

Employment Dynamics of \$15 Minimum Wage Phase-ins: Evidence from New Jersey

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Abstract

In 2019, New Jersey enacted legislation to phase in a \$15 minimum wage, rapidly boosting the state minimum by 71 percent in under five years. I provide one of the first empirical analyses of a wage increase of this nature and introduce a novel empirical design that combines synthetic control with a wage-distribution binning approach. I examine the employment dynamics resulting from five wage increases taking effect between July 2019 and January 2023. Each increase generates missing jobs below the new wage floor and excess jobs above it, with excess jobs dominating and producing temporary boosts in employment. Overall, I find no evidence of a sustained increase or decrease in employment from the phase-in. These findings inform debates on whether gradual phase-ins mitigate concerns about disemployment from large minimum wage hikes.

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1 Introduction

The minimum wage debate has divided policy makers and economists for much of the past 100 years. In theory, wages should be set by market forces such that the supply of labor is perfectly matched by demand from firms. Although this is a simplified model made under many assumptions, it does give some intuition into what we expect in the real world. This is the neoclassical argument: wages are determined by workers productivity, and any implementation or increase of a wage floor will lead to unemployment among low-wage workers (Stigler, 1946). A minimum wage above the going wage will create an excess supply of labor where more workers will be seeking work at the higher wage, but firms will be looking to hire fewer workers for the same reason. Proponents of the minimum wage argue that firms have more bargaining power and tend to take advantage of workers by offering low wages. They believe a minimum wage is necessary to protect workers, induce more people to seek work, and increase the purchasing power of workers.

In 1938, Congress passed the Fair Labor Standards Act and established a federal minimum wage of \$0.25/hour. The government increased the minimum wage sporadically over the following decades, with the most recent increase occurring in 2009 when Congress raised the federal minimum wage to \$7.25. In addition, many states have decided to increase their own state minimum wages in recent years. With the “Fight for \$15” movement as a backdrop, California, New York, New Jersey, Massachusetts, Illinois, Maryland, Connecticut, Florida, and Virginia have all enacted legislation to gradually increase their minimum wages. The Raise the Wage Act of 2021 (HR 603), introduced in the House of Representatives, would have raised the federal minimum wage from \$7.25 to \$15 by 2025 if enacted. Understanding the potential impacts of a \$15 minimum wage is more important now than ever (Decker, 2021).

I aim to inform this policy debate by exploiting New Jersey’s \$15 minimum wage phase-in to estimate the causal impact of minimum wage increases on employment. The state minimum wage was raised six times between July 2019 and January 2024, increasing from \$8.85 to \$15.13. This policy intervention differs notably from previous minimum wage increases, which historically have been small, incrementalist, and uncoordinated in nature. In contrast, New Jersey’s minimum wage phase-in was rolled out on a pre-determined schedule over a longer time period with substantial notice to employers.

Due to the timing of my study, I examine the first five of these wage increases. To evaluate the employment effects, I implement a synthetic control framework to estimate employment changes local to the minimum wage. I estimate the number of “missing” jobs below the new minimum wage and compare to the number of “excess” jobs at and above the new minimum wage by breaking down the distribution of hourly wages

into wage bins (see Table 2) and estimating employment changes within each bin. This approach (developed in Cengiz et al. (2019)) leverages the idea that, in response to a minimum wage hike, firms will increase wages of affected workers to be in compliance with the new law. As a result, a bunching of jobs will emerge at and just above the new minimum wage. This bunching represents the excess jobs. On the other hand, all jobs earning below the minimum wage are expected to be destroyed. This represents the missing jobs, or the “bite” of the policy. Therefore, the total change in employment can be inferred by comparing the magnitude of missing and excess jobs local to the minimum wage. If missing jobs outnumber excess jobs, then this would imply an overall reduction in employment (and vice versa). If they match each other, then there would be no change in employment.

My strategy of decomposing the employment changes by wage bins as done by Cengiz et al. (2019) has four main advantages. First, this decomposed approach allows for estimating employment changes throughout the entire distribution of wages instead of focusing on specific sectors or demographic groups. Second, I can observe employment changes local to the minimum wage. This is especially important because most of the employment changes are expected to occur around the minimum wage. Third, filtering off employment changes in the upper tail of the distribution from those around the minimum wage helps improve the precision of my estimates. Any changes to the upper tail of the distribution are unlikely to have been caused by the minimum wage policy, so it is important to separate them out to get a more accurate estimate. In addition, the upper tail estimates provide a falsification test for the model. Finally, estimating employment changes by wage bins allows for pinpointing spillover effects resulting from the minimum wage increase.

