in the Minimum Wage

Figure 13 presents transitional dynamics arising from an announced increase in the minimum wage, as in the case of Saint Paul. In 2017, there is an announcement that the minimum wage will increase from 9 to 15 dollars in 2020. As shown with the solid black line ($\nu = \infty$), the baseline model is qualitatively consistent with the empirical evidence, because employment falls upon announcement of a future increase in the minimum wage without a corresponding change in the wage. The decline in employment is driven by lower entry, as establishments that would have entered without the announcement now perceive a lower present discounted value of expected profits and choose not to enter. However, employment falls by only 3 log points in the model, whereas in the data for Saint Paul before 2020 it falls by roughly 15 log points when averaged across full-service and limited-service restaurants in the DEED and the QCEW. The failure of the model to quantitatively account for the drop in employment is related to the relatively low discount factor that we calibrated. With $\beta = 0.85$, there is a high discount of future periods when the minimum wage is implemented and, thus, the drop in entry is small.

We propose a simple modification of the baseline model that allows us to generate larger effects from announcements of future changes in the minimum wage. The setup resembles

[41] We pick the maximum decline relative to 2019, which is $-124$ log points in 2020(2) for full-service restaurants. In conjunction with the minimum wage, this requires a 37 percent decline in aggregate productivity. For the right panel, we pick the maximum decline relative to 2008, which is 12 log points in 2010(1) for limited-service restaurants. This requires a 6.5 percent decline in aggregate productivity.

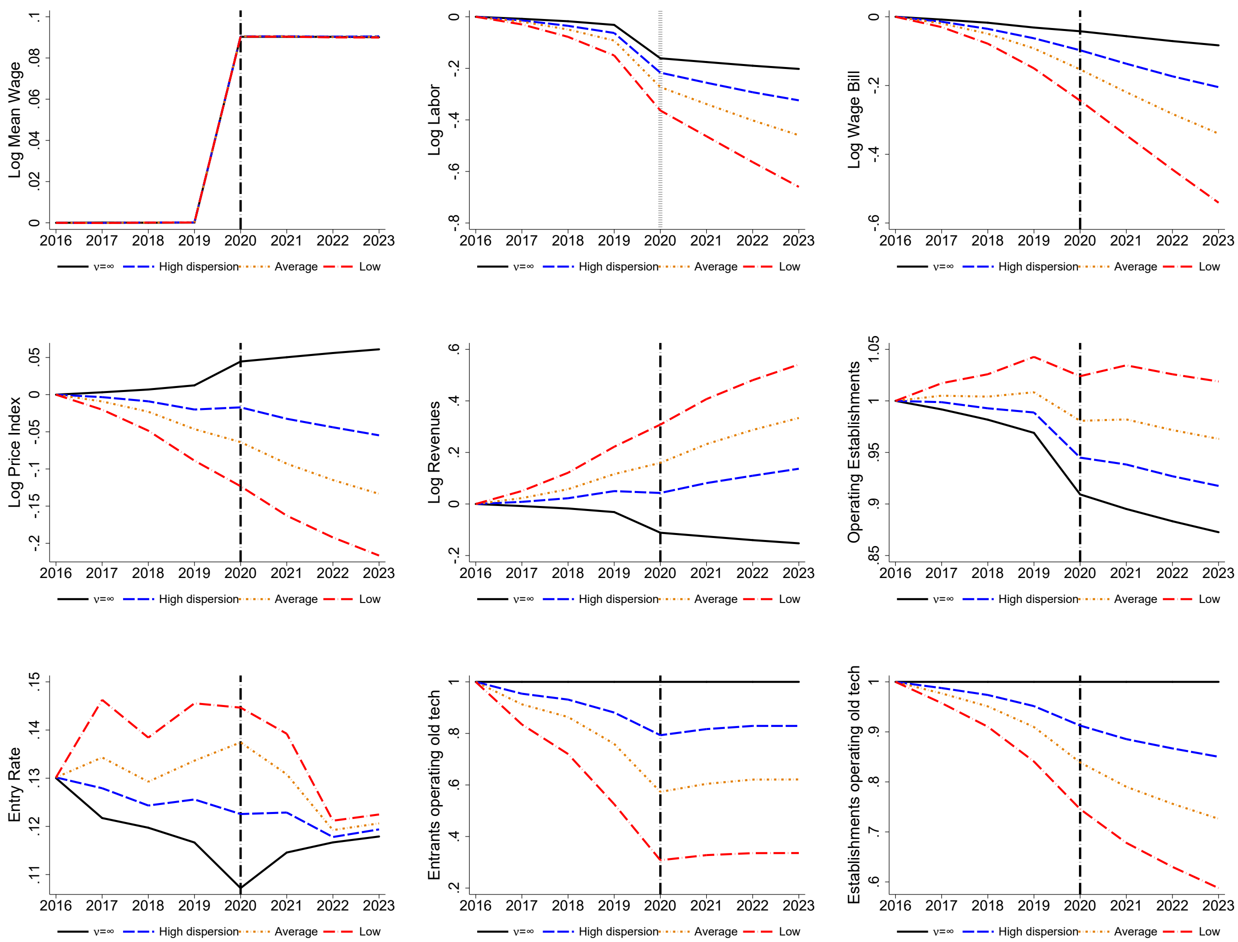



Figure 13: Model Responses to an Anticipated Increase in the Minimum Wage

Notes: The figure shows the transitional dynamics of the model economy in response to a permanent change in the minimum wage from 9 to 15 dollars that is announced in 2017 and implemented in 2020. The black solid line shows the responses under the baseline parameterization that features no choice of technology upon entry ($\nu = \infty$), and the other three lines show responses in the augmented model with technology choice under high dispersion of entry costs in the new technology ($\nu_1 = 0.05$), average dispersion ($\nu_1 = 0.10$), and high dispersion ($\nu_1 = 0.15$).

putty-clay models, such as those in Sorkin (2015) and Aaronson, French, Sorkin, and To (2018), which highlight the importance of higher entry of less labor-intensive establishments over time in response to a minimum wage increase. In our setup, firms choose between two technologies, the "old" technology which was described before and the "new" technology that uses only other inputs. Concretely, if an entrant uses the less labor-intensive technology, $\phi = 1$ in the production function (15), the price is $p_{\iota t} = \mu_p / a_\iota$, production is $y_{\iota t} = \psi p_{\iota t}^{-\varepsilon} P_t^{\varepsilon - \gamma}$, and other inputs are $m_{\iota t} = y_{\iota t} / a_\iota$. Only entrants have a choice of technology and this choice is irreversible, meaning that an entrant cannot switch to the other technology once they have entered with a given technology.

Denoting by $\pi^j$ the profits when using technology $j$, establishments choose to enter with the old technology when

$$\sum_{t=s}^{\infty}(\beta(1-\delta))^{t-s+1}\,\mathbb{E}\pi_t^o \geq \max\left\{\kappa_\iota, \sum_{t=s}^{\infty}(\beta(1-\delta))^{t-s+1}\,\mathbb{E}\pi_t^n\right\}. \tag{22}$$

Similarly, establishments choose to enter with the new technology when

$$\sum_{t=s}^{\infty}(\beta(1-\delta))^{t-s+1}\,\mathbb{E}\pi_t^n > \max\left\{\nu_\iota, \sum_{t=s}^{\infty}(\beta(1-\delta))^{t-s+1}\,\mathbb{E}\pi_t^o\right\}, \tag{23}$$

where $\nu_\iota$ denotes the entry cost of using the new technology.

We discipline the model by using the previous parameters and by requiring that no entrant uses the new technology before the announcement of the future minimum wage increase. This is desirable because it disciplines the augmented model to reproduce exactly the same targeted moments as the baseline model. To achieve that, we assume that the cost of using the new technology is $\nu_\iota = \kappa_\iota + \mu_\kappa\left(\nu_0 + \nu_1\mathbb{U}[0,1]\right)$. The entry cost of using the new technology is higher than the cost of using the old technology, because the new technology is more profitable. The second term in the equation for $\nu_\iota$ represents the increased cost to use the technology. We calibrate the level parameter to $\nu_0 = 2.2$ and consider different values for the slope parameter $\nu_1$, which disciplines the dispersion of entry costs around the level shifter.[42]

The key for understanding the model with a choice of labor intensity is the fraction of establishments that are close to indifferent between using the two technologies. In Figure 13, we present three cases, when the dispersion of the entry cost of using the less labor-intensive technology is high, when it is average, and when it is low. As seen in the figure, lower dispersion of entry costs around the level shifter generates larger employment responses. The logic is that establishments that were previously nearly indifferent between the two technologies, decide to switch to the less labor-intensive technology upon announcement of the future increase in the cost of labor because the old technology is less profitable. The lower the dispersion of entry costs using the new technology, the larger is the mass of establishments that enter with the new technology, and the higher is the responsiveness of employment.

Quantitatively, the model with low dispersion of entry costs generates more than 15 log points decline in employment in 2019. Even the model with average levels of dispersion comes

[42] Mean $\nu$ relative to $\kappa$ equals $1+\nu_0+\nu_1/2$, which ranges from 3.2 to 3.3, given our calibrated $\nu_0$ value and the values of $\nu_1$ that we use in the figure. To give a sense of the reasonableness of these magnitudes, industry experts document that a robot that flips burgers cost 60,000 dollars in 2019 (https://tinyurl.com/2ekb5jkv) and that some robots that cost 30,000 dollars in 2016 can substitute for around 3.6 workers (https://tinyurl.com/2xn2v8ex). The median establishment in our data employs around 63 workers before the minimum wage increase, which implies an incremental cost of entry using the new technology of around 788,000 dollars when applying the average of the two cost estimates. Our mean value of $\kappa$ is 350,000 dollars, so the new technology is roughly 3.3 times as expensive as the old technology.

much closer to the data, generating a roughly 10 log points decline. Differently from the baseline model without a choice of technology, the price index falls and revenues increase in all cases, because new entrants are using a more efficient technology. The effects of the announcement of a future increase in the minimum wage on entry and number of operating establishments are ambiguous. When a large fraction of entrants chooses the new technology, the entry rate increases before the implementation of the minimum wage policy. This is consistent with the actual experience of full-service restaurants in Saint Paul in Figure 9, which shows an increase in jobs due to entry by 2019 and a decline after the implementation of the policy in 2020.

# 7 Conclusion

We use high-quality administrative data from the state of Minnesota to analyze the labor market effects of two large increases in the minimum wage from Minneapolis and Saint Paul. Our analysis proceeds in three steps. Leveraging recent advances in synthetic difference-in-differences approaches, we estimate counterfactual outcomes in the absence of the minimum wage using variation at the zip code within Minnesota or at the city level from the rest of the country. Using variation from the cross sections of establishments and workers within the Twin Cities, we estimate the labor market effects of differential exposure to the minimum wage increase. Finally, we use a quantitative equilibrium model with establishment entry and exit to shed light on the economic mechanisms that rationalize our estimates.

We reach several substantial conclusions. The minimum wage increase is associated with wage gains in most low-wage industries. The time series analysis shows that in the Twin Cities, the minimum wage increase is associated with an average jobs decline of roughly 3 percent. The jobs losses are concentrated in the restaurant, retail, and health industries. The analysis using variation from the cross section leads to estimates of jobs losses that are half as large as the estimates from the time series. The quantitative model reconciles the results from the time series with those from the cross section, because the estimates from the cross section do not account for the effects of reduced entry. We show evidence that reduced entry was a major force in accounting for the job losses. The quantitative model also rationalizes why our estimated job losses are larger than the losses found in previous literature. The Twin Cities enacted minimum wage policies that are local, large, permanent, and interacted with a recession. Finally, our model also rationalizes the negative jobs effects of an announcement of a future minimum wage increase, as in the case of Saint Paul, if establishments use a less labor-intensive technology upon entry.

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# Minimum Wages and Labor Markets in the Twin Cities

## Online Appendix

Loukas Karabarbounis    Jeremy Lise    Anusha Nath

# A Additional Results

This Appendix reports additional results and analyses.

- Table A.1 presents the statewide minimum wage for Minnesota during the period of our study.

- Table A.2 details the minimum wage policy changes introduced by the cities of Minneapolis and Saint Paul.

- Table A.3 presents the synthetic difference-in-differences weights $\hat{\omega}_i$ applied to control zip codes by two-sector industry, variable, and city. Table A.4 presents the weights for full-service and limited-service restaurants. In both cases, we present the 10 zip codes that are weighted the most in the estimation. Figure A.1 presents a map with all estimated weights for jobs in restaurants in the Twin Cities.

- Table A.5 presents R-squared coefficients from regressions of outcome variables in Minneapolis or Saint Paul on the outcome variables of the synthetic control calculated using the weights $\hat{\omega}_i$. To set a baseline of comparison, we also present the R-squared coefficients when using the outcome variables of the unweighted average of all other zip codes within cities in Minnesota, which corresponds to a standard difference-in-differences specification. The regressions are performed only during the pre-treatment period.

- Figures A.2 and A.3 show the time series of the wage and jobs in Minneapolis and Saint Paul, as well as for the Minnesota average of other cities and for the synthetic control, for retail; Figures A.4 and A.5 for administration and support; Figures A.6 and A.7 for health care and social assistance; Figures A.8 and A.9 for arts, entertainment, and recreation; Figures A.10 and A.11 for accommodation and food services; Figures A.12 and A.13 for other services; Figures A.14 and A.15 for full-service restaurants; and Figures A.16 and A.17 for limited-service restaurants.

- Table A.6 reports the industry distribution of employment shares and the fraction of workers earning below 15 dollars in 2017 by industry. The shares of employment do not add up to 100 percent, as some industries have been excluded because of confidentiality concerns based on the presence of few establishments. The excluded industries are Agriculture, Forestry, Fishing, and Hunting (11); Mining, Quarrying, and Oil and Gas Extraction (21); Construction (23); Information (51); Real Estate and Rental and Leasing (53); and Public Administration (92).

- Figures A.18, A.19 and A.20 present time-varying responses for the wage, jobs, and total hours for all two-digit low-wage industries.

- Table A.7 repeats our estimates by adding time weights $\lambda_t$, following Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021). Equation (3) is replaced by $\left(\hat{\tau}, \hat{\alpha}, \hat{\beta}\right) = \arg\min_{\tau,\alpha,\beta} \left\{\sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \alpha_i - \beta_t - \tau W_{it}\right)^2 \hat{\omega}_i \hat{\lambda}_t\right\}$. The time weights $\hat{\lambda}_t$ are chosen so that $(\hat{\lambda}_0, \hat{\lambda}_t) = \arg\min_{\lambda} \sum_{i=1}^{N_{\text{co}}} \left(\lambda_0 + \sum_{t=1}^{T_{\text{pre}}} \lambda_t Y_{it} - T_{\text{post}}^{-1} \sum_{t=T_{\text{pre}}+1}^{T} Y_{it}\right)^2$.

- Table A.8 repeats our estimates from the DEED data when we exclude bordering cities from the sample of cities that form the synthetic control.

- Table A.9 repeats our estimates from the DEED data based on common weights estimated by concatenating the series for wages and jobs within industry. We exclude total hours because they depend on jobs and earnings because they are the product of total hours and the wage. We concatenate the outcome series and find a single set of weights $\hat{\omega}^{cat}$ that minimizes the discrepancy between treated and control units across all outcomes in the pre-treatment series. The common weights are estimated by replacing equation (2) with $(\hat{\omega}_0^{cat}, \hat{\omega}^{cat}) = \arg\min_{\omega_0 \in \mathbb{R}, \omega \in \Omega} \sum_{k=1}^{K} \sum_{t=1}^{T_{\text{pre}}} \left(\omega_0 + \sum_{i=1}^{N_{\text{co}}} \omega_i Y_{kit} - \frac{1}{N_{\text{tr}}} \sum_{i=N_{\text{co}}+1}^{N} Y_{kit}\right)^2 + \zeta^2 T_{\text{pre}} ||\omega||_2^2$, where $Y_{kit}$ is the $k$th outcome for unit $i$ in period $t$, with $k = 1, \ldots, K$.

- Table A.10 presents the list of cities included in the control group of Minneapolis and Saint Paul for the analyses using QCEW data from other U.S. cities of similar size. The data collection process we followed to construct our control group, before the size restriction is applied, is to include municipalities or local government units for which data could be compiled from the publicly available files. This was possible in the following circumstances: 1) the city consists of two or more counties; 2) the city is coterminous with a county or is governed by a consolidated city-county government; 3) the city is independent; 4) the local minimum wage policy is enacted or harmonized at the county level. To further expand our control group, we also include cities that are the county seat and whose population accounted for more than 75 percent of their county's population. In these circumstances, we use the county as a reliable proxy for the corresponding city.

- Figure A.21 presents estimates from the QCEW for restaurants, retail, and health industries, adding time weights $\lambda_t$ to the specification.

- Table A.11 presents Monte Carlo simulations to assess the size and sources of bias of the synthetic difference-in-differences method when the true data generating process is a factor model.

- Figures A.22, A.23, and A.24 repeat the analysis of Figure 4 in the main text for the jobs effects when we adjust jobs for workplace mobility, violent protests, and total protests.

- Figures A.25, A.26, and A.27 repeat the analysis of Figure 5 in the main text for the jobs effects when we adjust jobs for workplace mobility, violent protests, and total protests.

- Table A.12 presents robustness checks on the main specification shown in Table 2 by adding lagged outcomes and three additional calendar years of sample before the minimum wage policy change.

- Table A.13 presents robustness checks on the main specification shown in Table 2 by adding size fixed effects.

- Figure A.28 shows how each parameter affects each targeted moment in the model.

- Figure A.29 presents decompositions of job losses between continuing establishments, entering establishments, and exiting establishments for the retail and health industries.

- Figure A.30 shows the transitional dynamics of the model economy in response to an unexpected permanent increase in the minimum wage for different values of the elasticity of substitution across varieties $\theta$.

# B Solution of the Model

We first describe a general algorithm for computing the equilibrium of the model and then discuss some special cases.

1. Draw sources of heterogeneity across firms $\{\chi_\iota, a_\iota, \kappa_\iota, \nu_\iota, \delta_{\iota t}\}$. Let $\mu_x$ and $\sigma_x$ be the mean and standard deviation of the level of $x$, for $x \in \{\chi, a, \kappa\}$. We specify that $\log x \sim N\left(\log\left(\frac{\mu_x^2}{\sqrt{\mu_x^2+\sigma_x^2}}\right), \sqrt{\log\left(1+\frac{\sigma_x^2}{\mu_x^2}\right)}\right)$. For the cost of entering with the new technology, $\nu_\iota = \kappa_\iota + \mu_\kappa\left(\nu_0 + \nu_1 \mathbb{U}[0,1]\right)$, where $\mathbb{U}[0,1]$ is a uniform random variable between 0 and 1. The destruction shock $\delta_{\iota t}$ is i.i.d. over time and establishments and it hits establishment $\iota$ in period $t$ with probability $\delta$.

2. For an anticipated minimum wage policy $\{\bar{w}_t\}$, guess a path for the aggregate price and wage $\{P_t, W_t\}$. Using the household's optimality decisions this implies a path of $\{Y_t, L_t\}$, where aggregate output $Y_t = \psi P_t^{-\gamma}$ and aggregate labor $L_t = W_t^{\xi}$.

3. Given $\{\bar{w}_t, P_t, W_t\}$, for $t = 1$:

   (a) Calculate decisions for each potential entrant $\iota$ under the two technologies $j \in \{o, n\}$: $y_{\iota 1}^j, p_{\iota 1}^j, \ell_{\iota 1}^j, w_{\iota 1}^j, m_{\iota 1}^j$. To calculate these decisions, we first equalize labor supply, $\ell_{\iota 1}^o = \chi_\iota^\theta \left(w_{\iota 1}^o\right)^\theta W_1^{\xi-\theta}$, to labor demand in equation (20) for establishment $\iota$ and check if $w_{\iota 1}^o > \bar{w}_1$. If not, then we set $w_{\iota 1}^o = \bar{w}_1$ and equilibrium labor is given by equation (21). Then, we calculate equilibrium $m, y, p$ using the equations in the text. Calculate profits $\pi_{\iota 1}^j$ using equation (18).

   (b) Use equations (22) and (23) to determine whether potential entrant $\iota$ prefers to enter using the old technology, the new technology, or not to enter.

   (c) Determine who operates in equilibrium by using the entry decision, the condition that establishments with $\pi_{\iota 1} < 0$ exit endogenously, and the shock $\delta_{\iota 1}$ which destroys establishment $\iota$ in period 1 exogenously.

   (d) Given the number of operating establishments, $I_1$, calculate implied aggregate output $\tilde{Y}_1 = \left(\sum_i \left(y_i^j\right)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$ and implied aggregate labor $\tilde{L}_1 = \left(\sum_i \chi_i^{-1} \left(\ell_i^j\right)^{\frac{1+\theta}{\theta}}\right)^{\frac{\theta}{1+\theta}}$.