With hourly wage data from the 2014-2023 Current Population Survey, I estimate employment changes by wage bins resulting from the phase-in of a \$15 minimum wage in New Jersey. Using a synthetic control to create a plausible counterfactual wage distribution, I find the emergence of both missing and excess jobs which coincide with each minimum wage increase. However, missing and excess jobs do not persist and generally return back to zero prior to the next wage increase. Additionally, I find that excess jobs outnumber missing jobs, causing temporary boosts in employment as a result of each wage increase. By the end of my period of study, I find no change in total employment relative to the synthetic counterfactual.

Literature and Contribution

My paper’s main contribution is to offer a policy-relevant, case study analysis of the employment effects of New Jersey’s \$15 minimum wage phase-in. To the best of my knowledge, no prior research has been done to evaluate this policy intervention. Although the literature on the employment effects of minimum wage

increases is extensive, I aim to contribute by examining the employment dynamics resulting from a staggered phase-in of a \$15 minimum wage, a policy setting which differs substantially from canonical papers which examined small, standalone increases. Large minimum wage phase-ins have become common policy tools over the past ten years, yet they are largely absent in the literature. To my knowledge, only two studies have examined this type of policy intervention. [Jardim et al. \(2022\)](#) study Seattle’s two-period phase-in of a \$13 minimum wage, and [Wiltshire et al. \(2025\)](#) study California and New York’s run-ups to \$15. In addition to examining a new policy setting, I provide a novel combination of two well-established methodologies: synthetic control and wage-distribution binning.¹ I believe my study is especially policy-relevant and of general interest given that many states have implemented similar minimum wage phase-ins and the federal government has recently considered a \$15 minimum wage phase-in. My findings provide valuable insights to policy makers in New Jersey in addition to informing policy makers both at the state and federal level as future minimum wage changes are considered.

My research contributes to the extensive and controversial literature on employment effects of minimum wages. In the early 1990s, the “new minimum wage research” marked a significant shift in the research landscape surrounding minimum wages. Distinct from the existing literature (summarized in [Brown et al. \(1982\)](#)), these studies utilized state-specific data and revealed nuanced insights into the impacts of minimum wage changes on employment. However, they failed to reach a consensus. [Neumark and Wascher \(1992\)](#) found disemployment effects similar to the existing literature, [Card \(1992\)](#) found no effect, while [Katz and Krueger \(1992\)](#) and [Card and Krueger \(1994\)](#) found positive employment effects.

Most studies in the literature have focused on specific demographic groups ([Card, 1992](#); [Neumark and Wascher, 1992](#); [Allegretto et al., 2011](#); [Sabia et al., 2012](#)) or workers in certain sectors ([Katz and Krueger, 1992](#); [Card and Krueger, 1994](#); [Dube et al., 2010](#); [Wiltshire et al., 2025](#)), raising questions about external validity. To address this concern, I estimate employment effects on the entire frequency distribution of wages to find the impact on overall employment. [Meer and West \(2016\)](#) and [Jardim et al. \(2022\)](#) also examine aggregate employment, finding negative effects of minimum wage increases. My approach is most closely related to [Cengiz et al. \(2019\)](#) who estimate employment changes by bin for the entire frequency distribution of wages and find no change in low-wage employment. [Cengiz et al. \(2022\)](#) find no effect of minimum wage increases on employment, the unemployment rate, labor force participation rate, or labor market transitions using modern machine learning techniques to predict which workers are most likely to be affected by the minimum wage.

¹In concurrent and independent work, [Wiltshire et al. \(2025\)](#) use a similar method as an appendix exercise.

My research contributes to the literature on bunching to observe the effects of public policy interventions (Kleven, 2016). Previous studies have created a counterfactual distribution by leveraging cross-sectional variation (Saez, 2010; Chetty et al., 2013), by fitting a polynomial on the empirical distribution excluding data near the kink (Chetty et al., 2011) or by using the distribution prior to the minimum wage increase (Harasztosi and Lindner, 2019). In contrast, I use a synthetic control to create a counterfactual wage distribution, a strategy which most closely resembles Cengiz et al. (2019)’s approach. In this paper, I observe the bunching of jobs at and just above the new minimum wage to reveal the behavioral responses of firms and workers.

My research contributes to the literature on policy evaluation, comparative case studies, and synthetic controls. Difference-in-differences (DID) has been one of the most important methodological tools for empirical research since the 1990s (Card, 1990; Card and Krueger, 1994; Bertrand et al., 2004). However, the development of the synthetic control method (SCM) (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2015; Abadie, 2021) provided an improvement to the difference-in-differences framework, and synthetic control has been considered “arguably the most important innovation in the policy evaluation literature in the past 15 years” (Athey and Imbens, 2017). The motivation behind synthetic control stems from the concern that the parallel trends assumption in difference-in-differences studies may not always hold. Synthetic control solves this concern by using pre-treatment outcome data to create a weighted combination of control units that most closely resembles the treated units, thus reducing discretion when selecting control units by providing a data-driven approach. This method is quite useful in policy evaluation when policies are enacted on aggregate entities (such as cities, states, or countries) and there are one or few treated units. Sabia et al. (2012); Neumark et al. (2014); Dube and Zipperer (2015); Reich et al. (2017); Allegretto et al. (2017); Jardim et al. (2022); Powell (2022); Wiltshire et al. (2025) have applied synthetic controls to minimum wage questions. My use of a synthetic control is unique to previous applications in the minimum wage literature because I combine synthetic control with wage-distribution binning to create a counterfactual distribution of wages.

The standard implementation of synthetic control is specific to only one outcome. There is not much practical guidance for using synthetic controls when dealing with multiple outcome variables, and the default in the literature has been to estimate a different set of weights for each outcome variable (Jardim et al., 2022). This would imply that I may have a potentially different combination of control states for each bin. This is not an ideal strategy given that my goal is to estimate a counterfactual wage distribution composed of 27 wage bins, meaning I want to balance across all 27 outcome variables at once. Trejo et al. (2024) fit a single set of weights that simultaneously balances across all four of their outcome variables after subtracting each treated and control unit’s pre-treatment outcome mean from all pre- and post-treatment observations.

Tian et al. (2023) extend the synthetic control method to a multiple-outcome framework, and Sun et al. (2023) suggest balancing either a vector of all outcomes or an index or average of them. I follow Trejo et al. (2024) and estimate a single set of weights to create a counterfactual wage distribution for New Jersey that simultaneously balances across employment in all 27 wage bins. I believe this strategy provides the most realistic counterfactual.

The paper is structured as follows. Section 2 describes New Jersey’s minimum wage laws. Section 3 reviews the data and sample construction. Section 4 describes the theoretical framework and empirical implementation. Section 5 presents the results of the synthetic control employment, with robustness checks in Section 6. Section 7 concludes.

2 New Jersey’s \$15 Minimum Wage Phase-In

Table 1: New Jersey \$15.00 Minimum Wage Phase-in Schedule

Effective Date	Most Employers	Seasonal and Small Employers	Agricultural Employers	Cash Wage for Tipped Employees	Tipped Employee Credit
Jan 1, 2019	\$8.85	\$8.85	\$8.85	\$2.13	\$6.72
Jul 1, 2019	\$10.00	\$8.85	\$8.85	\$2.63	\$7.37
Jan 1, 2020	\$11.00	\$10.30	\$10.30	\$3.13	\$7.87
Jan 1, 2021	\$12.00	\$11.10	\$10.30	\$4.13	\$7.87
Jan 1, 2022	\$13.00	\$11.90	\$11.05	\$5.13	\$7.87
Jan 1, 2023	\$14.13	\$12.93	\$12.01	\$5.26	\$8.87
Jan 1, 2024	\$15.13	\$13.73	\$12.81	\$5.26	\$9.87
Jan 1, 2025	\$15.49	\$14.53	\$13.40	\$5.62	TBD
Jan 1, 2026	TBD	\$15.00	\$14.20	TBD	TBD
Jan 1, 2027	TBD	TBD	\$15.00	TBD	TBD

Note: Tipped credit is the difference between cash wage and minimum wage. Total hourly earnings for tipped employees must be at least equal to the minimum wage.