4. Repeat for every period $t = 2, ..., T$, for a large number of periods $T$. For each $t > 1$, we know in each period who is an incumbent and who is a potential entrant from the decisions in the previous period. Derive $\{\tilde{Y}_t, \tilde{L}_t\}$ for all $t = 1, 2, ..., T$.

5. If $\tilde{Y}_t > Y_t$ lower the guess for $P_t$. If $\tilde{L}_t > L_t$, increase the guess for $W_t$. Repeat until convergence, defined as a sufficiently small distance between $\tilde{Y}_t$ and $Y_t$ and $\tilde{L}_t$ and $L_t$.

A simplification of the computation of the model can be achieved for the case $\gamma = \varepsilon$ or $\xi = \theta$, because establishment-level decisions do not depend on $P_t$ and $W_t$. In these cases, we can solve for establishment-level outcomes without knowledge of $P_t$ and $W_t$ and calculate ex-post the price and wage index by aggregating establishment decisions.

*Computation of the initial equilibrium.* Given an initial minimum wage policy, the economy reaches a stationary state in period $t = 2$. Thus, the computation can be simplified by guessing a constant price and wage in each period after $t = 2$. The economy reaches immediately a stationary equilibrium because we start with $I_0 = 0$, which implies that every potential entrant is making a decision regarding entry in period $t = 1$. If we allow another arbitrary initial condition on who operated in $t = 0$, the economy would reach the same stationary equilibrium, but in more than one period.

*Unexpected change in the minimum wage.* For this experiment, we start in some period $T^*$ with a given number of operating establishments and their decisions, corresponding to the stationary equilibrium of the model under policy $\{\bar{w}_t\}$. Under the new policy $\{\overline{w}_t\}$, we repeat the steps outlined before, assuming that establishments perceive the new policy as permanent. The model here features transitional dynamics and takes a non-trivial number of periods to converge to the new stationary equilibrium, because the initial state is given by the previous stationary equilibrium, in which some establishments have already entered (so there is no first period in which everyone is a potential entrant).

*Unexpected change in the minimum wage and interaction with recession.* For this experiment, we start in some period $T^*$ with a given number of operating establishments and their decisions, corresponding to the stationary equilibrium of the model under policy $\{\bar{w}_t\}$. Under the new policy $\{\overline{w}_t\}$, we repeat the steps outlined before, assuming that establishments perceive the new policy as permanent. Denote by $T^{**} > T^*$ the period when a recession hits the economy. Having solved the model for periods $T^*, ..., T$, we start in period $T^{**}$ with a distribution of establishments who operate and then introduce a one-time shock that reduces productivity. We solve the model between $T^{**}, ..., T$ assuming that establishments expect productivity to rebound in the next period and the minimum wage to remain at its new level $\{\overline{w}_t\}$ permanently.

*Anticipated change in the minimum wage.* For this experiment, we also start in some period $T^*$ with a given number of operating establishments and their decisions, corresponding to the stationary equilibrium of the model under policy $\{\bar{w}_t\}$. Under the new policy $\{\overline{w}_t\}$ that is enacted in some future period $T^{**}$, we repeat the steps outlined before, assuming that establishments perceive the new policy as permanent. The difference with the case of an unexpected change in the minimum wage is that, even when $\gamma = \varepsilon$ and $\xi = \theta$, there exist transitional dynamics in the present discounted value of expected profits necessary to calculate the entry decisions. With an unexpected change in the minimum wage, the present discounted value of expected profits does not depend on the path of $P_t$ and $W_t$ and converge to their new level in the first period with the new policy $T^*$. With an anticipated change in the minimum wage, the present discounted value of expected profits does not depend on the path of $P_t$ and $W_t$ and converge to their new level in period $T^{**}$. Between $T^*$ and $T^{**}$, the present discounted value of expected profits exhibits transitional dynamics, because in between these periods the old policy is still in effect.

Table A.1: Minimum Wage Policy in the State of Minnesota

| | Youth | Small Firms | Large Firms |
|---|---|---|---|
| (Annual Revenue in Dollars) | | $(< 500,000)$ | $(\geq 500,000)$ |
| 2000-2005 | 4.25 | 4.90 | 5.15 |
| 2006-2013 | 4.90 | 5.25 | 6.15 |
| 2014 | 6.50 | 6.50 | 8.00 |
| 2015 | 7.25 | 7.25 | 9.00 |
| 2016 | 7.75 | 7.75 | 9.50 |
| 2017 | 7.75 | 7.75 | 9.50 |
| 2018 | 7.87 | 7.87 | 9.65 |
| 2019 | 8.04 | 8.04 | 9.86 |
| 2020 | 8.15 | 8.15 | 10.00 |
| 2021 | 8.21 | 8.21 | 10.08 |
| 2022 | 8.42 | 8.42 | 10.33 |
| 2023 | 8.63* | 8.63* | 10.59* |

Notes: Symbol * denotes that the minimum wage is scheduled to increase every year according to the price deflator for personal consumption expenditures produced by the Bureau of Economic Analysis. The threshold of $500,000$ represents revenue reported to the state of Minnesota.

Table A.2: Minimum Wage Policy in the Twin Cities

| | Minneapolis | | Saint Paul | | | |
|---|---|---|---|---|---|---|
| Firms | Small | Large | Micro | Small | Large | Macro |
| (Employees) | $(< 100)$ | $(\geq 100)$ | $(\leq 5)$ | (6-100) | (101-10,000) | $(> 10,000)$ |
| 2018 (Jan) | | 10.00 | | | | |
| 2018 (Jul) | 10.25 | 11.25 | | | | |
| 2019 (Jul) | 11.00 | 12.25 | | | | |
| 2020 (Jan) | | | | | | 12.50 |
| 2020 (Jul) | 11.75 | 13.25 | 9.25 | 10.00 | 11.50 | |
| 2021 (Jul) | 12.50 | 14.25 | 10.00 | 11.00 | 12.50 | |
| 2022 (Jul) | 13.50 | 15.00* | 10.75 | 12.00 | 13.50 | 15.00* |
| 2023 (Jul) | 14.50 | | 11.50 | 13.00 | 15.00 | |
| 2024 (Jul) | equal to large | | 12.25 | 14.00 | equal to macro | |
| 2025 (Jul) | | | 13.25 | 15.00 | | |
| 2026 (Jul) | | | 14.25 | equal to macro | | |
| 2027 (Jul) | | | 15.00 | | | |
| 2028 (Jul) | | | equal to macro | | | |

Notes: Symbol * denotes that the minimum wage is scheduled to increase every year according to the price deflator for personal consumption expenditures produced by the Bureau of Economic Analysis. The size thresholds represent total firm employment across all establishments. Franchises are considered large firms if they have more than 10 franchises nationally. For full-service restaurants, if there are fewer than 10 locations nationally, each restaurant counts as a separate business for the purpose of determining size.

Table A.3: Synthetic Control Weights for Low Wage Sectors

## Retail Trade (44)

| MPLS | | | | | | | | SP | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wage | | Jobs | | Hours | | Earnings | | Wage | | Jobs | | Hours | | Earnings | |
| Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts |
| 56364 | 0.19 | 55371 | 0.13 | 55082 | 0.22 | 55303 | 0.21 | 56156 | 0.17 | 56156 | 0.25 | 55082 | 0.23 | 55971 | 0.23 |
| 55441 | 0.12 | 55428 | 0.12 | 55303 | 0.16 | 55443 | 0.11 | 55037 | 0.13 | 55442 | 0.11 | 55077 | 0.12 | 55442 | 0.13 |
| 55426 | 0.11 | 55391 | 0.11 | 55428 | 0.10 | 55428 | 0.10 | 55302 | 0.12 | 55311 | 0.09 | 55331 | 0.12 | 56379 | 0.11 |
| 55421 | 0.08 | 56307 | 0.08 | 55371 | 0.10 | 55901 | 0.10 | 56751 | 0.11 | 55082 | 0.08 | 55971 | 0.09 | 56721 | 0.10 |
| 55429 | 0.07 | 55311 | 0.07 | 55811 | 0.08 | 55311 | 0.08 | 56364 | 0.09 | 55369 | 0.08 | 55126 | 0.07 | 55441 | 0.10 |
| 55082 | 0.05 | 55303 | 0.06 | 56307 | 0.05 | 55811 | 0.08 | 56232 | 0.08 | 55331 | 0.07 | 56379 | 0.07 | 55082 | 0.07 |
| 56347 | 0.05 | 55042 | 0.06 | 55391 | 0.05 | 56304 | 0.05 | 56377 | 0.07 | 55443 | 0.07 | 55371 | 0.06 | 55311 | 0.06 |
| 56379 | 0.04 | 55976 | 0.06 | 55311 | 0.05 | 55441 | 0.05 | 55369 | 0.04 | 99999 | 0.06 | 55369 | 0.05 | 56401 | 0.05 |
| 55125 | 0.04 | 56721 | 0.06 | 55077 | 0.04 | 56560 | 0.04 | 55118 | 0.04 | 55971 | 0.06 | 56156 | 0.04 | 55121 | 0.05 |
| 55369 | 0.03 | 55331 | 0.04 | 55976 | 0.04 | 55082 | 0.04 | 55371 | 0.04 | 56379 | 0.05 | 55442 | 0.04 | 99999 | 0.04 |

## Administration and Support (56)

| MPLS | | | | | | | | SP | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wage | | Jobs | | Hours | | Earnings | | Wage | | Jobs | | Hours | | Earnings | |
| Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts |
| 55121 | 0.22 | 56401 | 0.19 | 56303 | 0.26 | 56073 | 0.23 | 55337 | 0.15 | 55987 | 0.28 | 55987 | 0.19 | 55345 | 0.47 |
| 55305 | 0.21 | 55391 | 0.10 | 55343 | 0.12 | 55426 | 0.18 | 55033 | 0.14 | 55433 | 0.12 | 55437 | 0.14 | 55391 | 0.30 |
| 55987 | 0.18 | 55423 | 0.10 | 55423 | 0.11 | 56303 | 0.10 | 56401 | 0.13 | 56401 | 0.11 | 55124 | 0.13 | 55303 | 0.09 |
| 55318 | 0.13 | 55303 | 0.09 | 55128 | 0.08 | 56187 | 0.06 | 55343 | 0.08 | 55124 | 0.10 | 55343 | 0.10 | 55344 | 0.06 |
| 55378 | 0.08 | 55438 | 0.08 | 55438 | 0.08 | 55113 | 0.06 | 55441 | 0.08 | 55344 | 0.08 | 56401 | 0.09 | 55449 | 0.04 |
| 55303 | 0.07 | 55121 | 0.07 | 55439 | 0.07 | 55432 | 0.06 | 55379 | 0.07 | 55343 | 0.08 | 55416 | 0.07 | 56560 | 0.02 |
| 55416 | 0.05 | 55343 | 0.07 | 55425 | 0.06 | 55449 | 0.05 | 55901 | 0.06 | 55060 | 0.05 | 55432 | 0.06 | 55125 | 0.01 |
| 55117 | 0.03 | 55439 | 0.07 | 55987 | 0.06 | 56401 | 0.05 | 55431 | 0.05 | 55416 | 0.06 | 55423 | 0.05 | 55343 | 0.00 |
| 56401 | 0.03 | 55117 | 0.06 | 56187 | 0.04 | 55343 | 0.04 | 55445 | 0.05 | 55431 | 0.04 | 55431 | 0.04 | | |
| 55437 | 0.00 | 55427 | 0.05 | 56560 | 0.04 | 55117 | 0.04 | 55428 | 0.03 | 55423 | 0.03 | 55439 | 0.04 | | |

## Health Care and Social Assistance (62)

| MPLS | | | | | | | | SP | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wage | | Jobs | | Hours | | Earnings | | Wage | | Jobs | | Hours | | Earnings | |
| Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts |
| 99999 | 0.07 | 99999 | 0.07 | 55109 | 0.10 | 55318 | 0.11 | 55372 | 0.10 | 56353 | 0.11 | 55123 | 0.10 | 55110 | 0.13 |
| 55121 | 0.06 | 55124 | 0.06 | 55372 | 0.09 | 56762 | 0.08 | 55906 | 0.07 | 55906 | 0.10 | 55124 | 0.06 | 55992 | 0.09 |
| 55425 | 0.05 | 55421 | 0.06 | 55303 | 0.07 | 55971 | 0.06 | 56071 | 0.07 | 55992 | 0.10 | 55431 | 0.06 | 55051 | 0.07 |
| 55334 | 0.05 | 55436 | 0.05 | 55447 | 0.06 | 99999 | 0.06 | 55092 | 0.06 | 55033 | 0.07 | 99999 | 0.05 | 56538 | 0.05 |
| 56572 | 0.05 | 56283 | 0.05 | 99999 | 0.05 | 55421 | 0.06 | 55075 | 0.05 | 55431 | 0.05 | 55422 | 0.05 | 55424 | 0.05 |
| 56232 | 0.05 | 55427 | 0.04 | 55398 | 0.05 | 56649 | 0.05 | 55436 | 0.05 | 55057 | 0.04 | 55992 | 0.05 | 55077 | 0.05 |
| 55436 | 0.05 | 55077 | 0.04 | 55803 | 0.05 | 55718 | 0.05 | 99999 | 0.04 | 56538 | 0.04 | 55068 | 0.04 | 56258 | 0.04 |
| 55313 | 0.04 | 55109 | 0.04 | 56364 | 0.04 | 55436 | 0.04 | 55427 | 0.04 | 55124 | 0.03 | 56001 | 0.04 | 55033 | 0.04 |
| 56011 | 0.04 | 56649 | 0.04 | 55318 | 0.04 | 55077 | 0.04 | 55398 | 0.04 | 55428 | 0.03 | 55904 | 0.04 | 55422 | 0.04 |
| 55387 | 0.04 | 56377 | 0.04 | 56387 | 0.03 | 55305 | 0.04 | 55110 | 0.04 | 56031 | 0.03 | 56345 | 0.04 | 55072 | 0.03 |

## Arts, Entertainment and Recreation (71)

| MPLS | | | | | | | | SP | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wage | | Jobs | | Hours | | Earnings | | Wage | | Jobs | | Hours | | Earnings | |
| Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts |
| 55790 | 0.25 | 55987 | 0.16 | 99999 | 0.17 | 55436 | 0.29 | 99999 | 0.23 | 55066 | 0.46 | 99999 | 0.47 | 55391 | 0.44 |
| 55082 | 0.22 | 55066 | 0.16 | 55124 | 0.17 | 99999 | 0.27 | 99999 | 0.19 | 99999 | 0.13 | 55082 | 0.31 | 99999 | 0.24 |
| 99999 | 0.19 | 55124 | 0.12 | 55436 | 0.11 | 55987 | 0.26 | 99999 | 0.15 | 99999 | 0.10 | 55124 | 0.21 | 55124 | 0.21 |
| 55449 | 0.16 | 55901 | 0.12 | 99999 | 0.11 | 55379 | 0.07 | 55124 | 0.09 | 55436 | 0.09 | 55344 | 0.00 | 55901 | 0.06 |
| 55391 | 0.08 | 99999 | 0.11 | 55044 | 0.11 | 55802 | 0.05 | 55344 | 0.08 | 55987 | 0.07 | 55901 | 0.00 | 55033 | 0.04 |
| 99999 | 0.06 | 99999 | 0.09 | 55066 | 0.10 | 55344 | 0.03 | 55901 | 0.06 | 55344 | 0.07 | 55344 | 0.00 | 55372 | 0.01 |
| 55124 | 0.02 | 55436 | 0.09 | 55790 | 0.09 | 55372 | 0.02 | 55379 | 0.06 | 55044 | 0.05 | 55901 | 0.00 | 55344 | 0.00 |
| 56001 | 0.01 | 55044 | 0.07 | 55449 | 0.04 | 55790 | 0.01 | 55790 | 0.05 | 55372 | 0.03 | | | | |
| 55033 | 0.00 | 55449 | 0.06 | 99999 | 0.04 | | | 55044 | 0.04 | 55379 | 0.00 | | | | |
| | | 55033 | 0.01 | 55344 | 0.03 | | | 55436 | 0.04 | 56241 | 0.00 | | | | |

## Accommodation and Food Services (72)

| MPLS | | | | | | | | SP | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wage | | Jobs | | Hours | | Earnings | | Wage | | Jobs | | Hours | | Earnings | |
| Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts |
| 56011 | 0.20 | 55387 | 0.08 | 55371 | 0.12 | 56716 | 0.07 | 55362 | 0.12 | 55371 | 0.18 | 55075 | 0.16 | 56001 | 0.12 |
| 55447 | 0.12 | 55075 | 0.07 | 55309 | 0.07 | 99999 | 0.06 | 55803 | 0.11 | 55426 | 0.11 | 56156 | 0.15 | 55113 | 0.12 |
| 56031 | 0.11 | 56701 | 0.06 | 55313 | 0.07 | 55113 | 0.05 | 55303 | 0.11 | 55037 | 0.10 | 56001 | 0.14 | 55037 | 0.11 |
| 55309 | 0.08 | 55331 | 0.06 | 56270 | 0.05 | 55431 | 0.05 | 55420 | 0.10 | 55731 | 0.09 | 55443 | 0.11 | 55720 | 0.10 |
| 55021 | 0.07 | 55343 | 0.05 | 55303 | 0.05 | 56304 | 0.04 | 56345 | 0.09 | 55803 | 0.09 | 56751 | 0.07 | 56007 | 0.08 |
| 55016 | 0.05 | 55110 | 0.04 | 55731 | 0.05 | 55362 | 0.04 | 56031 | 0.07 | 55121 | 0.08 | 55992 | 0.06 | 55033 | 0.06 |
| 55720 | 0.05 | 55051 | 0.04 | 55110 | 0.05 | 55343 | 0.04 | 55612 | 0.07 | 55113 | 0.07 | 55439 | 0.06 | 56484 | 0.05 |
| 55330 | 0.04 | 55350 | 0.04 | 55430 | 0.05 | 55110 | 0.04 | 56093 | 0.06 | 55432 | 0.06 | 56320 | 0.05 | 55432 | 0.05 |
| 55803 | 0.04 | 55431 | 0.03 | 55075 | 0.05 | 56623 | 0.04 | 55112 | 0.06 | 55128 | 0.05 | 55432 | 0.05 | 55337 | 0.05 |
| 56484 | 0.03 | 55432 | 0.03 | 55439 | 0.05 | 55318 | 0.04 | 55906 | 0.04 | 55374 | 0.04 | 55426 | 0.05 | 56537 | 0.04 |

## Other Services (81)

| MPLS | | | | | | | | SP | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Wage | | Jobs | | Hours | | Earnings | | Wage | | Jobs | | Hours | | Earnings | |
| Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts | Zip | Wts |
| 55350 | 0.23 | 55421 | 0.11 | 55378 | 0.10 | 55806 | 0.10 | 55435 | 0.22 | 55435 | 0.08 | 56301 | 0.13 | 55309 | 0.10 |
| 55128 | 0.15 | 55432 | 0.07 | 55421 | 0.09 | 55318 | 0.10 | 56537 | 0.21 | 55318 | 0.08 | 55436 | 0.10 | 55436 | 0.10 |
| 55447 | 0.09 | 56303 | 0.07 | 55318 | 0.09 | 55337 | 0.09 | 55439 | 0.13 | 55311 | 0.07 | 55391 | 0.09 | 56301 | 0.09 |
| 56258 | 0.08 | 55309 | 0.07 | 55309 | 0.08 | 55305 | 0.06 | 55379 | 0.12 | 56301 | 0.07 | 55318 | 0.07 | 55425 | 0.08 |
| 56082 | 0.07 | 55318 | 0.06 | 55391 | 0.07 | 56537 | 0.06 | 55121 | 0.07 | 55391 | 0.07 | 99999 | 0.07 | 56001 | 0.08 |
| 55987 | 0.06 | 55317 | 0.05 | 55806 | 0.06 | 55902 | 0.06 | 55425 | 0.06 | 55124 | 0.07 | 55426 | 0.07 | 55806 | 0.07 |
| 55443 | 0.05 | 55434 | 0.05 | 55124 | 0.06 | 55309 | 0.05 | 55429 | 0.04 | 55436 | 0.06 | 55358 | 0.06 | 55391 | 0.06 |
| 55379 | 0.05 | 55021 | 0.04 | 55426 | 0.05 | 55421 | 0.05 | 55441 | 0.04 | 55033 | 0.06 | 55311 | 0.05 | 55420 | 0.06 |
| 55318 | 0.04 | 55435 | 0.04 | 55345 | 0.05 | 56345 | 0.05 | 55112 | 0.04 | 55304 | 0.05 | 55122 | 0.05 | 55432 | 0.04 |
| 55441 | 0.04 | 55122 | 0.04 | 55358 | 0.05 | 55113 | 0.04 | 55122 | 0.02 | 55303 | 0.05 | 55109 | 0.05 | 55124 | 0.04 |