Source: New Jersey Department of Labor and Workforce Development

On February 4, 2019, Governor Phil Murphy signed legislation to gradually increase New Jersey’s minimum wage to at least \$15.00 per hour by 2024. On July 1, 2019, the minimum wage increased from \$8.85 to \$10.00 and increased by at least an additional \$1.00 (or more depending on the CPI) on January 1st of every year until it reached \$15.13 in 2024. Although no more wage increases are scheduled, the minimum wage will continue to increase depending on the CPI. Seasonal employers, small employers, and employers of farm laborers were given more time to adjust to the wage increases. In addition, minimum wage increases for tipped workers followed a different schedule. Table 1 reports past and planned wage changes.

3 Data and Sample Construction

I access data from the individual-level NBER Merged Outgoing Rotation Group (ORG) of the Current Population Survey (CPS) to calculate monthly distributions of hourly earnings for each state from January 2014 through September 2023. The CPS is a survey of between 50,000 - 60,000 U.S. households conducted on a monthly basis by the U.S. Census Bureau and Bureau of Labor Statistics. Households are followed for four months, then drop from the sample for eight months, after which they return for four months. The outgoing rotation group, also known as the earner study, consists of households in the months before they rotate out, so those in month four and eight of being in the sample.² These households are asked additional questions regarding their earnings and hours worked. My data is taken from the Integrated Public Use Microdata Series (IPUMS), a database of census data with similarly coded variables from across different surveys to allow for easier cross-year analysis.

I calculate hourly wages based on available data. For hourly workers, I simply use their reported hourly wage. For all other workers, I calculate their hourly earnings by dividing their usual weekly earnings by usual weekly hours worked. I cannot calculate usable wages for about 2.1% of the sample, so I drop these individuals. Dropped individuals include hourly workers that do not report an hourly wage (unless they also report weekly earnings and hours worked) and non-hourly workers that either do not report weekly earnings, do not report usual weekly hours worked, or report “hours vary”.

I assign each individual to a wage bin based on their hourly wage and then collapse the data by bin into monthly, state-level employment counts using the person-level ORG sampling weights. Wage bins are constructed relative to the 2024 minimum wage of \$15.13. For example, bin 0 captures all observations with hourly earnings between \$15.13 and \$16.12. Wage bin -1 captures all observations between \$13.13 and \$14.12, and so on. I combine all bins above bin 16 into bin 16 and all bins below bin -10 into bin -10. Table 2 details the breakdown of the hourly wage distribution by bin.

I divide these weighted employment counts by the state’s population aged 16 and over to calculate employment per capita in each bin. This gives the percentage of the population aged 16 and over employed in each bin.

Given that the CPS only interviews a subset of workers each month, my dataset suffers from sampling bias changing compositions due to rotating samples. In particular, I observe that the monthly employment counts

²For example, a household entering the sample in January will be followed from January to April, then from January to April of the following year. In April of both years, this household would enter the outgoing rotation group.

by bin are quite noisy. I smooth the data by taking a five month moving average.

My resulting data set contains an observation for each bin, state, and month from January 2014 through September 2023. As a result, I am able to track employment per capita in each bin/state combination for a period of just under ten years (117 months).

In addition, I gather monthly total employment data from the 2014 - 2023 Quarterly Census of Employment and Wages (QCEW) to calculate monthly employment-to-population ratios by state. The QCEW is a near universe of workers, so using these total employment counts are more reliable than the implied total employment counts from the CPS.

4 Methodology

4.1 Theoretical Framework

The conceptual goal of this paper is to assess the change in employment that results from a given increase in the minimum wage by focusing on the lower part of the wage distribution local to the minimum wage. I focus on the particular case study of New Jersey's \$15 minimum wage phase-in. The introduction (or increase) of a binding minimum wage will cause all jobs below it to be destroyed. In reality, the data will still show some jobs below the minimum wage because of imperfect compliance and misreporting of wages/earnings. The number of missing jobs below the minimum wage reflects the "bite" of the policy. However, not all of these missing jobs are destroyed. Firms may respond to the minimum wage policy by simply bumping up its workers' wages to be in compliance with the new minimum. Firms may even adjust workers' wages that were already above the minimum to preserve the wage hierarchy within the firm. If firms react in this way, we expect to see a "bunching" of jobs earning at and just above the new minimum wage. The degree to which firms respond in this way will determine the overall effect on employment resulting from the minimum wage policy. As a result, I can estimate the total employment effect by comparing the magnitude of missing jobs to that of excess jobs. This is done by comparing the observed distribution of earnings in New Jersey to a counterfactual distribution.

4.2 Empirical Implementation

To achieve this goal, I calculate the number of missing jobs below the new minimum wage and compare to the number of "new" jobs above the new minimum wage. This nets out the overall change in employment resulting from the wage increases. To calculate these employment changes, I estimate the employment effect

Table 2: Wage Bins and Dates of Treatment

Wage Bin	Dollar Range	Date of Treatment
-10	\$0.01 - \$5.99	-
-9	\$6.00 - \$6.99	-
-8	\$7.00 - \$7.99	-
-7	\$8.00 - \$8.84	-
-6	\$8.85 - \$9.99	Jul 1, 2019
-5	\$10.00 - \$10.99	Jan 1, 2020
-4	\$11.00 - \$11.99	Jan 1, 2021
-3	\$12.00 - \$12.99	Jan 1, 2022
-2	\$13.00 - \$14.12	Jan 1, 2023
-1	\$14.13 - \$15.12	Jan 1, 2024
0	\$15.13 - \$16.12	TBD
1	\$16.13 - \$17.12	TBD
2	\$17.13 - \$18.12	TBD
3	\$18.13 - \$19.12	TBD
4	\$19.13 - \$20.12	TBD
5	\$20.13 - \$21.12	TBD
6	\$21.13 - \$22.12	TBD
7	\$22.13 - \$23.12	TBD
8	\$23.13 - \$24.12	TBD
9	\$24.13 - \$25.12	TBD
10	\$25.13 - \$26.12	TBD
11	\$26.13 - \$27.12	TBD
12	\$27.13 - \$28.12	TBD
13	\$28.13 - \$29.12	TBD
14	\$29.13 - \$30.12	TBD
15	\$30.13 - \$31.12	TBD
16	\$31.13 and up	TBD

Note: Wage bins are constructed relative to the 2024 minimum wage of \$15.13 at bin 0. Date of treatment indicates when the minimum wage moved above each wage bin. Bins in gray are considered “treated” bins, which include all bins affected by the minimum wage and bins that could be affected by spillovers.

in each wage bin to see how the new policy affects workers along the entire distribution.

Calculating employment changes requires estimating a counterfactual wage distribution with which to compare. I take advantage of state-level variation in minimum wages and use a synthetic control to create a counterfactual distribution of earnings in New Jersey. The synthetic New Jersey is constructed by finding a weighted combination of states which did not increase their minimum wages during the period of study (the donor pool of control states includes 20 states, see Figure 1). Specifically, I find one set of weights by balancing across employment per capita in all 27 wage bins simultaneously. Since my goal is to create a counterfactual distribution of wages, I believe finding a single set of weights that takes into account employment across all wage bins to be a more realistic counterfactual than estimating a separate set of weights for each wage bin. In other words, I find a single set of concatenated weights which minimize the imbalance in the concatenated pre-treatment series for employment in all bins (Sun et al., 2023; Trejo et al., 2024). Weights are found using the augsynth package in R.

I fit the synthetic control using data from January 2014 through January 2019. The \$15 phase-in legislation was signed into law in February 2019, so I exclude February 2019 through June 2019 when creating the counterfactual to avoid any potential bias from anticipation effects.

After calculating the optimal set of weights, I can create a counterfactual for each wage bin. As a result, I am able to visualize trends in employment per capita in New Jersey and the synthetic New Jersey for each bin. For each period t corresponding to a month, I estimate the following equation for each bin k :

$$ATT_{kt} = (Y_{kt}^{\text{NJ}} - Y_{kt}^{\text{Syn}}) - (\bar{Y}_{k,\text{baseline}}^{\text{NJ}} - \bar{Y}_{k,\text{baseline}}^{\text{Syn}}) \quad (1)$$

Here, Y_{kt}^{NJ} and Y_{kt}^{Syn} represent employment per capita in month t and bin k for New Jersey and synthetic New Jersey. $\bar{Y}_{k,\text{baseline}}^{\text{NJ}}$ and $\bar{Y}_{k,\text{baseline}}^{\text{Syn}}$ are the pre-treatment means of employment per capita in bin k in New Jersey and synthetic New Jersey. Y_{kt}^{Syn} and $\bar{Y}_{k,\text{baseline}}^{\text{Syn}}$ are found as follows:

$$Y_{kt}^{\text{Syn}} = \sum_{i=2}^N w_i Y_{ikt} \quad (2)$$

$$\bar{Y}_{k,\text{baseline}}^{\text{Syn}} = \sum_{i=2}^N w_i \bar{Y}_{ik} \quad (3)$$

where w_i is the synthetic control weight for state i , with New Jersey having $i = 1$, and $\bar{Y}_{ik}$ is the pre-treatment mean of employment per capita in state i in bin k .