Table A.4: Synthetic Control Weights for Restaurant Industries

## Minneapolis Full-Service Restaurants (722511)

| Wage | | Jobs | | Hours | | Earnings | |
|---|---|---|---|---|---|---|---|
| **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** |
| 55128, OAKDALE | 0.18 | 56560, MOORHEAD | 0.15 | 55082, STILLWATER | 0.13 | 99999, POOLED | 0.19 |
| 55316, CHAMPLIN | 0.14 | 55902, ROCHESTER | 0.13 | 55305, MINNETONKA | 0.08 | 55744, GRAND RAPIDS | 0.14 |
| 56601, BEMIDJI | 0.11 | 99999, POOLED | 0.06 | 55423, RICHFIELD | 0.08 | 55122, EAGAN | 0.08 |
| 55125, WOODBURY | 0.10 | 55802, DULUTH | 0.06 | 55122, EAGAN | 0.07 | 55305, MINNETONKA | 0.08 |
| 56721, EAST GRAND F. | 0.10 | 56601, BEMIDJI | 0.06 | 56401, BRAINERD | 0.06 | 55350, HUTCHINSON | 0.08 |
| 56308, ALEXANDRIA | 0.09 | 55109, MAPLEWOOD | 0.04 | 55433, COON RAPIDS | 0.05 | 55044, LAKEVILLE | 0.08 |
| 55057, NORTHFIELD T. | 0.09 | 55305, MINNETONKA | 0.04 | 55987, WINONA | 0.05 | 55423, RICHFIELD | 0.06 |
| 55912, AUSTIN | 0.09 | 56721, EAST GRAND F. | 0.04 | 55124, APPLE VALLEY | 0.05 | 56601, BEMIDJI | 0.04 |
| 55448, COON RAPIDS | 0.08 | | | 55372, PRIOR LAKE | 0.04 | 56308, ALEXANDRIA | 0.03 |
| 56401, BRAINERD | 0.01 | | | 99999, POOLED | 0.04 | 55391, WAYZATA | 0.03 |

## Saint Paul Full-Service Restaurants (722511)

| Wage | | Jobs | | Hours | | Earnings | |
|---|---|---|---|---|---|---|---|
| **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** |
| 99999, POOLED | 0.22 | 56308, ALEXANDRIA | 0.24 | 56308, ALEXANDRIA | 0.18 | 55387, WACONIA | 0.17 |
| 56601, BEMIDJI | 0.14 | 55113, ROSEVILLE | 0.12 | 55113, ROSEVILLE | 0.09 | 55113, ROSEVILLE | 0.12 |
| 56301, ST CLOUD | 0.12 | 55082, STILLWATER | 0.11 | 55391, WAYZATA | 0.08 | 56308, ALEXANDRIA | 0.12 |
| 55448, COON RAPIDS | 0.10 | 55387, WACONIA | 0.09 | 55387, WACONIA | 0.07 | 55391, WAYZATA | 0.11 |
| 55060, OWATONNA | 0.10 | 55391, WAYZATA | 0.09 | 99999, POOLED | 0.07 | 99999, POOLED | 0.10 |
| 55125, WOODBURY | 0.07 | 55811, DULUTH | 0.08 | 55811, DULUTH | 0.06 | 55811, DULUTH | 0.06 |
| 55433, COON RAPIDS | 0.05 | 99999, POOLED | 0.06 | 55987, WINONA | 0.06 | 55303, ANOKA | 0.06 |
| 55044, LAKEVILLE | 0.05 | 56560, MOORHEAD | 0.04 | 55082, STILLWATER | 0.06 | 55901, ROCHESTER | 0.04 |
| 56308, ALEXANDRIA | 0.04 | 56401, BRAINERD | 0.03 | 55122, EAGAN | 0.05 | 55987, WINONA | 0.04 |
| 55121, EAGAN | 0.03 | 56721, EAST GRAND F. | 0.03 | 55744, GRAND RAPIDS | 0.05 | 55449, BLAINE | 0.03 |

## Minneapolis Limited-Service Restaurants (722513)

| Wage | | Jobs | | Hours | | Earnings | |
|---|---|---|---|---|---|---|---|
| **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** |
| 55122, EAGAN | 0.82 | 55313, BUFFALO | 0.21 | 56007, ALBERT LEA | 0.14 | 55060, OWATONNA | 0.16 |
| 55362, MONTICELLO | 0.18 | 56007, ALBERT LEA | 0.16 | 55313, BUFFALO | 0.14 | 56007, ALBERT LEA | 0.16 |
| | | 55125, WOODBURY | 0.15 | 56401, BRAINERD | 0.12 | 55125, WOODBURY | 0.12 |
| | | 56201, WILLMAR | 0.09 | 55362, MONTICELLO | 0.11 | 56201, WILLMAR | 0.11 |
| | | 55362, MONTICELLO | 0.09 | 55113, ROSEVILLE | 0.10 | 55313, BUFFALO | 0.11 |
| | | 55433, COON RAPIDS | 0.08 | 55912, AUSTIN | 0.09 | 55912, AUSTIN | 0.08 |
| | | 55912, AUSTIN | 0.08 | 55987, WINONA | 0.08 | 99999, POOLED | 0.06 |
| | | 55060, OWATONNA | 0.06 | 55125, WOODBURY | 0.06 | 55337, BURNSVILLE | 0.06 |
| | | 55330, ELK RIVER | 0.05 | 55060, OWATONNA | 0.06 | 55330, ELK RIVER | 0.04 |
| | | 55303, ANOKA | 0.02 | 55433, COON RAPIDS | 0.04 | 56073, NEW ULM | 0.04 |

## Saint Paul Limited-Service Restaurants (722513)

| Wage | | Jobs | | Hours | | Earnings | |
|---|---|---|---|---|---|---|---|
| **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** | **Zip Code, City** | **Wts** |
| 55369, MAPLE GROVE | 0.30 | 56301, ST CLOUD | 0.33 | 56301, ST CLOUD | 0.48 | 56301, ST CLOUD | 0.32 |
| 55109, MAPLEWOOD | 0.14 | 55337, BURNSVILLE | 0.17 | 55060, OWATONNA | 0.30 | 55337, BURNSVILLE | 0.20 |
| 55433, COON RAPIDS | 0.14 | 55425, BLOOMINGTON | 0.14 | 56201, WILLMAR | 0.14 | 55303, ANOKA | 0.16 |
| 55125, WOODBURY | 0.13 | 56001, MANKATO | 0.10 | 56073, NEW ULM | 0.06 | 56073, NEW ULM | 0.12 |
| 55420, BLOOMINGTON | 0.08 | 55901, ROCHESTER | 0.10 | 99999, POOLED | 0.01 | 56201, WILLMAR | 0.12 |
| 55902, ROCHESTER | 0.07 | 55433, COON RAPIDS | 0.07 | 55423, RICHFIELD | 0.01 | 55901, ROCHESTER | 0.07 |
| 55124, APPLE VALLEY | 0.06 | 56201, WILLMAR | 0.04 | | | 55362, MONTICELLO | 0.02 |
| 55362, MONTICELLO | 0.05 | 55369, MAPLE GROVE | 0.03 | | | 99999, POOLED | 0.00 |
| 99999, POOLED | 0.02 | 99999, POOLED | 0.02 | | | 55423, RICHFIELD | 0.00 |
| 55057, NORTHFIELD T. | 0.01 | 55303, ANOKA | 0.00 | | | 55369, MAPLE GROVE | 0.00 |

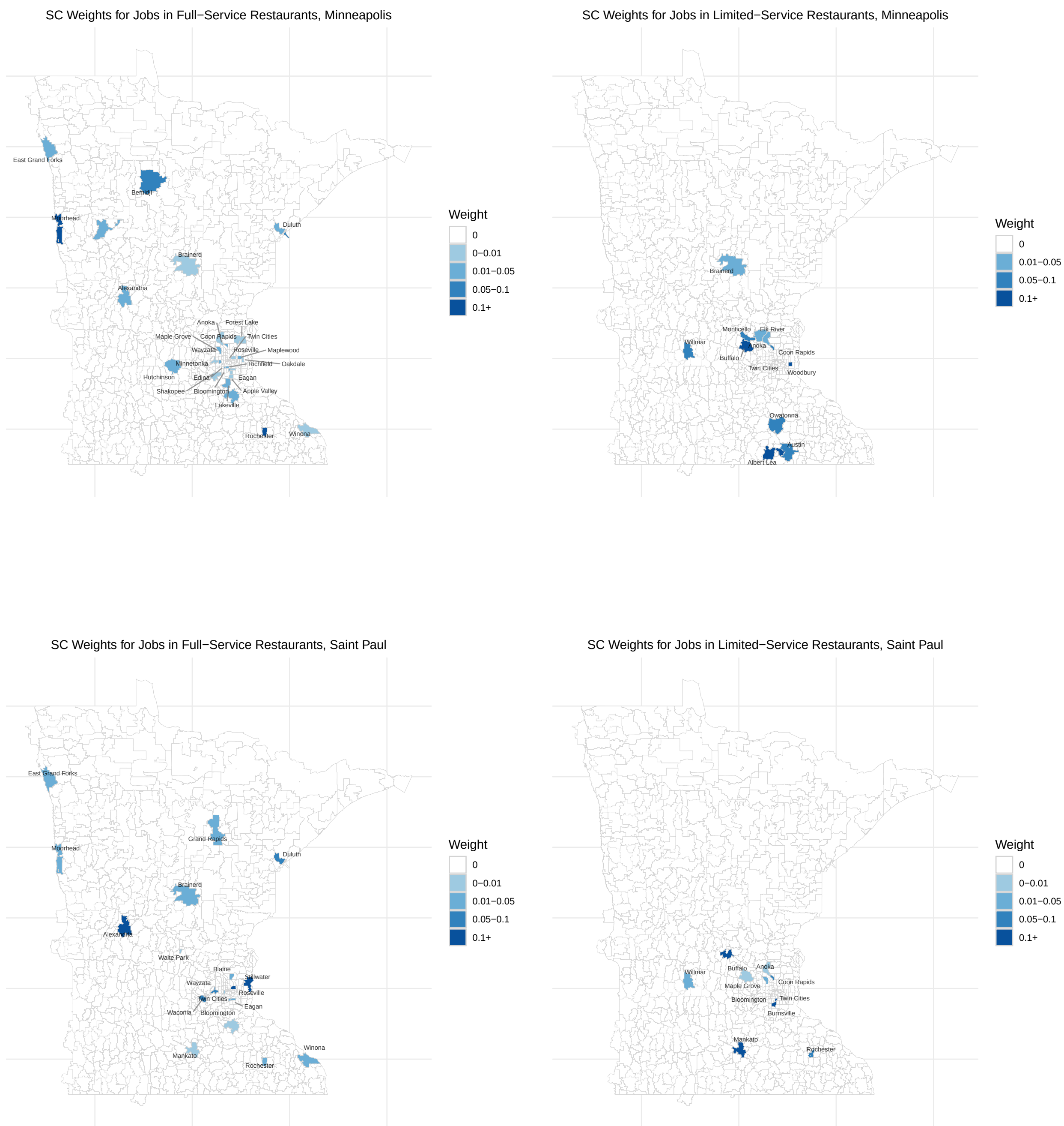



Figure A.1: Weight Maps for Jobs in Restaurants

Table A.5: Pre-treatment Fit: Synthetic Control versus Difference-in-Differences

| | Wage | | Jobs | | Hours | | Earnings | |
|---|---|---|---|---|---|---|---|---|
| (R-squared, percent) | SC | DD | SC | DD | SC | DD | SC | DD |
| **Minneapolis** | | | | | | | | |
| Retail Trade (44) | 83 | 30 | 86 | 0 | 80 | 5 | 69 | 1 |
| Administration and Support (56) | 53 | 3 | 88 | 17 | 77 | 17 | 84 | 24 |
| Health Care and Social Assistance (62) | 95 | 26 | 96 | 6 | 88 | 18 | 94 | 8 |
| Arts, Entertainment and Recreation (71) | 31 | 8 | 40 | 8 | 32 | 11 | 19 | 6 |
| Accommodation and Food Services (72) | 86 | 57 | 96 | 44 | 96 | 33 | 97 | 58 |
| Other Services (81) | 68 | 1 | 82 | 5 | 83 | 4 | 87 | 16 |
| Full-Service Restaurants (722511) | 65 | 31 | 88 | 24 | 85 | 36 | 82 | 23 |
| Limited-Service Restaurants (722513) | 63 | 30 | 58 | 9 | 54 | 3 | 51 | 3 |
| **Saint Paul** | | | | | | | | |
| Retail Trade (44) | 61 | 0 | 64 | 0 | 63 | 0 | 69 | 3 |
| Administration and Support (56) | 65 | 4 | 66 | 5 | 74 | 7 | 66 | 3 |
| Health Care and Social Assistance (62) | 96 | 15 | 95 | 0 | 96 | 7 | 98 | 29 |
| Arts, Entertainment and Recreation (71) | 36 | 12 | 15 | 6 | 35 | 8 | 24 | 0 |
| Accommodation and Food Services (72) | 79 | 40 | 68 | 5 | 55 | 0 | 66 | 11 |
| Other Services (81) | 83 | 34 | 85 | 22 | 87 | 9 | 92 | 12 |
| Full-Service Restaurants (722511) | 78 | 50 | 76 | 1 | 65 | 1 | 70 | 4 |
| Limited-Service Restaurants (722513) | 66 | 44 | 48 | 5 | 41 | 0 | 56 | 8 |

Notes: SC: synthetic control. DD: difference-in-differences.

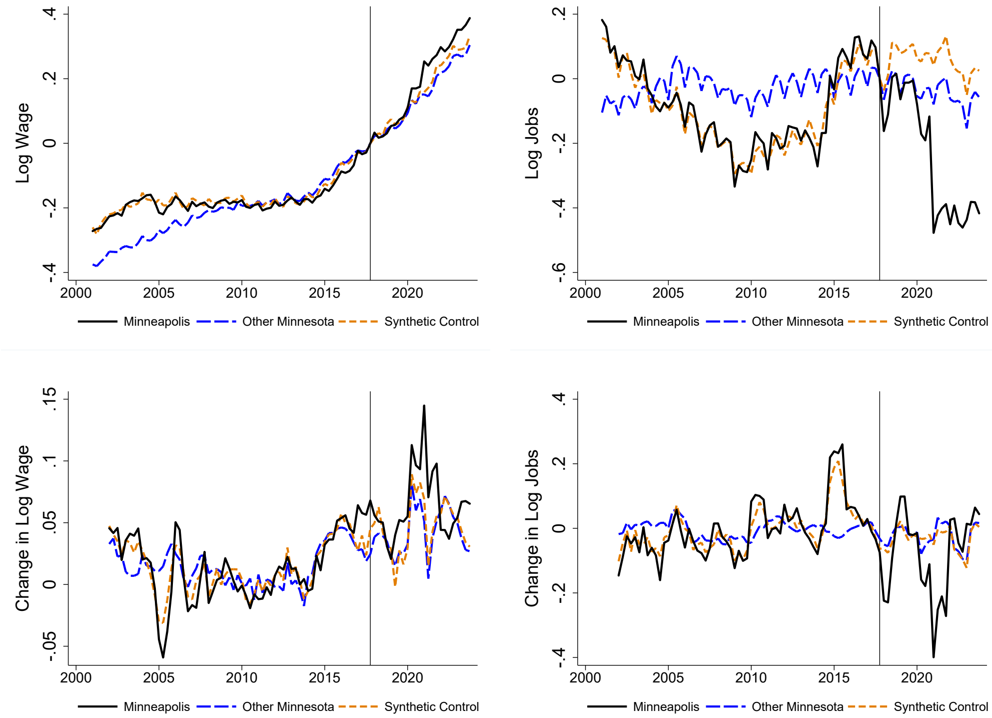



Figure A.2: Time Series of Retail Trade in Minneapolis

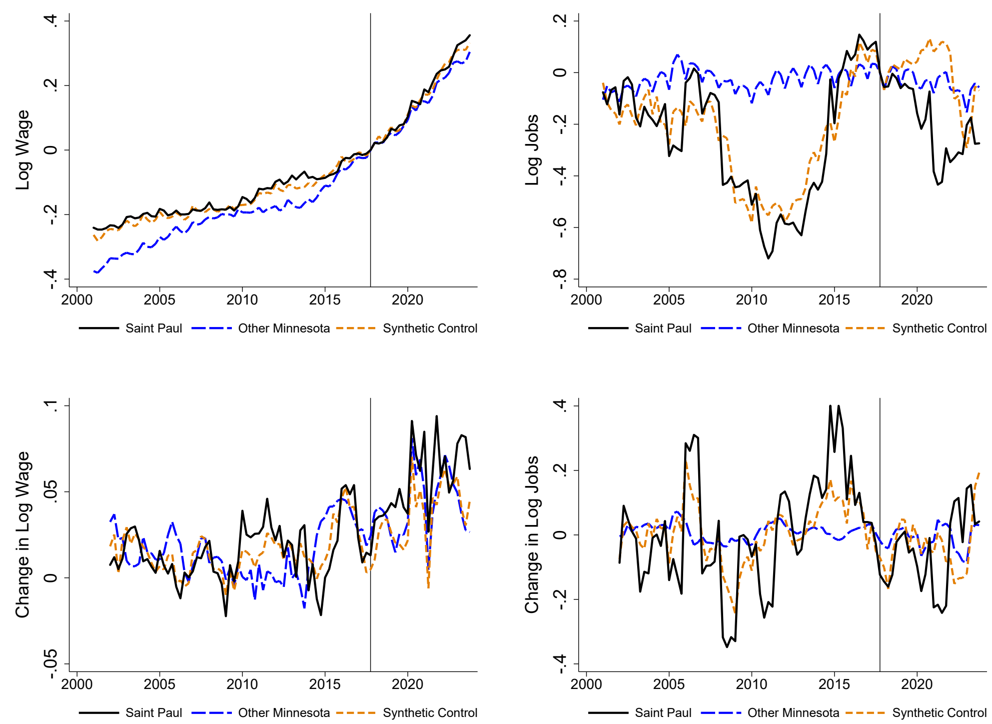



Figure A.3: Time Series of Retail Trade in Saint Paul

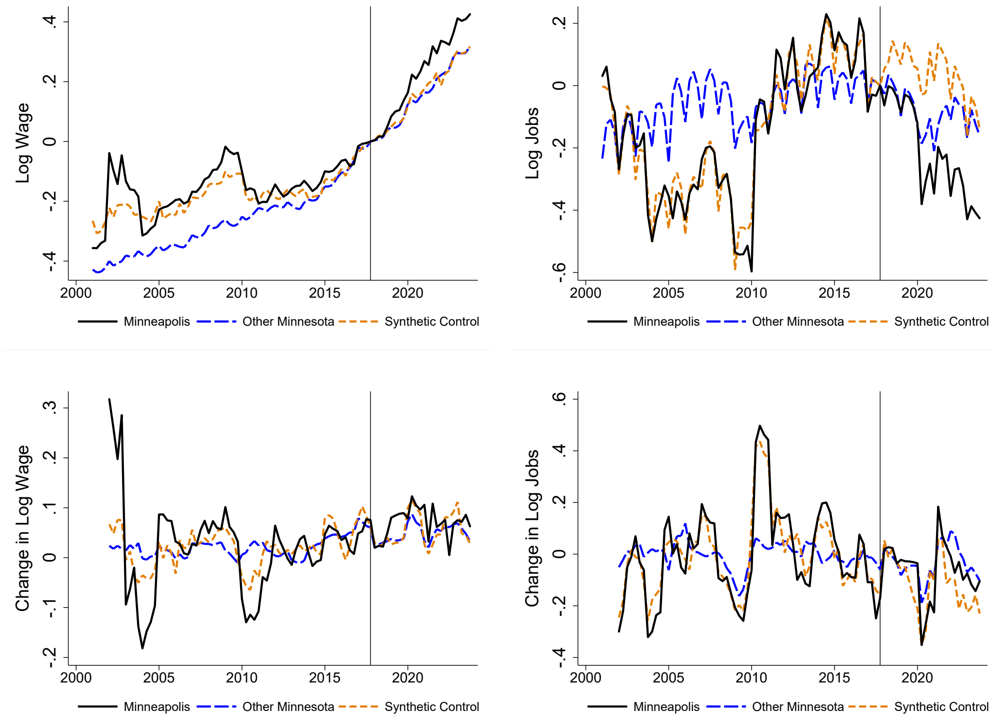



Figure A.4: Time Series of Administration and Support in Minneapolis

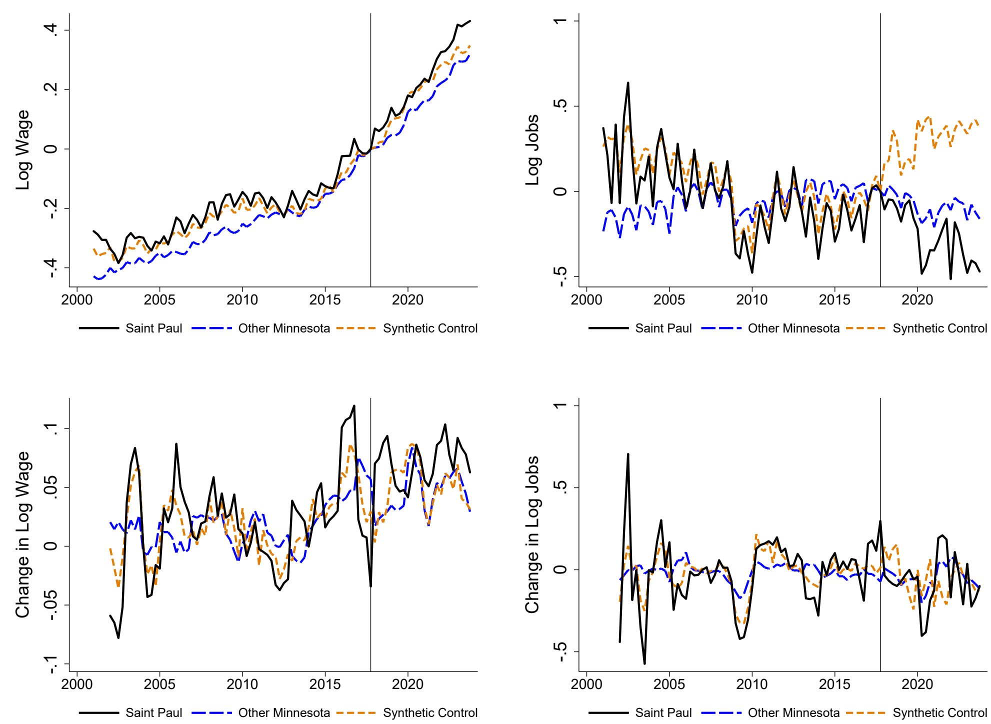



Figure A.5: Time Series of Administration and Support in Saint Paul

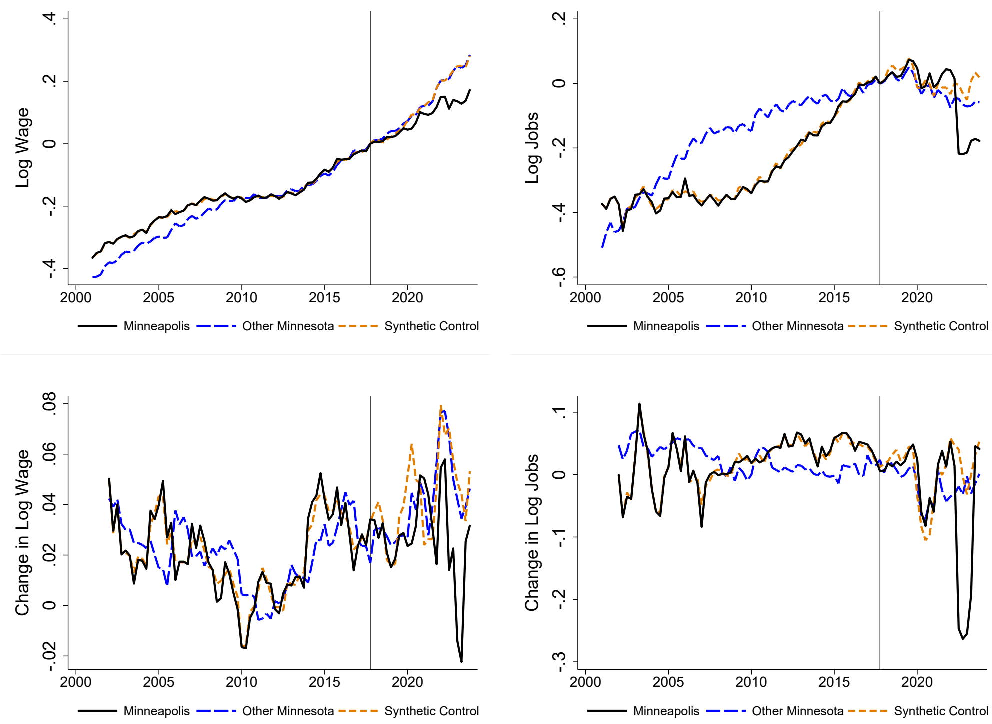



Figure A.6: Time Series of Health Care and Social Assistance in Minneapolis

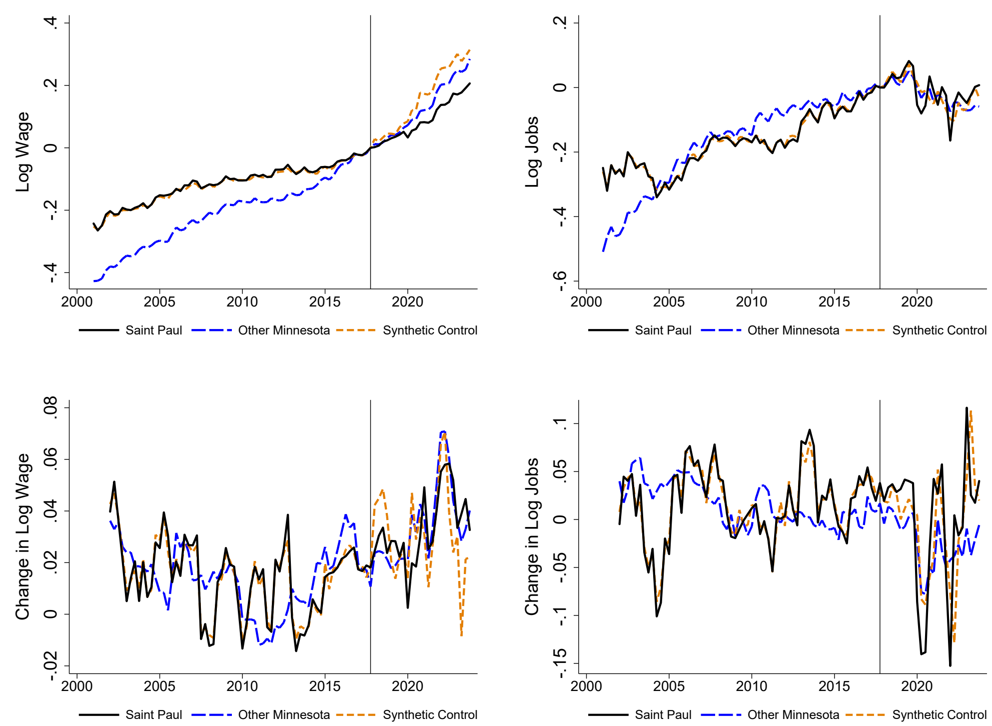



Figure A.7: Time Series of Health Care and Social Assistance in Saint Paul

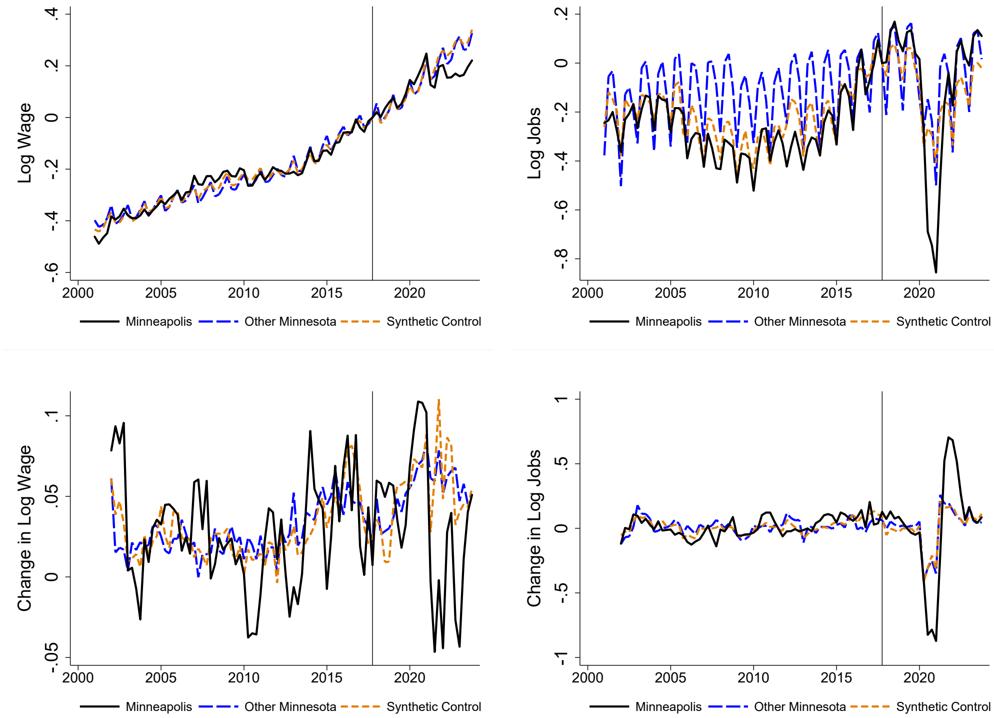



Figure A.8: Time Series of Arts, Entertainment, and Recreation in Minneapolis

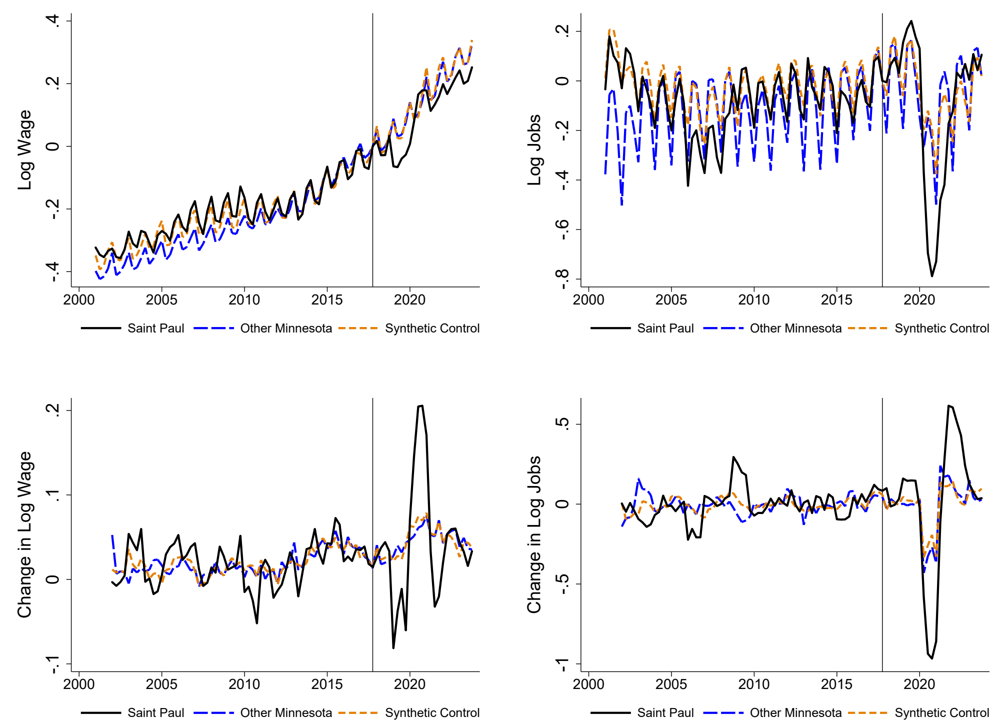



Figure A.9: Time Series of Arts, Entertainment, and Recreation in Saint Paul

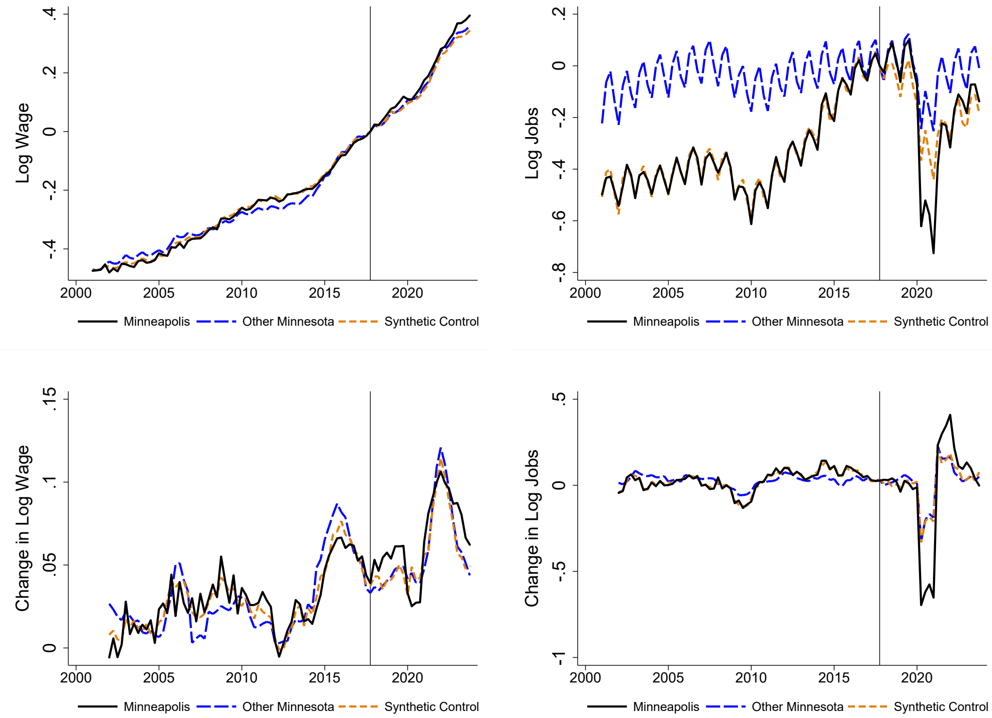



Figure A.10: Time Series of Accommodation and Food Services in Minneapolis

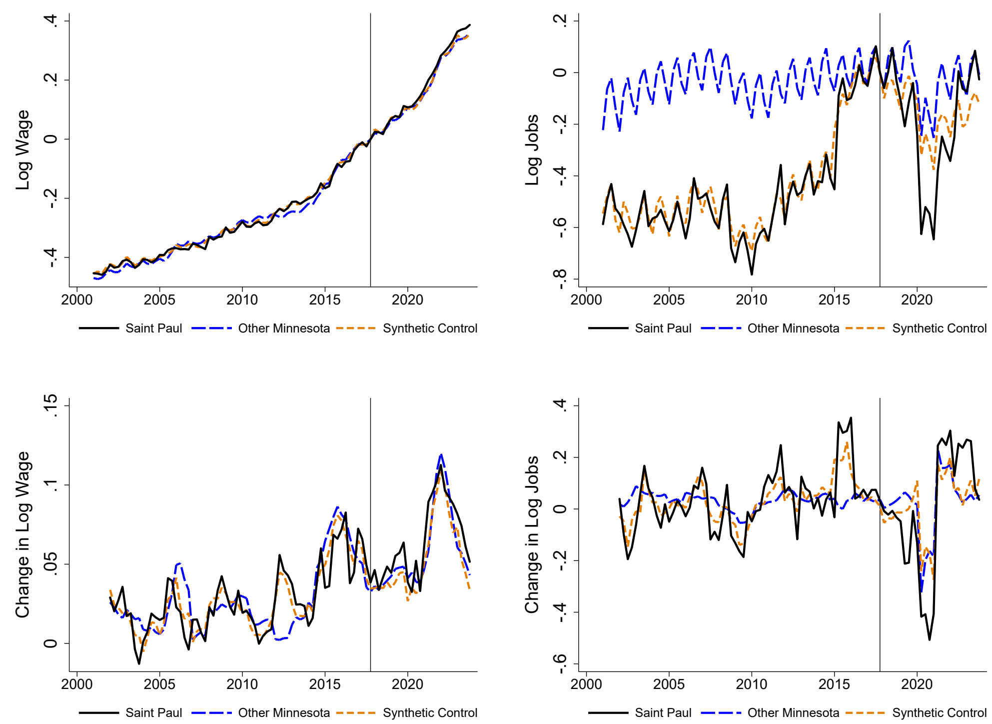



Figure A.11: Time Series of Accommodation and Food Services in Saint Paul

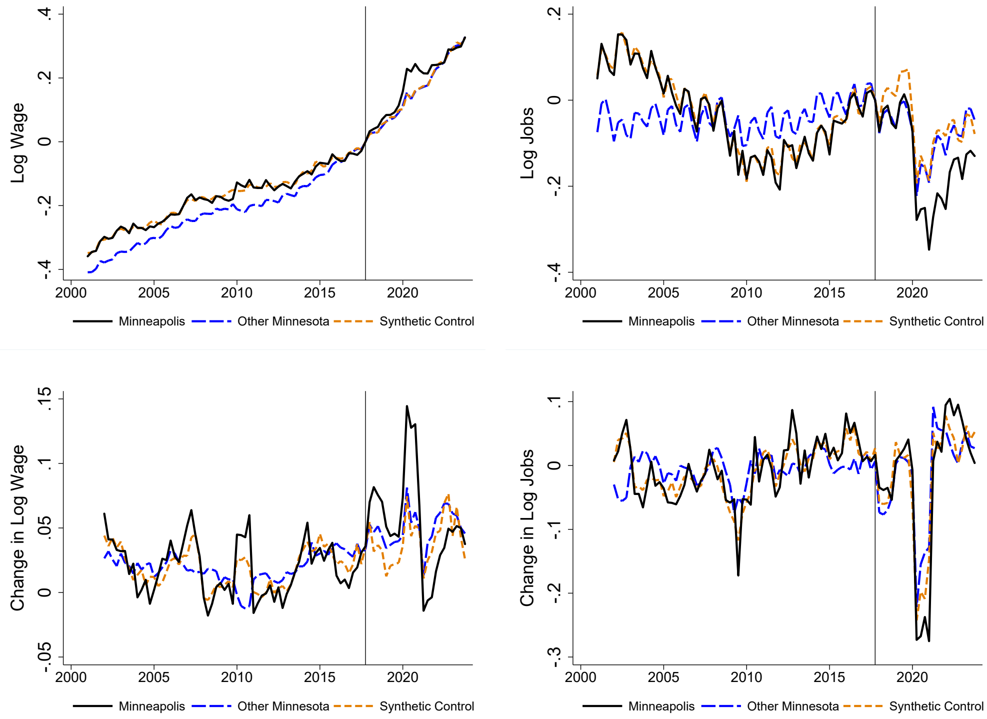



Figure A.12: Time Series of Other Services in Minneapolis

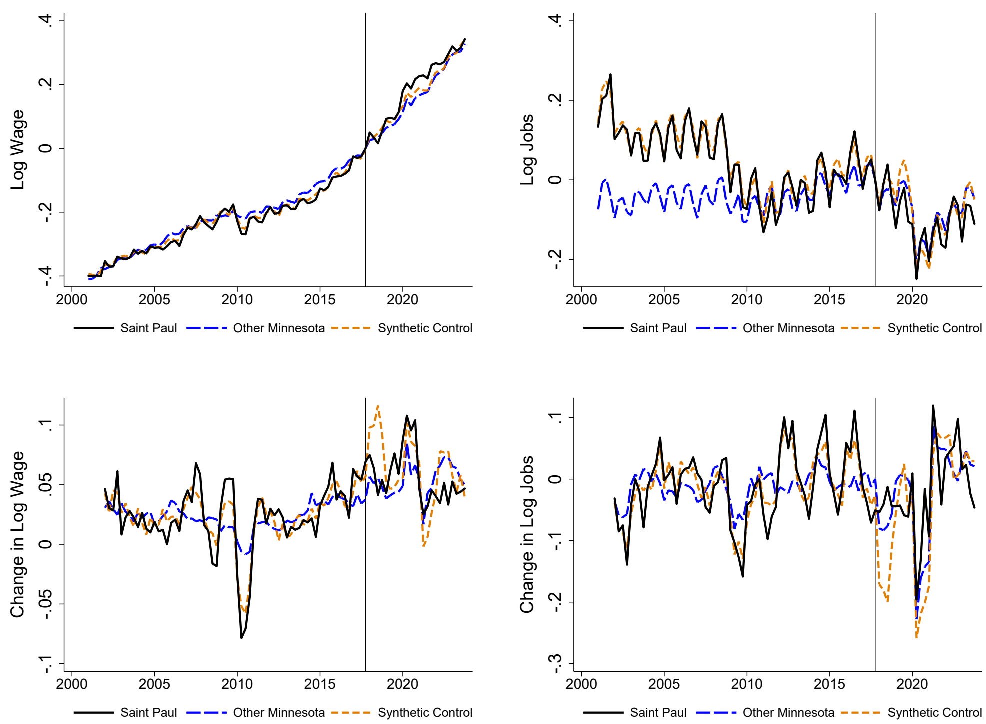



Figure A.13: Time Series of Other Services in Saint Paul

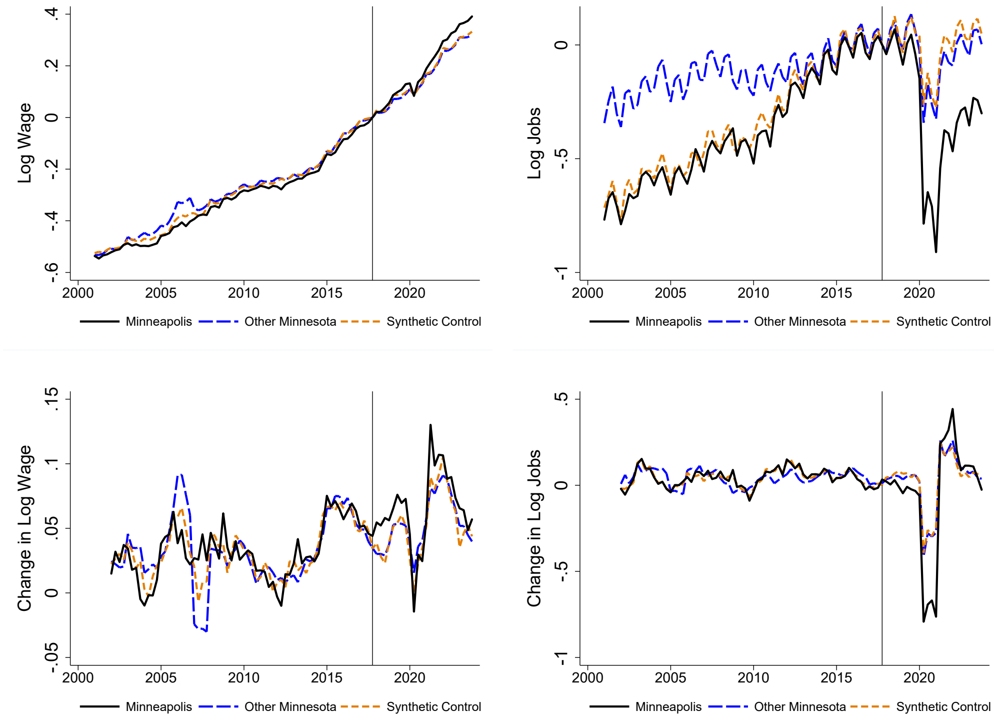



Figure A.14: Time Series of Full-Service Restaurants in Minneapolis

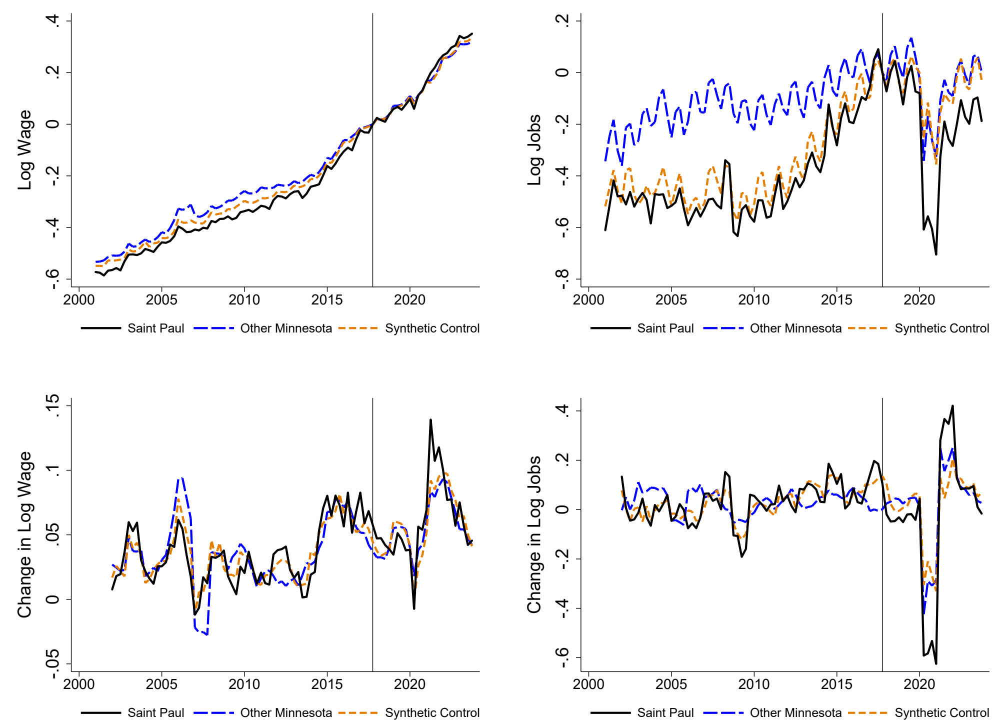



Figure A.15: Time Series of Full-Service Restaurants in Saint Paul

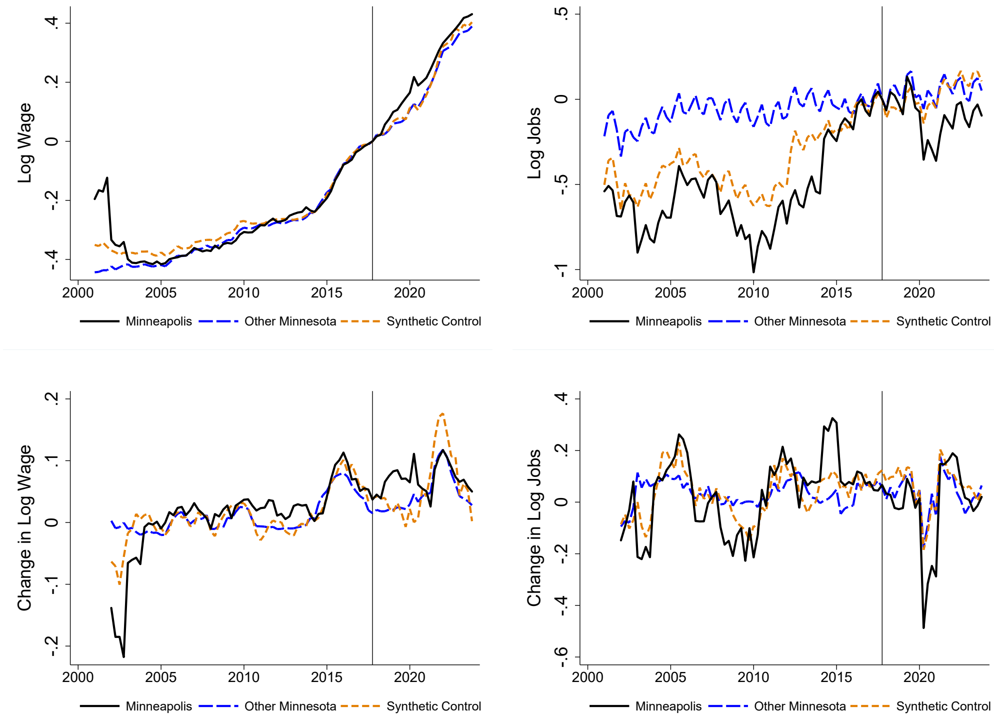



Figure A.16: Time Series of Limited-Service Restaurants in Minneapolis

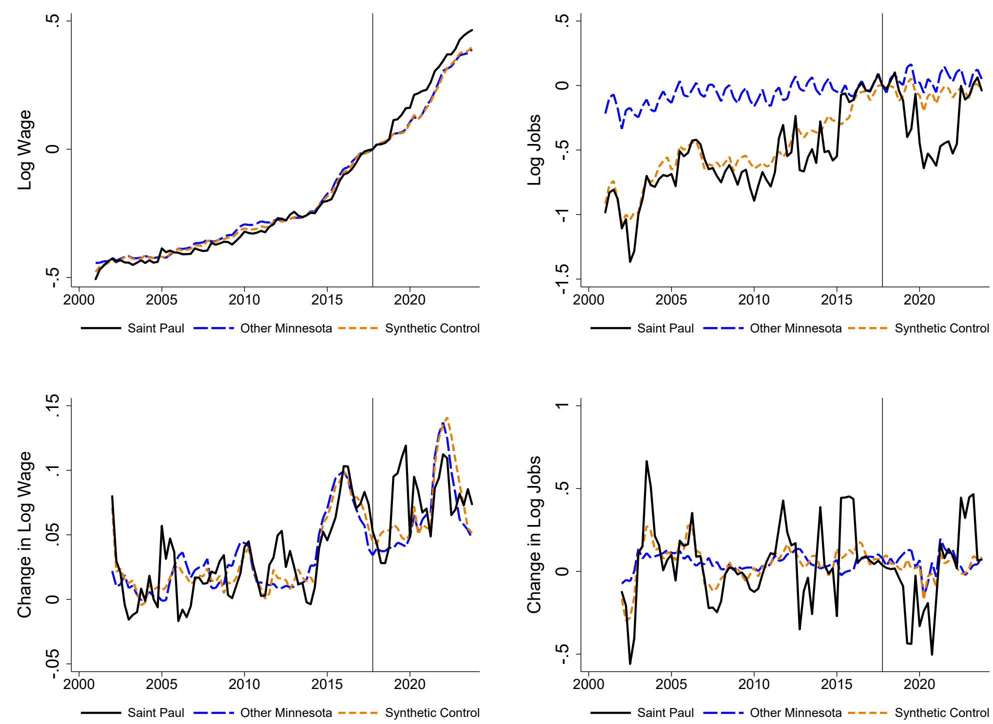
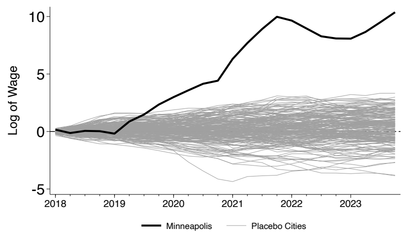



Figure A.17: Time Series of Limited-Service Restaurants in Saint Paul

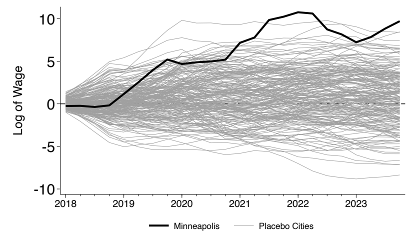
Table A.6: Employment Shares and Fraction of Workers Earning below 15 Dollars

| (2017) | Share of Employment (percent) | | | Fraction of Workers Earning Below 15 Dollars | | |
|---|---|---|---|---|---|---|
| | MPLS | SP | Other MN | MPLS | SP | Other MN |
| Manufacturing (31) | 5 | 4 | 13 | 14 | 18 | 17 |
| Wholesale Trade (42) | 3 | 3 | 4 | 11 | 16 | 15 |
| Retail Trade (44) | 5 | 7 | 11 | 59 | 62 | 65 |
| Transportation (48) | 2 | 2 | 3 | 20 | 21 | 23 |
| Finance and Insurance (52) | 11 | 6 | 4 | 5 | 6 | 13 |
| Professional Services (54) | 11 | 4 | 4 | 5 | 12 | 13 |
| Management of Companies (55) | 5 | 5 | 3 | 15 | 29 | 11 |