I can then track how employment per capita changes in each bin over time as each wage increase takes effect. After estimating the employment effect on each bin in each month post treatment as described above, I can find the estimated missing jobs below the new minimum wage and the estimated excess jobs above the new minimum wage. Following [Cengiz et al. \(2019\)](#), for each month post treatment, I define the missing jobs (Δb) below the minimum wage and excess jobs (Δa) above the minimum wage as follows:

$$\Delta b_t = \left(\sum_{k \in \text{bins below}} ATT_{kt} \right) / \overline{EPOP}_{NJ} \quad (4)$$

$$\Delta a_t = \left(\sum_{k \in \text{bins above}} ATT_{kt} \right) / \overline{EPOP}_{NJ} \quad (5)$$

ATT_{kt} is the estimated employment effect in bin k in month t calculated in equation (1). I consider the set of “treated bins” as all bins which are affected by the minimum wage in my period of study plus bins that could be affected by spillovers (four bins above). This results in the set of treated bins being bins -7 through 2 (see Table 2). I calculate the missing jobs (Δb) as the sum of the ATT s for treated bins below the minimum wage and excess jobs (Δa) as the sum of the ATT s for treated bins at and above the minimum wage. For the first wage increase in July 2019, bins -7 and -6 are considered missing jobs and bins -5 through 2 are considered excess jobs. With each new wage increase, one bin moves from excess to missing jobs. $\overline{EPOP}_{NJ}$ indicates the sample average employment-to-population ratio in New Jersey over the twelve months prior to treatment (July 2018 - June 2019). This normalizes the missing and excess jobs by the pretreatment total employment.

Given this construction, the estimated percentage change in total employment (Δe) as a result of the minimum wage increases is revealed by:

$$\Delta e_t = \Delta a_t + \Delta b_t \quad (6)$$

I am able to track the dynamics of employment changes over time by calculating Δe , Δa , and Δb for each month after treatment.

5 Results

This section discusses results. First, I explore the construction of synthetic New Jersey and the strength of fit. Next, I report employment estimates by wage bin, which I use to construct estimates for missing, excess, and total change in jobs. Finally, I execute a series of permutation tests to evaluate the significance of my estimates.

5.1 New Jersey versus Synthetic New Jersey

Figure 1 shows a map of the donor pool for synthetic New Jersey, and Table 3 reports the state weights that comprise synthetic New Jersey. A combination of Pennsylvania, New Hampshire, Texas, Georgia, North Carolina, Louisiana, and Alabama best mimics New Jersey’s wage distribution (with states listed in order of importance). The remaining states have negligible or zero weight. It is notable to see that Pennsylvania is the state with the largest weight, comprising just about one-third of synthetic New Jersey. This finding provides some credence to [Card and Krueger \(1994\)](#)’s use of Pennsylvania as the sole control state for New Jersey. However, my weights suggest that just using Pennsylvania is not the best choice.

Another observation is that weight importance is loosely correlated with geographic proximity. Pennsylvania and New Hampshire, the two closest states to New Jersey in the donor pool, account for just under two-thirds of synthetic New Jersey, with the next closest state, North Carolina, contributing another 10%. However, the remaining contributions don’t necessarily come from the next closest states. Texas, Georgia, Louisiana, and Alabama all have positive weights despite there being other candidate states, such as Kentucky, Tennessee, and South Carolina, that are closer to New Jersey. Also of note, the six furthest states from New Jersey (Idaho, Utah, Wyoming, North Dakota, Kansas, and Oklahoma) are all given zero weight. Clearly, geographic proximity is correlated with weight importance, but it’s not the sole determinant.

My findings help inform the minimum wage literature regarding the construction of a valid counterfactual. A common strategy has been to use nearby states ([Card and Krueger, 1994](#); [Allegretto et al., 2011](#)) or contiguous counties ([Dube et al., 2010](#)) as controls. [Neumark et al. \(2014\)](#) replicate [Dube et al. \(2010\)](#) and [Allegretto et al. \(2011\)](#) with synthetic controls, finding that greater weights were not placed on states in the same census division as the treated state or on contiguous cross-border counties. [Allegretto et al. \(2017\)](#) and [Dube and Zipperer \(2015\)](#) refute [Neumark et al. \(2014\)](#), finding that nearby states are in fact assigned greater weights. My findings support these results, but suggest that simply using one or more nearby controls may not provide the best counterfactual.