| Administration and Support (56) | 6 | 6 | 5 | 58 | 70 | 47 |
| Educational Services (61) | 13 | 10 | 8 | 22 | 24 | 23 |
| Health Care and Social Assistance (62) | 17 | 20 | 17 | 30 | 42 | 34 |
| Arts, Entertainment, and Recreation (71) | 2 | 3 | 2 | 43 | 45 | 61 |
| Accommodation and Food Services (72) | 9 | 9 | 9 | 54 | 64 | 71 |
| Other Services (81) | 3 | 4 | 3 | 39 | 34 | 50 |
| Restaurant Industries | | | | | | |
| Full-Service Restaurants (722511) | 4 | 4 | 3 | 46 | 49 | 56 |
| Limited-Service Restaurants (722513) | 2 | 3 | 3 | 80 | 82 | 90 |

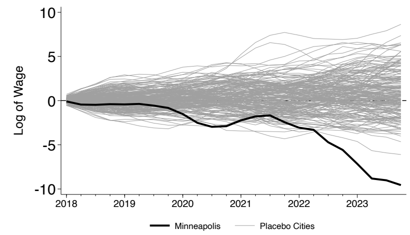
Note: MPLS denotes Minneapolis, SP denotes Saint Paul and Other MN denotes the sum of all other cities in Minnesota.



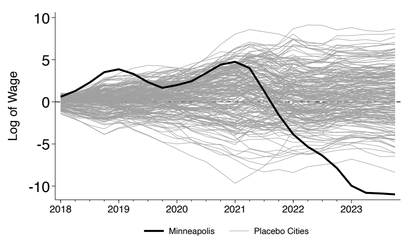

(a) Retail, MPLS



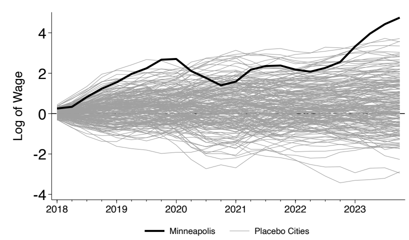

(b) Admin and Support, MPLS



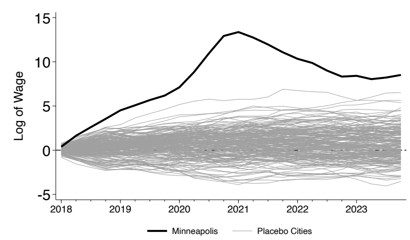

(c) Health and Social, MPLS



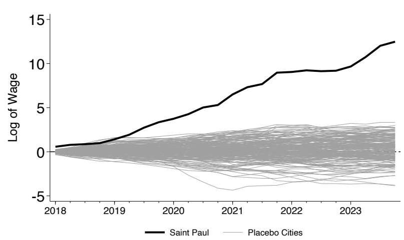

(d) Arts, Enter, and Rec, MPLS



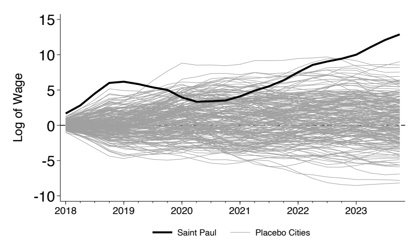

(e) Accommodation, MPLS



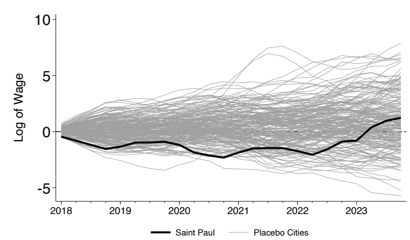

(f) Other Services, MPLS



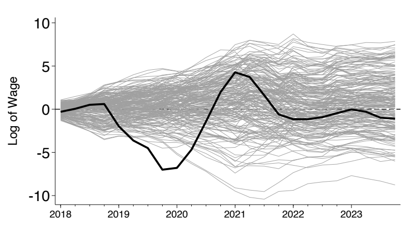

(g) Retail, SP



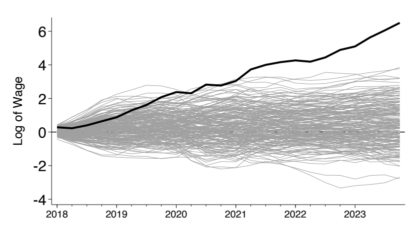

(h) Admin and Support, SP



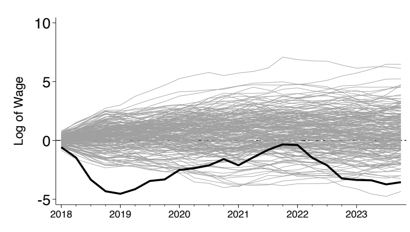

(i) Health and Social, SP




(j) Arts, Enter, and Rec, SP

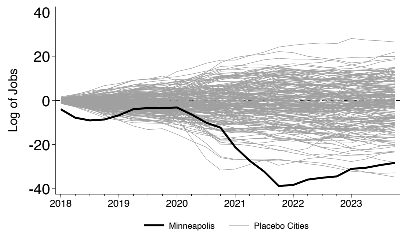



(k) Accommodation, SP

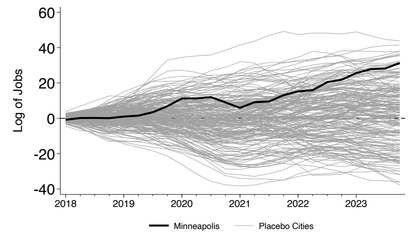



(l) Other Services, SP

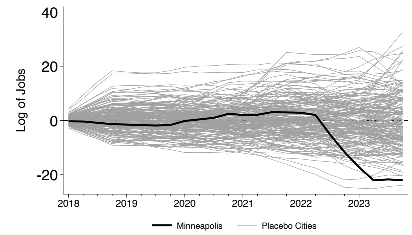
Figure A.18: Time-Varying Wage Effects in Other Industries



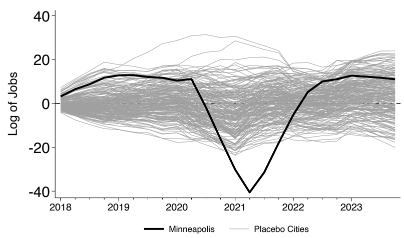

(a) Retail, MPLS



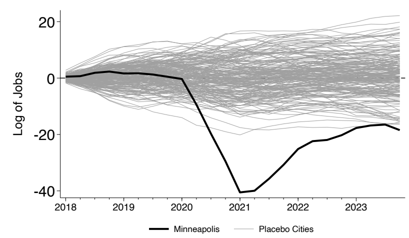

(b) Admin and Support, MPLS



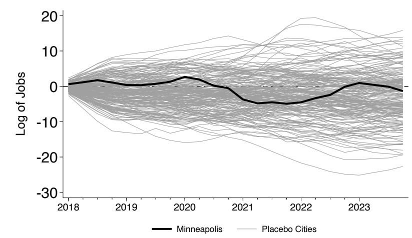

(c) Health and Social, MPLS



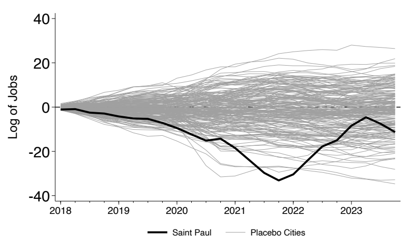

(d) Arts, Enter, and Rec, MPLS



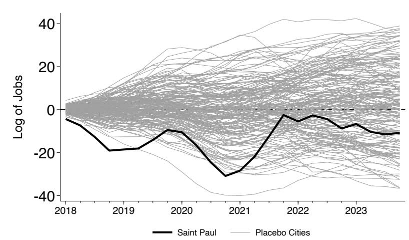

(e) Accommodation, MPLS



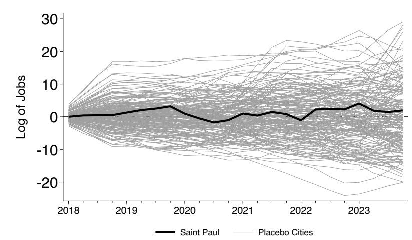

(f) Other Services, MPLS



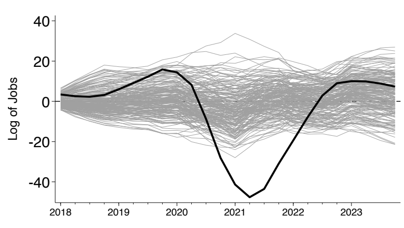

(g) Retail, SP



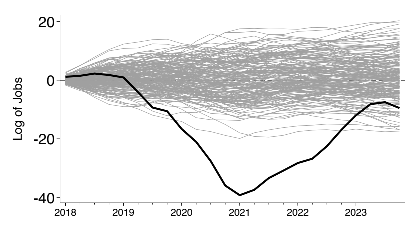

(h) Admin and Support, SP



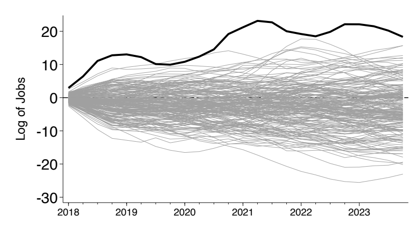

(i) Health and Social, SP




(j) Arts, Enter, and Rec, SP

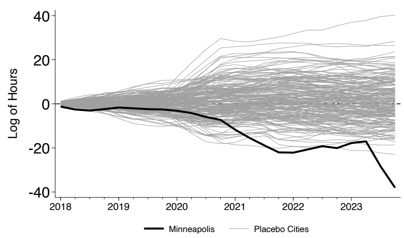



(k) Accommodation, SP

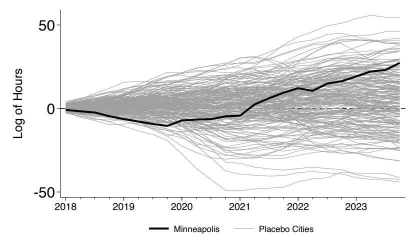



(l) Other Services, SP

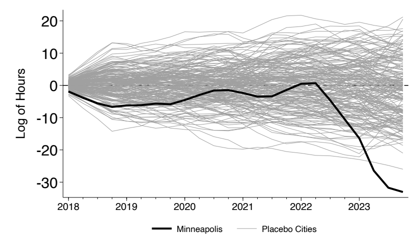
Figure A.19: Time-Varying Jobs Effects in Other Industries



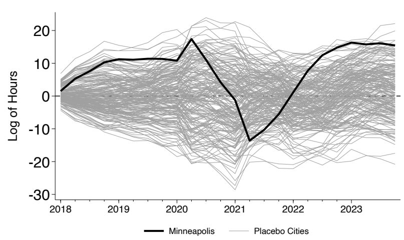

(a) Retail, MPLS



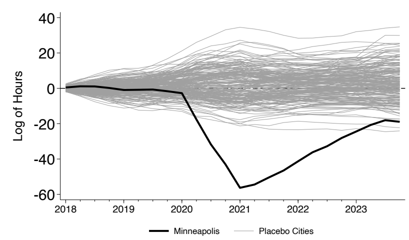

(b) Admin and Support, MPLS



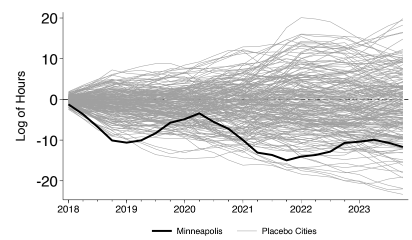

(c) Health and Social, MPLS



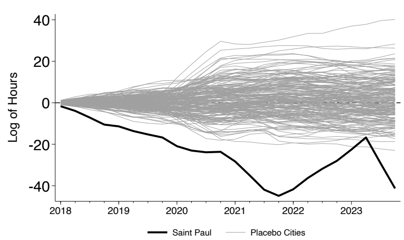

(d) Arts, Enter, and Rec, MPLS



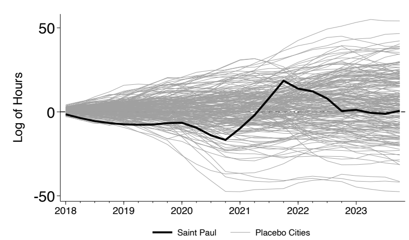

(e) Accommodation, MPLS



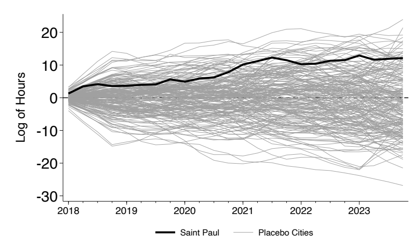

(f) Other Services, MPLS



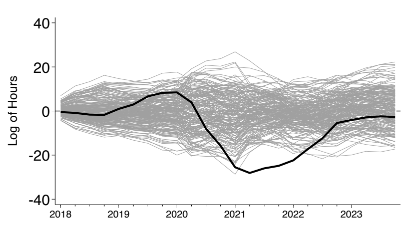

(g) Retail, SP



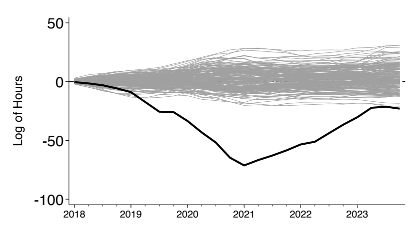

(h) Admin and Support, SP



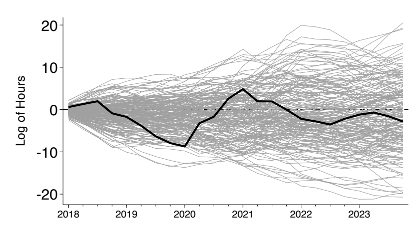

(i) Health and Social, SP




(j) Arts, Enter, and Rec, SP




(k) Accommodation, SP




(l) Other Services, SP

Figure A.20: Time-Varying Total Hours Effects in Other Industries

Table A.7: Minimum Wage Effects, Time Series of Minnesota Cities, Adding Time Weights

| Minneapolis | Wage | Jobs | Hours | Earnings |
|---|---|---|---|---|
| Retail Trade (44) | 10.1 | −41.4 | −30.2 | −25.4 |
| | (0.0) | (0.0) | (0.0) | (0.0) |
| Administration and Support (56) | 14.2 | 22.0 | 42.9 | 33.1 |
| | (0.0) | (14.6) | (0.2) | (1.6) |
| Health Care and Social Assistance (62) | −4.1 | −1.2 | −5.7 | −11.8 |
| | (0.2) | (90.1) | (51.9) | (12.4) |
| Arts, Entertainment and Recreation (71) | −4.9 | 16.4 | 7.6 | 33.7 |
| | (15.8) | (55.5) | (87.1) | (12.8) |
| Accommodation and Food Services (72) | 2.5 | −18.3 | −25.4 | −26.4 |
| | (3.0) | (0.4) | (0.0) | (0.0) |
| Other Services (81) | 4.5 | −2.6 | −8.8 | −7.1 |
| | (1.0) | (78.9) | (21.6) | (44.8) |
| Full-Service Restaurants (722511) | 5.4 | −50.7 | −48.0 | −38.7 |
| | (0.0) | (0.0) | (0.0) | (0.4) |
| Limited-Service Restaurants (722513) | 6.9 | 11.5 | 18.4 | 9.7 |
| | (0.0) | (48.2) | (18.6) | (54.5) |
| **Saint Paul** | **Wage** | **Jobs** | **Hours** | **Earnings** |
| Retail Trade (44) | 6.7 | −8.9 | −24.0 | −29.5 |
| | (0.0) | (22.2) | (0.0) | (0.0) |
| Administration and Support (56) | 10.9 | −8.0 | −9.1 | −93.7 |
| | (0.0) | (65.5) | (42.4) | (0.0) |
| Health Care and Social Assistance (62) | −2.1 | 7.7 | 3.9 | −9.5 |
| | (11.8) | (25.6) | (56.9) | (20.6) |
| Arts, Entertainment and Recreation (71) | −1.9 | 31.3 | −16.0 | −1.9 |
| | (54.9) | (5.2) | (8.4) | (40.8) |
| Accommodation and Food Services (72) | 6.2 | −24.3 | −40.2 | −25.6 |
| | (0.0) | (0.0) | (0.0) | (0.0) |
| Other Services (81) | −0.5 | 9.1 | −4.3 | 4.3 |
| | (61.1) | (13.2) | (58.9) | (42.6) |
| Full-Service Restaurants (722511) | 0.2 | −29.4 | −28.7 | −22.3 |
| | (89.5) | (0.4) | (1.2) | (10.0) |
| Limited-Service Restaurants (722513) | 1.6 | 8.2 | 23.6 | 12.0 |
| | (37.0) | (62.7) | (8.4) | (42.6) |

Notes: The estimates are in log points, multiplied by 100. Entries in parentheses are $p$-values, multiplied by 100, using the placebo method.

Table A.8: Minimum Wage Effects, Time Series of Minnesota Cities, Excluding Neighboring Cities

| Minneapolis | Wage | Jobs | Hours | Earnings |
|---|---|---|---|---|
| Retail Trade (44) | 8.8 | −33.2 | −20.2 | −25.0 |
| | (0.0) | (1.8) | (2.0) | (3.0) |
| Administration and Support (56) | 9.0 | 21.5 | 19.8 | 21.6 |
| | (0.6) | (23.0) | (38.2) | (25.6) |
| Health Care and Social Assistance (62) | −7.8 | −10.8 | −13.8 | −11.3 |
| | (0.0) | (21.8) | (13.6) | (12.6) |
| Arts, Entertainment and Recreation (71) | −7.7 | 10.3 | 15.9 | 7.7 |
| | (0.0) | (35.4) | (2.6) | (94.1) |
| Accommodation and Food Services (72) | 2.4 | −26.6 | −15.3 | −18.2 |
| | (11.8) | (0.0) | (3.2) | (4.2) |
| Other Services (81) | 8.3 | 6.9 | −9.5 | 3.8 |
| | (0.0) | (18.0) | (26.0) | (46.4) |
| Full-Service Restaurants (722511) | 6.7 | −40.3 | −44.3 | −45.1 |
| | (0.0) | (0.0) | (0.0) | (0.0) |
| Limited-Service Restaurants (722513) | 5.9 | −38.9 | −24.5 | −17.6 |
| | (0.0) | (0.0) | (7.2) | (10.8) |
| **Saint Paul** | **Wage** | **Jobs** | **Hours** | **Earnings** |
| Retail Trade (44) | 9.2 | −15.0 | −28.0 | −31.1 |
| | (0.0) | (18.0) | (1.0) | (0.4) |
| Administration and Support (56) | 9.4 | −8.8 | 3.4 | −39.9 |
| | (0.2) | (57.3) | (91.5) | (2.2) |
| Health Care and Social Assistance (62) | −0.4 | 2.5 | 11.5 | 0.7 |
| | (59.3) | (68.9) | (20.8) | (88.3) |
| Arts, Entertainment and Recreation (71) | −0.5 | 9.0 | −5.4 | −12.4 |
| | (86.1) | (38.2) | (28.6) | (2.6) |
| Accommodation and Food Services (72) | 4.9 | −18.4 | −36.6 | −13.6 |
| | (0.0) | (1.2) | (0.0) | (12.0) |
| Other Services (81) | −3.2 | 22.3 | −2.5 | 3.3 |
| | (4.2) | (0.0) | (94.5) | (52.9) |
| Full-Service Restaurants (722511) | 1.9 | −24.2 | −26.7 | −30.2 |
| | (17.0) | (2.4) | (1.0) | (1.8) |
| Limited-Service Restaurants (722513) | −0.8 | −37.6 | −35.2 | −46.9 |
| | (46.6) | (0.4) | (0.4) | (0.2) |

Notes: The estimates are in log points, multiplied by 100. Entries in parentheses are $p$-values, multiplied by 100, using the placebo method.

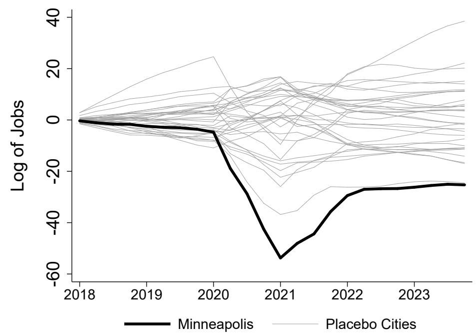
Table A.9: Minimum Wage Effects, Time Series of Minnesota Cities, Common Weights

| Minneapolis | Wage | Jobs |
|---|---|---|
| Retail Trade (44) | 14.0 | −33.4 |
| | (0.0) | (0.8) |
| Administration and Support (56) | 14.6 | 30.2 |
| | (0.0) | (3.0) |
| Health Care and Social Assistance (62) | −5.9 | −11.9 |
| | (2.2) | (13.8) |
| Arts, Entertainment and Recreation (71) | −6.3 | 7.1 |
| | (4.8) | (51.1) |
| Accommodation and Food Services (72) | 0.6 | −4.2 |
| | (83.1) | (51.7) |
| Other Services (81) | 3.6 | −10.7 |
| | (11.4) | (11.6) |
| Full-Service Restaurants (722511) | 3.1 | −31.5 |
| | (23.0) | (0.0) |
| Limited-Service Restaurants (722513) | 3.9 | −26.4 |
| | (37.6) | (2.2) |
| **Saint Paul** | **Wage** | **Jobs** |
| Retail Trade (44) | 9.5 | −12.2 |
| | (0.0) | (18.0) |
| Administration and Support (56) | 18.9 | −34.0 |
| | (0.0) | (1.6) |
| Health Care and Social Assistance (62) | −1.4 | 7.6 |
| | (50.9) | (33.8) |
| Arts, Entertainment and Recreation (71) | −1.8 | 9.5 |
| | (39.4) | (36.8) |
| Accommodation and Food Services (72) | −4.8 | −3.5 |
| | (0.2) | (58.7) |
| Other Services (81) | 2.4 | 0.9 |
| | (34.8) | (54.3) |
| Full-Service Restaurants (722511) | −1.8 | −17.0 |
| | (48.4) | (8.0) |
| Limited-Service Restaurants (722513) | −3.7 | −9.6 |
| | (4.6) | (27.4) |

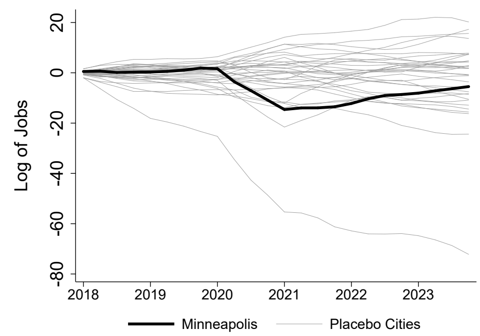
Notes: Average hourly wage, excluding the highest-paying 10 percent of jobs. The estimates are in log points, multiplied by 100. Entries in parentheses are $p$-values using the placebo method.

Table A.10: Cities of Similar Size to Minneapolis and Saint Paul

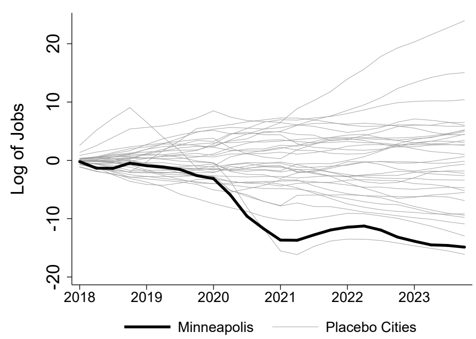
| City | Jobs (000's) | City | Jobs (000's) |
|---|---|---|---|
| Indianapolis, IN | 527 | Albuquerque, NM | 264 |
| Jacksonville, FL | 461 | Greensboro, NC | 251 |
| Denver, CO | 444 | El Paso, TX | 236 |
| Nashville, TN | 440 | Prince George's County, MD | 232 |
| Memphis, TN | 438 | Colorado Springs, CO | 225 |
| Milwaukee, WI | 434 | Baton Rouge, LA | 222 |
| Louisville, KY | 425 | Wichita, KS | 220 |
| Honolulu, HI | 380 | Little Rock, AR | 201 |
| Oklahoma City, OK | 374 | St. Louis, MO | 197 |
| Tulsa, OK | 322 | Reno, NV | 193 |
| Kansas City, MO | 314 | New Orleans, LA | 170 |
| Fresno, CA | 310 | Fort Wayne, IN | 169 |
| Omaha, NE | 301 | Winston-Salem, NC | 167 |
| Tucson, AZ | 299 | Lexington, KY | 159 |
| Aurora, CO | 295 | Huntsville, AL | 155 |
| Minneapolis, MN | 280 | Virginia Beach, VA | 149 |
| Baltimore, MD | 276 | Springfield, MO | 147 |
| Aurora, CO | 295 | Corpus Christi, TX | 135 |
| Baltimore, MD | 276 | Salem, OR | 132 |
| Albuquerque, NM | 264 | Anchorage, AK | 120 |
| Greensboro, NC | 251 | Sioux Falls, SD | 115 |
| El Paso, TX | 236 | Rockford, IL | 114 |
| Prince George's County, MD | 232 | Richmond, VA | 114 |
| Colorado Springs, CO | 225 | Lubbock, TX | 111 |
| Baton Rouge, LA | 222 | Norfolk, VA | 104 |
| Wichita, KS | 220 | Tallahassee, FL | 102 |
| Little Rock, AR | 201 | Montgomery, AL | 97 |
| St. Louis, MO | 197 | Shreveport, LA | 95 |
| Reno, NV | 193 | Amarillo, TX | 90 |
| New Orleans, LA | 170 | Jackson, MS | 86 |
| Fort Wayne, IN | 169 | Chesapeake, VA | 85 |
| Winston-Salem, NC | 167 | Midland, TX | 85 |
| Lexington, KY | 159 | Fayetteville, NC | 83 |
| Huntsville, AL | 155 | Newport News, VA | 83 |
| Virginia Beach, VA | 149 | Augusta, GA | 81 |
| Saint Paul, MN | 149 | Laredo, TX | 79 |
| Springfield, MO | 147 | Kansas City, KS | 78 |
| Lincoln, NE | 137 | Birmingham, AL | 77 |
| Savannah, GA | 136 | | |



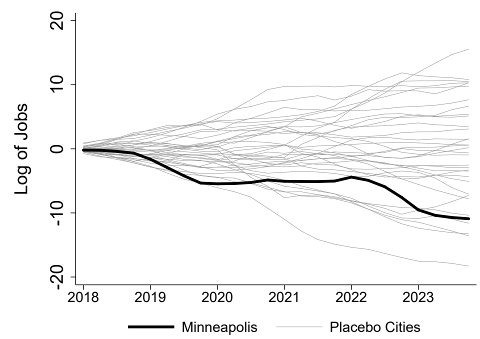

(a) Full-service restaurants, MPLS



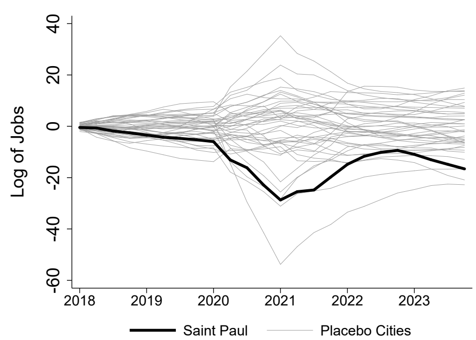

(b) Ltd-service restaurants, MPLS



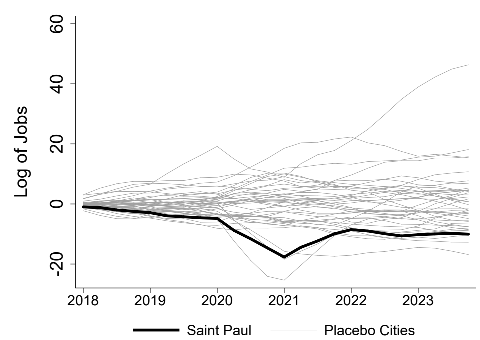

(c) Retail trade, MPLS



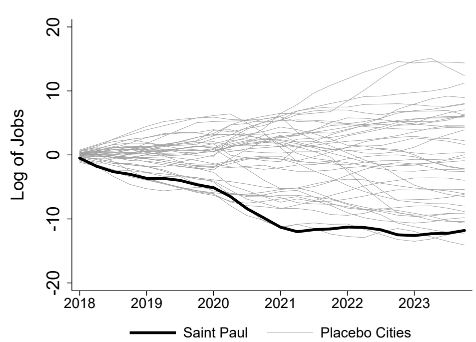

(d) Health and social, MPLS



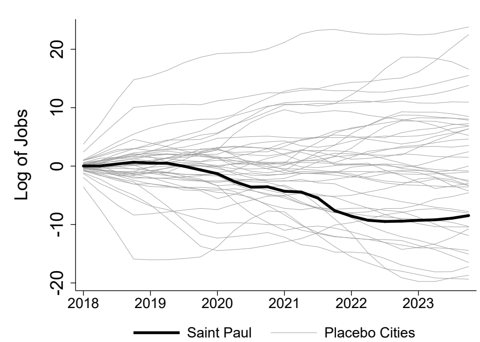

(e) Full-service restaurants, SP




(f) Ltd-service restaurants, SP




(g) Retail trade, SP



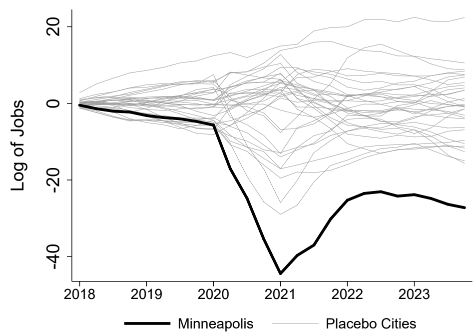

(h) Health and social, SP

Figure A.21: Time-Varying Jobs Effects, U.S. Cities, Adding Time Weights

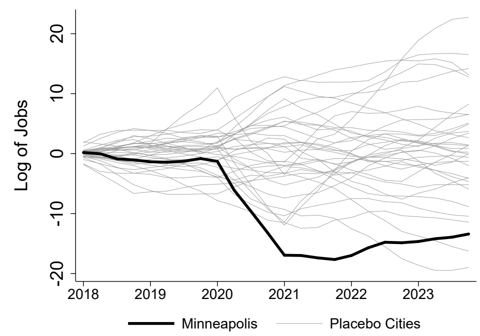
Table A.11: Assessing the Size and Sources of the Bias

| Minneapolis | Jobs Effect | Bias $\mu$ | Bias $u$ | Bias Total |
|---|---|---|---|---|
| Retail Trade (44) | −8 | 3 | −3 | 0 |
| Administration and Support (56) | −20 | 1 | −6 | −5 |
| Health Care and Social Assistance (62) | −13 | −2 | −3 | −5 |
| Arts, Entertainment and Recreation (71) | −16 | 4 | −6 | −2 |
| Accommodation and Food Services (72) | −15 | 0 | −4 | −4 |
| Other Services (81) | −5 | 5 | −2 | 3 |
| Full-Service Restaurants (722511) | −29 | 0 | −7 | −7 |
| Limited-Service Restaurants (722513) | −14 | −3 | −3 | −6 |
| **Saint Paul** | **Jobs Effect** | **Bias $\mu$** | **Bias $u$** | **Bias Total** |
| Retail Trade (44) | −12 | 2 | −4 | −2 |
| Administration and Support (56) | −20 | −13 | −2 | −15 |
| Health Care and Social Assistance (62) | −4 | −1 | −1 | −2 |
| Arts, Entertainment and Recreation (71) | 8 | −4 | 4 | 0 |
| Accommodation and Food Services(72) | −9 | −7 | −1 | −8 |
| Other Services (81) | −2 | 9 | −2 | 7 |
| Full-Service Restaurants (722511) | −20 | 0 | −5 | −5 |
| Limited-Service Restaurants (722513) | −8 | −5 | 0 | −5 |

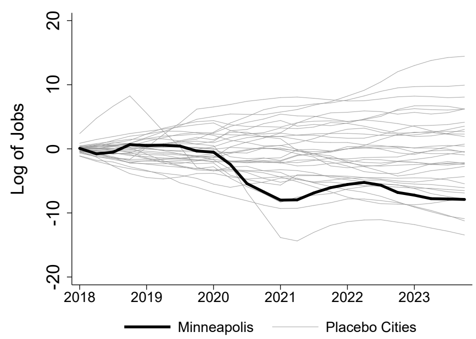
Notes: Estimates are in log points, multiplied by 100. The first column repeats our jobs estimates using synthetic difference-in-differences from the QCEW dataset. The data generating process is a factor model $Y_{it} = \alpha_i + \beta_t + \sum_{k=1}^{4} \mu_i^k \gamma_t^k + u_{it} + \sum_{s=T_{\text{pre}}+1}^{T} \tau_s W_{is}$. After generating data from this model assuming treatment effects of $\tau_s = 0$, we perform the synthetic difference-in-differences method to assess the bias of the estimates relative to those in the factor model. The bias $\mu$ column assumes $u_{Nt} = \sum_{i=1}^{N_{\text{co}}} \omega_i u_{it}, \forall t = 1, ..., T$ and yields the bias due to not fitting the underlying factor structure. The bias $u$ column assumes $\sum_{i=1}^{N_{\text{co}}} \omega_i \mu_i^k = \mu_N^k$ and yields the bias due to the scale of errors relative to the length of the pre-treatment period. The total bias column is the sum of the two columns.