5.2 Employment Effects

5.2.1 Bin by Bin Results

Visually, it appears that synthetic New Jersey is able to closely track real New Jersey in every bin, which is notable considering that weights were calculated to balance across all bins and not just within each bin. Appendix Table 5 reports the mean squared prediction error (MSPE) for each bin. Bin 16 has the greatest

Figure 1: Potential Donor Pool for Synthetic New Jersey

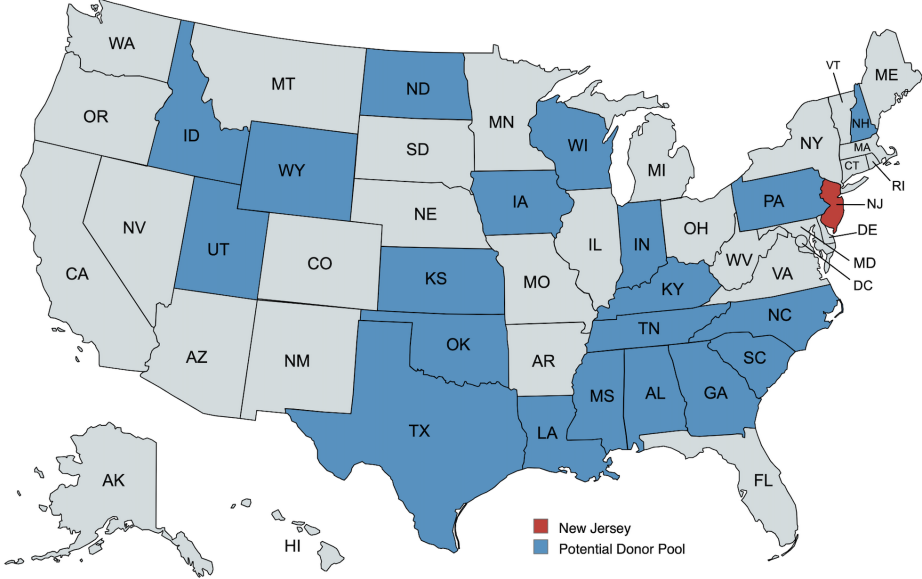


Table 3: State Weights for Synthetic New Jersey

State	Weight	State	Weight
Alabama	0.002	North Carolina	0.097
Georgia	0.119	North Dakota	0
Idaho	0	Oklahoma	0
Indiana	0	Pennsylvania	0.312
Iowa	0	South Carolina	0
Kansas	0	Tennessee	0
Kentucky	0	Texas	0.12
Louisiana	0.043	Utah	0
Mississippi	0	Wisconsin	0
New Hampshire	0.307	Wyoming	0

Note: Synthetic control does not allow extrapolation, so all weights are between $0 \leq w_i \leq 1$ and $\sum w_i = 1$

MSPE, meaning the synthetic control provides the poorest fit for this bin. New Jersey has the greatest employment per capita in this bin out of all control states, so it is not surprising that the synthetic control is unable to match on levels for this bin. As discussed in Section 6, my results are robust to excluding bin 16 when calculating weights. The ability of synthetic New Jersey to closely match New Jersey in the pre-treatment period provides strong support to my identification assumption that synthetic New Jersey serves as a realistic and accurate counterfactual for New Jersey in the absence of any wage interventions.

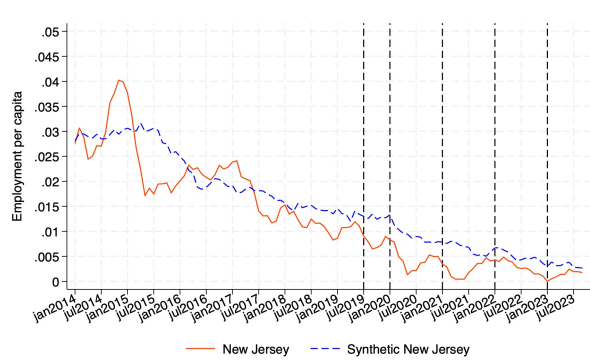
Some overall patterns and observations emerge. Reassuringly, employment in treated bins decreases immediately following treatment and does not recover to pre-treatment levels. This observation provides evidence that my research design is capturing the expected behavior. I also see evidence of bunching in bins above the new minimum wage. This observation provides evidence that employers are responding to the minimum wage increases by bumping up wages for affected workers to be in compliance with the new law, at least temporarily. The rest of this section explores employment results for particular bins to provide more detail on how I construct estimates for missing, excess, and total change in jobs.