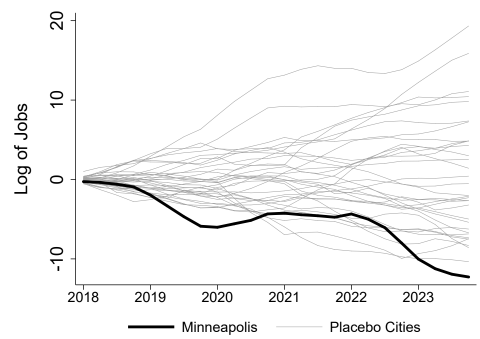

(a) Full-service restaurants, MPLS



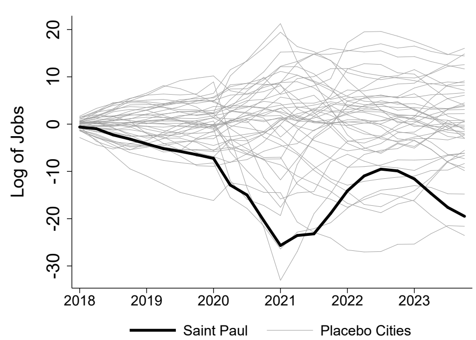

(b) Ltd-service restaurants, MPLS



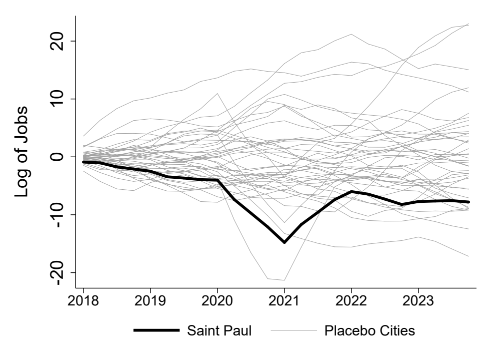

(c) Retail trade, MPLS



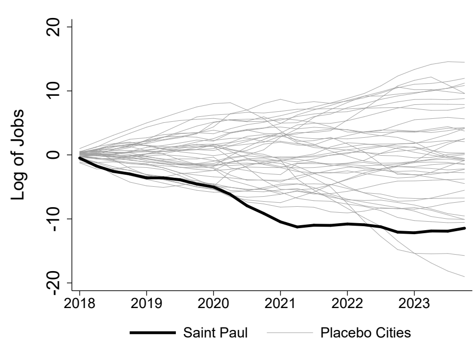

(d) Health and social, MPLS



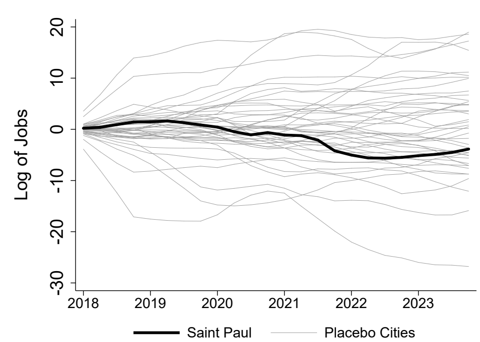

(e) Full-service restaurants, SP




(f) Ltd-service restaurants, SP

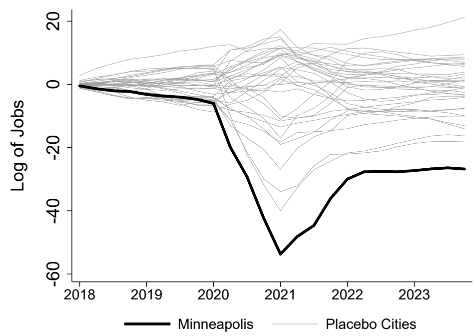



(g) Retail trade, SP

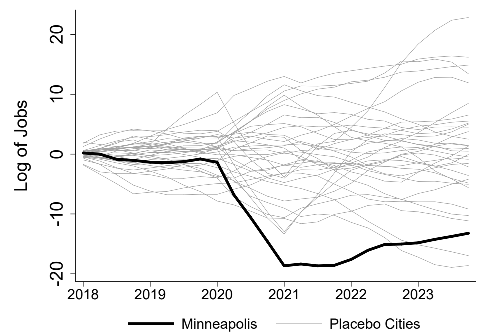



(h) Health and social, SP

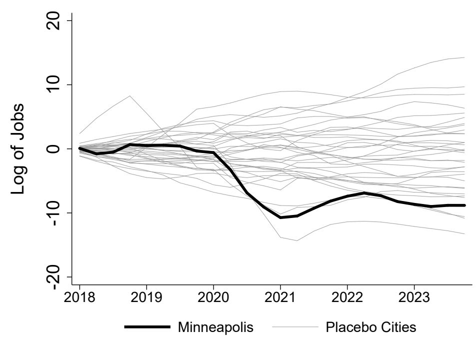
Figure A.22: Time-Varying Jobs Effects, Adjusted for Workplace Mobility



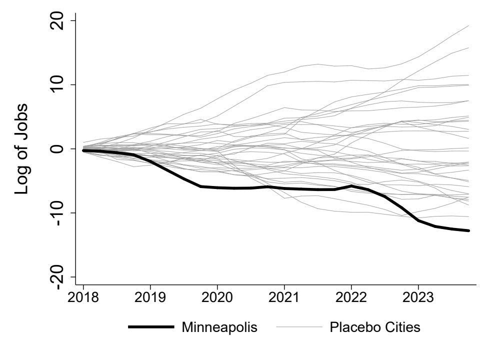

(a) Full-service restaurants, MPLS



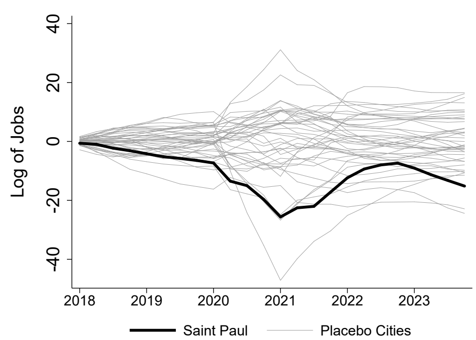

(b) Ltd-service restaurants, MPLS



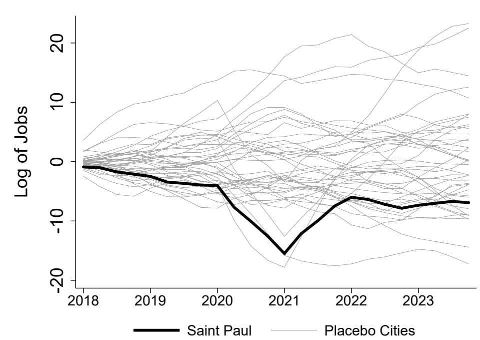

(c) Retail trade, MPLS



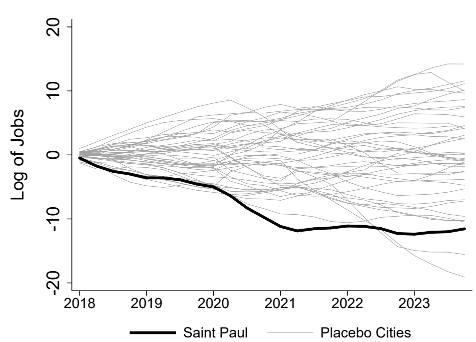

(d) Health and social, MPLS



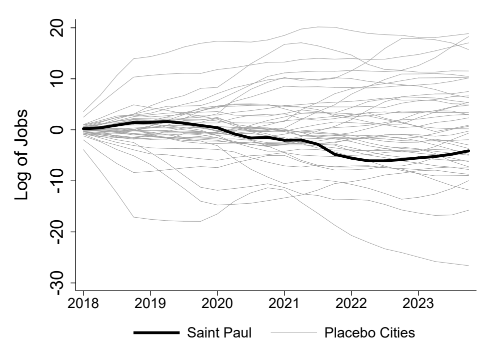

(e) Full-service restaurants, SP




(f) Ltd-service restaurants, SP

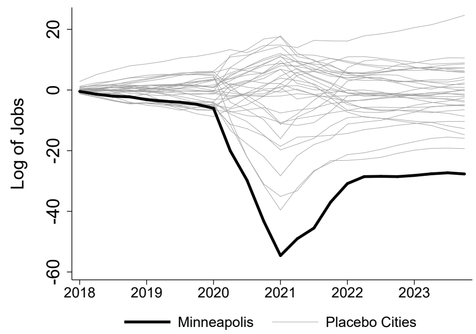



(g) Retail trade, SP

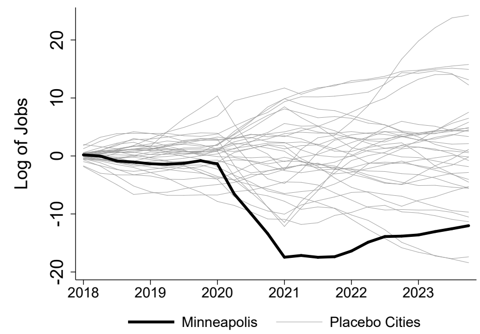



(h) Health and social, SP

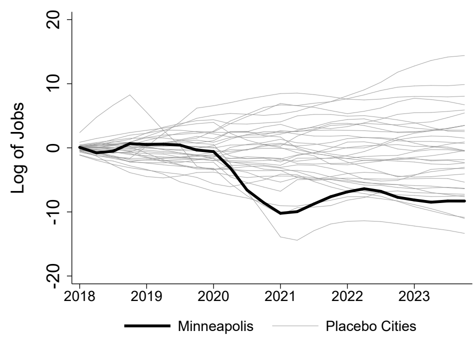
Figure A.23: Time-Varying Jobs Effects, Adjusted for Violent Protests



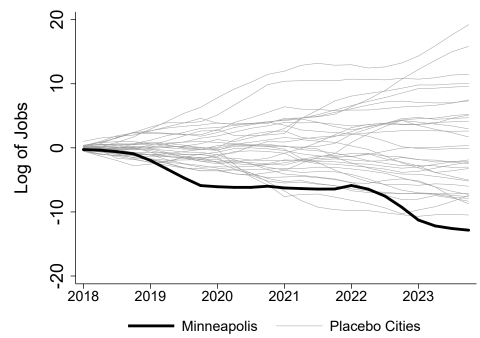

(a) Full-service restaurants, MPLS



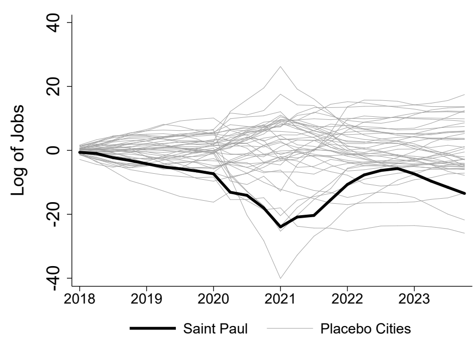

(b) Ltd-service restaurants, MPLS



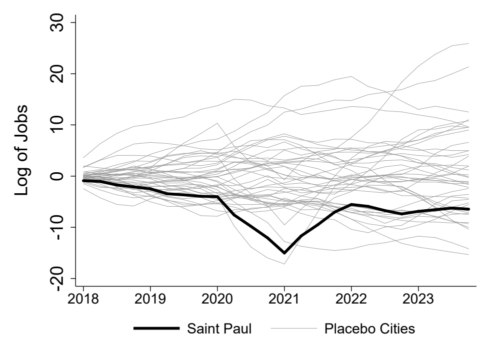

(c) Retail trade, MPLS



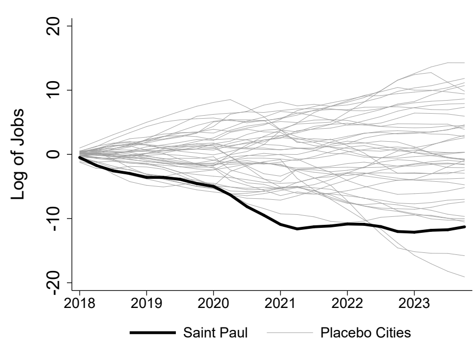

(d) Health and social, MPLS



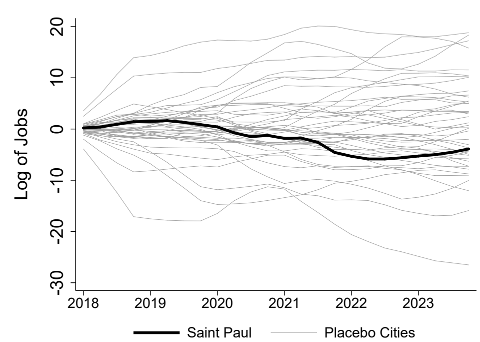

(e) Full-service restaurants, SP




(f) Ltd-service restaurants, SP




(g) Retail trade, SP




(h) Health and social, SP

Figure A.24: Time-Varying Jobs Effects, Adjusted for Total Protests

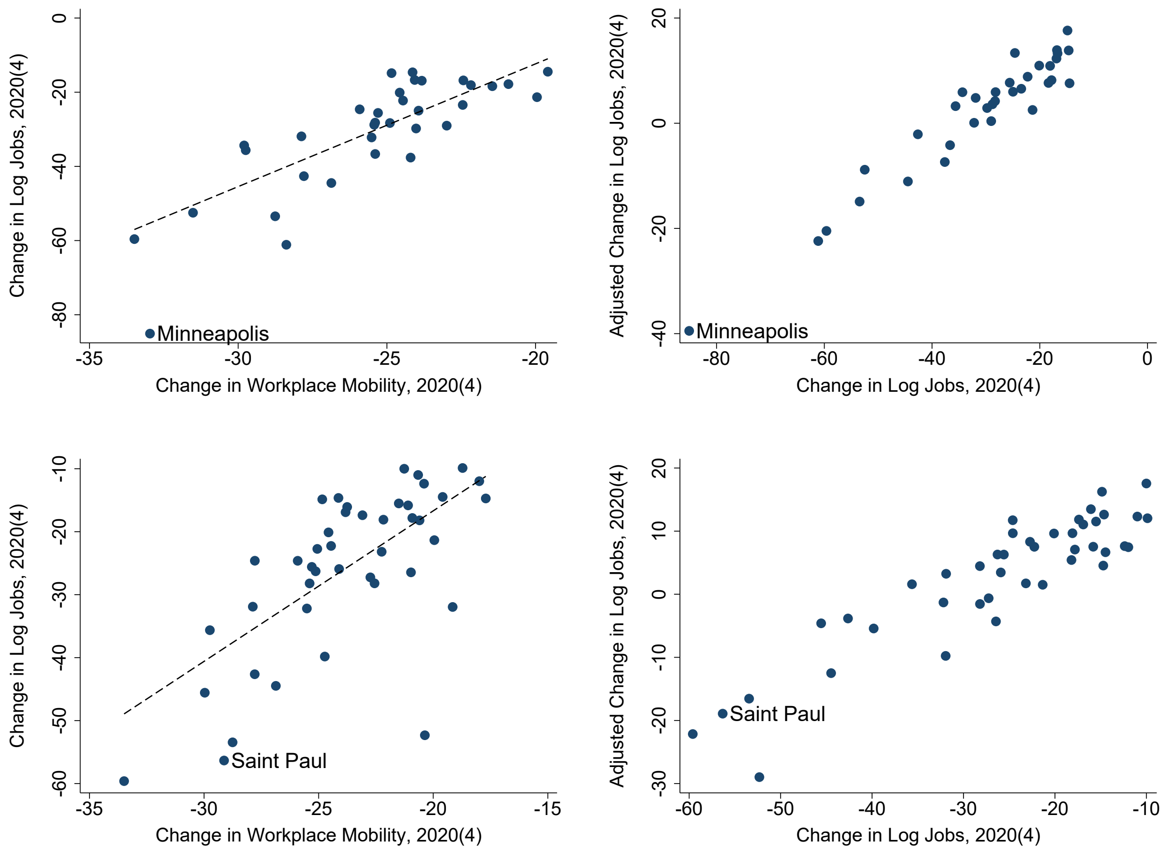



Figure A.25: Adjustments for Workplace Mobility

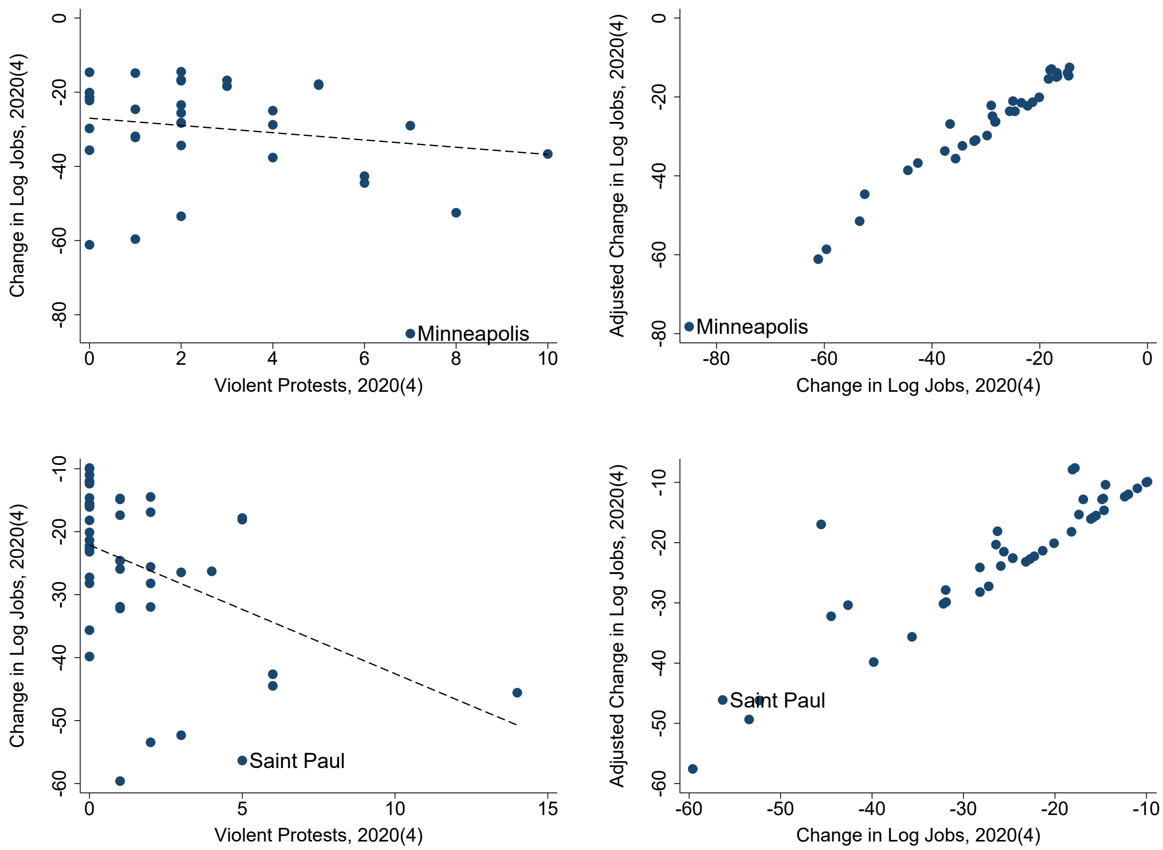



Figure A.26: Adjustments for Violent Protests

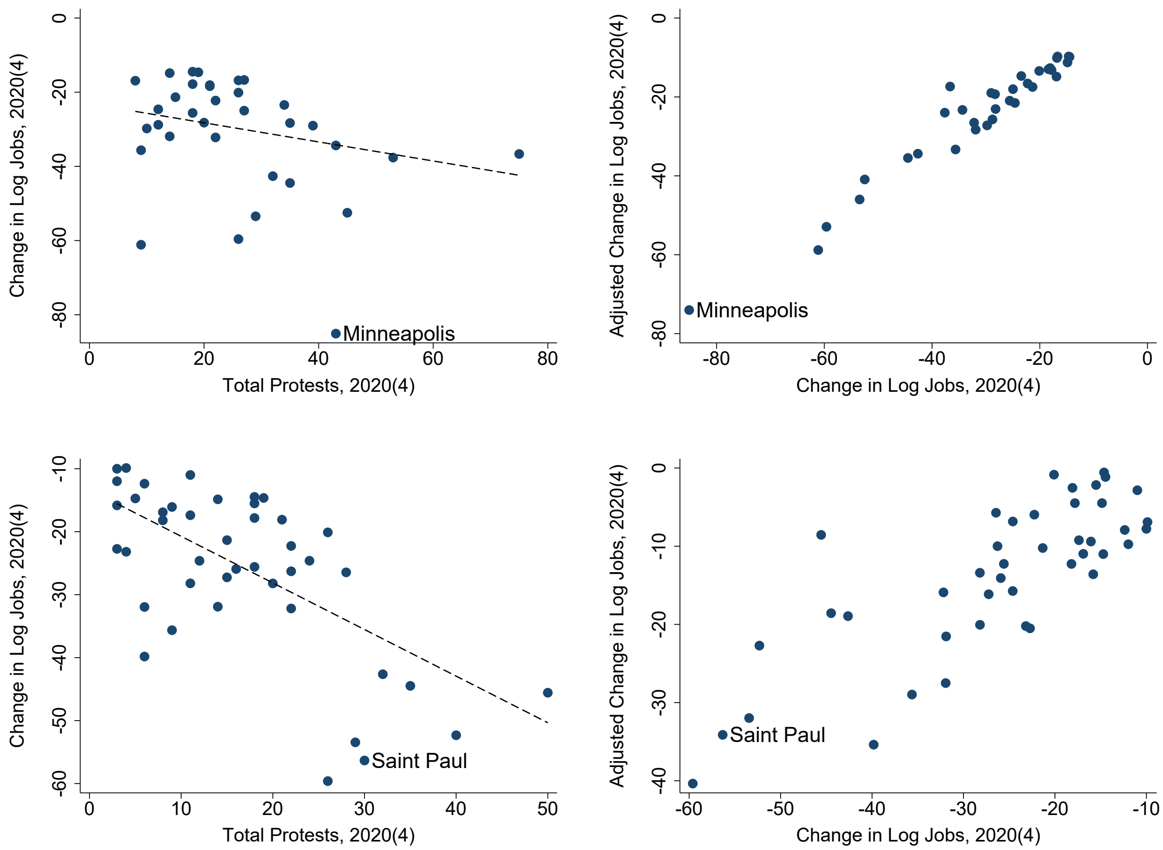



Figure A.27: Adjustments for Total Protests

Table A.12: Minimum Wage Effects, Cross Section of Twin Cities Establishments

| Change Since 2017 | Minneapolis | | | | Saint Paul | | | |
|---|---|---|---|---|---|---|---|---|
| Add Lagged Growth | Wage | Jobs | Hours | Earnings | Wage | Jobs | Hours | Earnings |
| 2017 – 2018 | 3.5 | −5.0 | −4.2 | −1.7 | −2.8 | −17.7 | −17.7 | −11.1 |
| | (8.9) | (21.8) | (33.1) | (71.7) | (25.4) | (0.1) | (0.2) | (6.5) |
| 2017 – 2019 | −0.1 | −3.1 | −3.1 | 0.0 | −0.1 | −18.8 | −19.5 | −12.9 |
| | (97.8) | (55.1) | (56.0) | (99.7) | (97.6) | (0.4) | (0.4) | (8.2) |
| 2017 – 2020 | 4.8 | −13.0 | −11.8 | −14.0 | 1.9 | −22.6 | −21.0 | −19.7 |
| | (18.5) | (1.7) | (3.0) | (2.4) | (71.6) | (0.1) | (0.2) | (1.2) |
| 2017 – 2021 | 10.6 | −15.3 | −14.9 | −17.2 | 9.7 | −11.4 | −11.1 | −7.7 |
| | (1.4) | (0.7) | (0.9) | (1.1) | (13.4) | (11.0) | (13.2) | (36.9) |
| 2017 – 2022 | 12.6 | −19.3 | −17.7 | −20.1 | 8.8 | −22.2 | −18.9 | −17.2 |
| | (1.3) | (0.1) | (0.3) | (0.5) | (10.1) | (0.4) | (1.4) | (6.2) |
| 2017 – 2023 | 14.5 | −15.3 | −14.8 | −15.2 | 10.8 | −28.1 | −25.9 | −26.3 |
| | (1.5) | (2.5) | (3.0) | (7.1) | (16.5) | (0.1) | (0.3) | (1.3) |
| Add Three More Years | Wage | Jobs | Hours | Earnings | Wage | Jobs | Hours | Earnings |
| 2017 – 2018 | 5.8 | −5.0 | −4.1 | −2.6 | 0.5 | −17.3 | −17.6 | −10.7 |
| | (0.3) | (21.9) | (34.9) | (57.5) | (84.2) | (0.1) | (0.2) | (7.6) |
| 2017 – 2019 | 7.3 | −3.9 | −3.5 | −1.8 | 5.8 | −18.6 | −19.7 | −13.4 |
| | (0.7) | (45.3) | (51.0) | (76.5) | (12.5) | (0.4) | (0.3) | (6.9) |
| 2017 – 2020 | 11.0 | −13.2 | −11.3 | −14.1 | 3.9 | −21.9 | −21.1 | −19.6 |
| | (0.0) | (1.6) | (3.7) | (2.4) | (39.6) | (0.1) | (0.2) | (1.2) |
| 2017 – 2021 | 14.0 | −14.6 | −13.5 | −17.9 | 8.1 | −10.4 | −11.6 | −6.4 |
| | (0.0) | (1.1) | (2.0) | (0.9) | (11.5) | (14.5) | (11.8) | (46.2) |
| 2017 – 2022 | 14.2 | −17.7 | −15.7 | −20.8 | 10.4 | −19.7 | −18.4 | −16.5 |
| | (0.1) | (0.3) | (0.9) | (0.4) | (3.2) | (0.9) | (1.7) | (7.2) |
| 2017 – 2023 | 17.1 | −13.2 | −12.6 | −16.7 | 10.9 | −23.8 | −22.9 | −24.6 |
| | (0.0) | (4.3) | (5.3) | (3.9) | (6.4) | (0.3) | (0.5) | (1.5) |

Notes: The estimates are in percent, multiplied by 100. Entries in parentheses are $p$-values, multiplied by 100, using standard errors clustered at the establishment level.

Table A.13: Minimum Wage Effects, Cross Section of Twin Cities Establishments

| | Minneapolis | | | | Saint Paul | | | |
|---|---|---|---|---|---|---|---|---|
| Add Size FE | Wage | Jobs | Hours | Earnings | Wage | Jobs | Hours | Earnings |
| 2017 – 2018 | 6.3 | −4.8 | −4.1 | −1.7 | 1.0 | −17.7 | −17.9 | −10.8 |
| | (0.2) | (23.9) | (34.4) | (71.8) | (68.9) | (0.1) | (0.2) | (8.0) |
| 2017 – 2019 | 7.5 | −3.2 | −3.3 | −0.9 | 5.3 | −19.0 | −19.9 | −13.9 |
| | (0.7) | (54.5) | (54.3) | (87.8) | (16.7) | (0.4) | (0.3) | (6.4) |
| 2017 – 2020 | 11.5 | −13.0 | −12.0 | −13.8 | 3.4 | −23.1 | −22.0 | −21.1 |
| | (0.0) | (1.8) | (2.9) | (3.0) | (45.0) | (0.1) | (0.1) | (0.8) |
| 2017 – 2021 | 14.6 | −15.5 | −15.1 | −18.1 | 7.3 | −12.4 | −12.6 | −8.4 |
| | (0.0) | (0.7) | (0.9) | (0.8) | (14.6) | (8.3) | (9.1) | (33.5) |
| 2017 – 2022 | 14.8 | −19.9 | −18.4 | −22.3 | 9.1 | −23.2 | −20.4 | −20.1 |
| | (0.0) | (0.1) | (0.2) | (0.2) | (6.0) | (0.2) | (0.8) | (3.1) |
| 2017 – 2023 | 19.1 | −16.5 | −16.4 | −19.0 | 10.4 | −28.5 | −26.6 | −28.1 |
| | (0.0) | (1.6) | (1.6) | (2.5) | (8.4) | (0.1) | (0.2) | (0.8) |

Notes: The estimates are in percent, multiplied by 100. Entries in parentheses are $p$-values, multiplied by 100, using standard errors clustered at the establishment level.

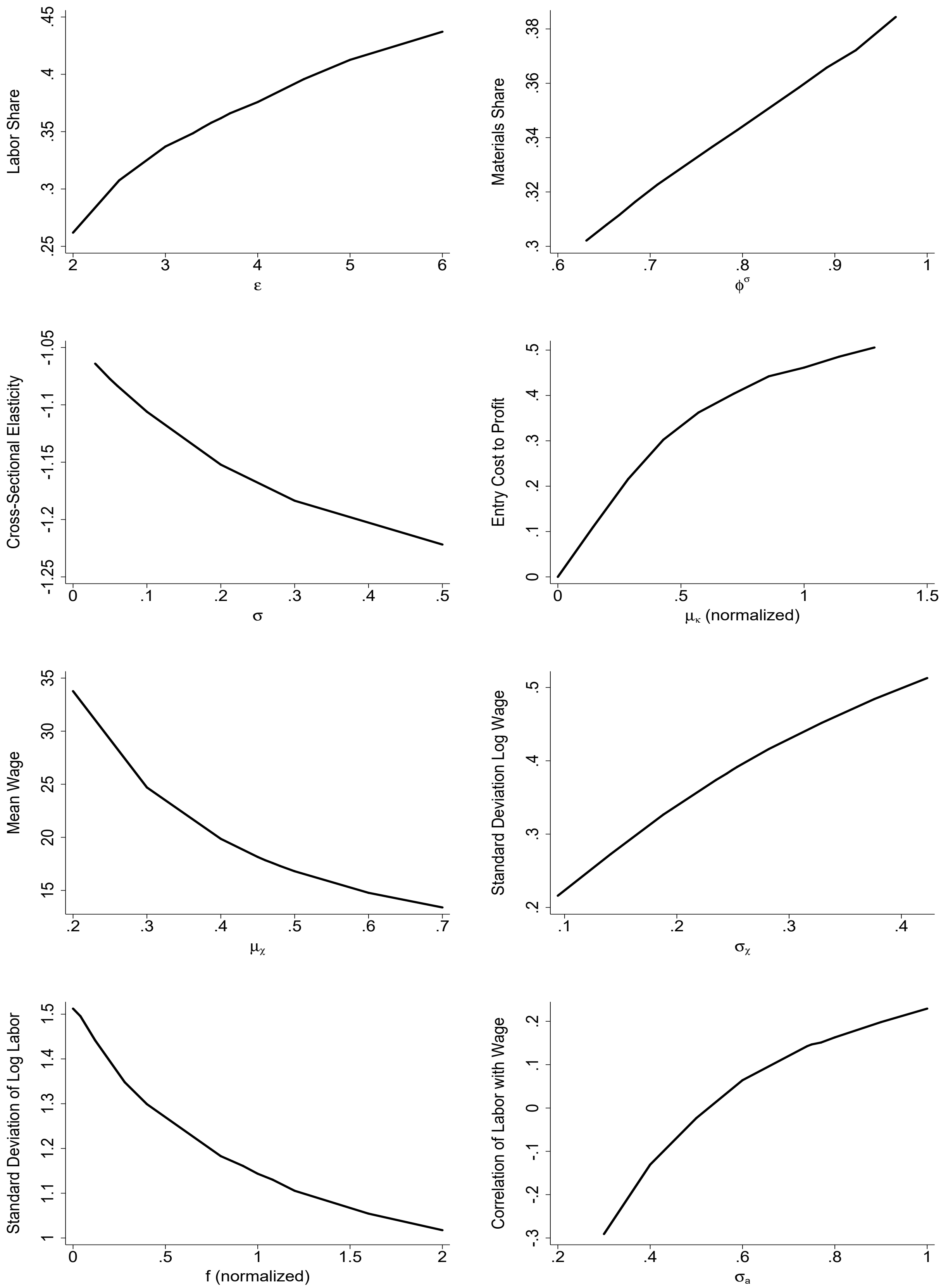
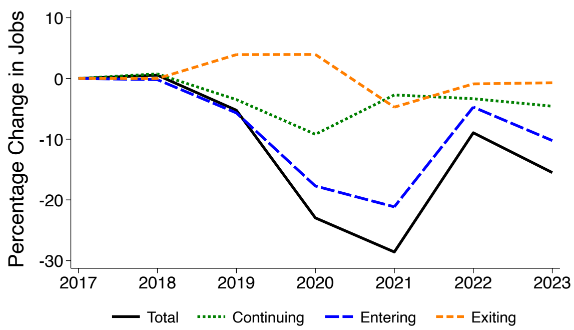
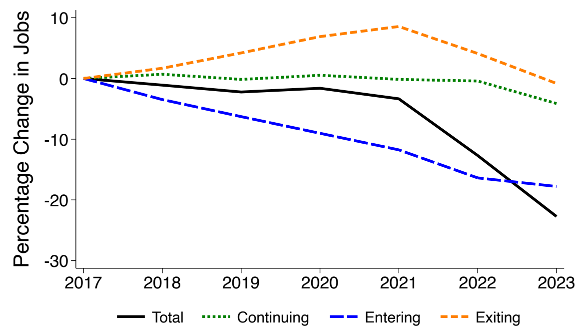


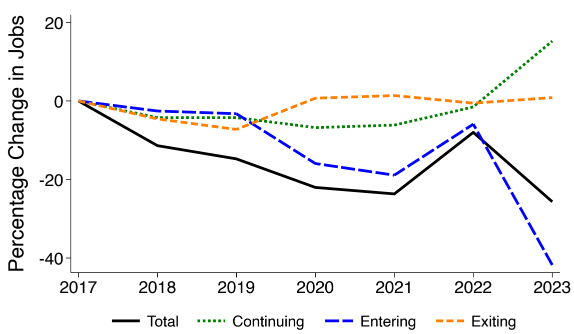

Figure A.28: Local Identification of Parameters



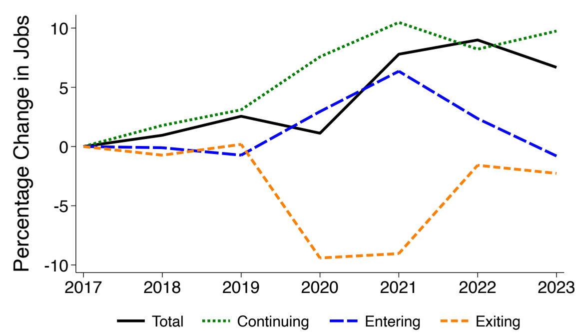

(a) Retail, MPLS




(b) Health, MPLS




(c) Retail, SP




(d) Health, SP

Figure A.29: Decomposition of Job Losses in Retail and Health

Notes: The figure presents the decomposition of changes in the net job creation rate ("Total") into changes from continuing establishments, changes from entering establishments, and changes from exiting establishments.

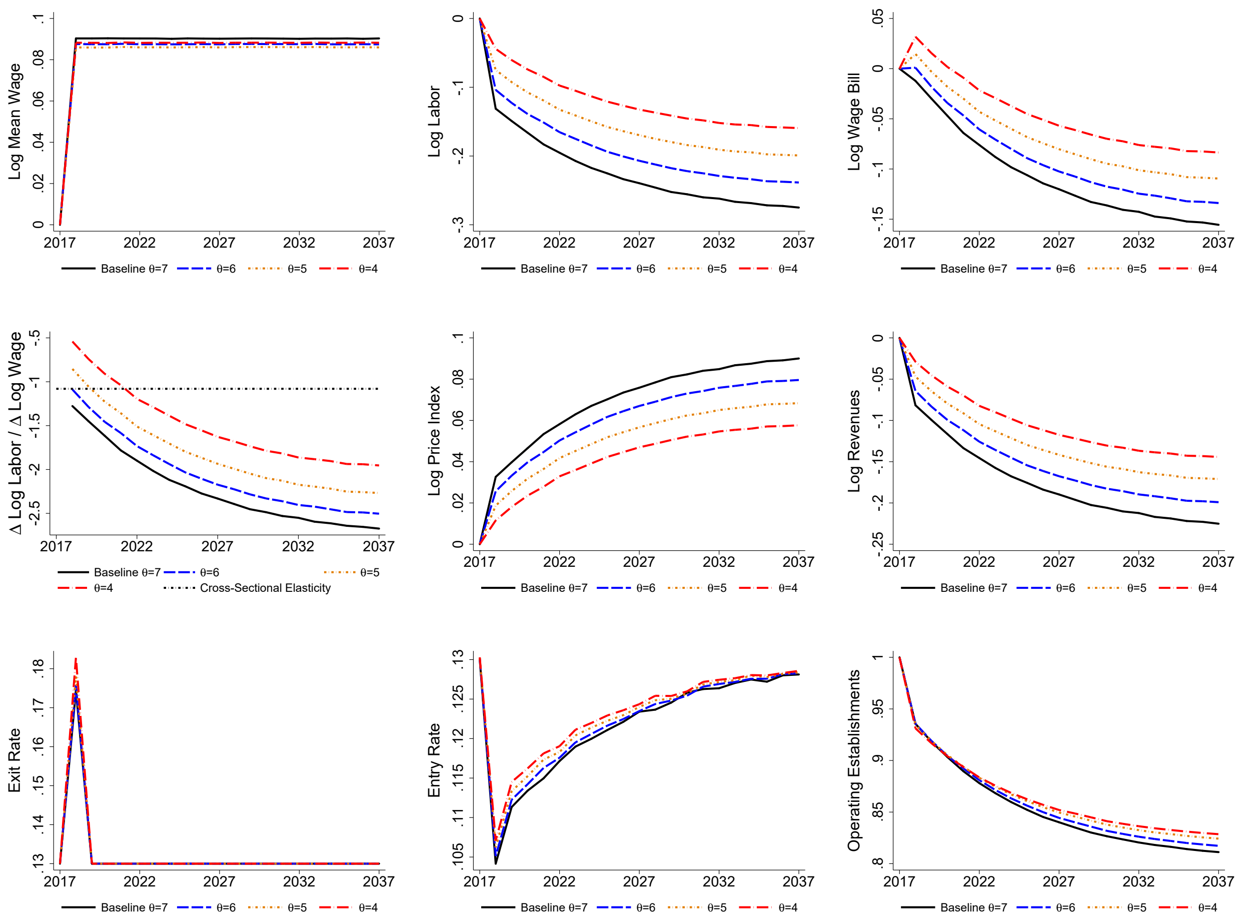



Figure A.30: Model Responses to an Unexpected Increase in the Minimum Wage

Notes: The figure shows the transitional dynamics of the model economy in response to an unexpected and permanent change in the minimum wage in 2018 from 9 to 15 dollars. The different lines correspond to different parameterizations for $\theta$.