Figure 2 displays employment estimates in bin -7, and Figure 3 displays employment estimates for bin -6. Panel A graphs employment per capita over time for New Jersey and synthetic New Jersey. Panel B shows the difference in employment per capita over time between New Jersey and synthetic New Jersey (as calculated in equation (1)). Each dotted line indicates a wage increase. Bin -6 was the first bin to be treated, and the red dotted line indicates the date at which the minimum wage moved above the bin. At the time of treatment, I observe a drop in jobs in bin -6, and employment never recovers to pre-treatment levels. This is exactly the behavior I expect to see after a bin becomes treated. In Panel B, there is a clear gap between New Jersey and synthetic New Jersey between July 2019 and January 2020, which I interpret as the causal impact of the minimum wage increase on employment in this bin. However, this difference disappears after January 2020 as a result of employment in synthetic New Jersey falling over time. Overall, the effect of the minimum wage increase on this bin seems to have been accelerating the trend of falling employment, thus causing a temporary negative employment effect that disappeared rather quickly.

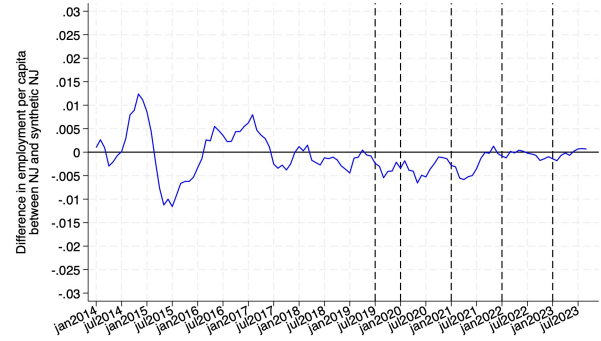
These two bins, bin -6 and -7, comprise the missing jobs for the period July 2019 through December 2019. To calculate the missing jobs estimate, I simply sum the ATTs for each month as graphed in Panels B.

Figure 4 displays employment estimates for bin -5. This bin captures all individuals earning the new minimum wage as of the first increase in July 2019. There is a clear increase in employment in this bin as can be seen visually in Panel A and relative to the synthetic control as can be seen in Panel B. This is an example of a bunching of new jobs at and just above the new minimum wage as employers bump up wages of affected

Figure 2: Employment Estimates in Bin -7 (\$8.00 - \$8.84)

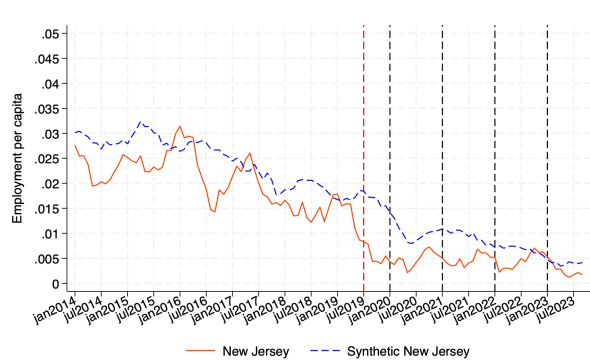


(a) Employment per capita over time

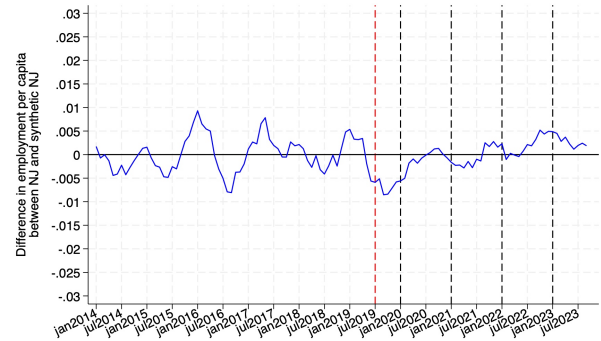


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 3: Employment Estimates in Bin -6 (\$8.85 - \$9.99)

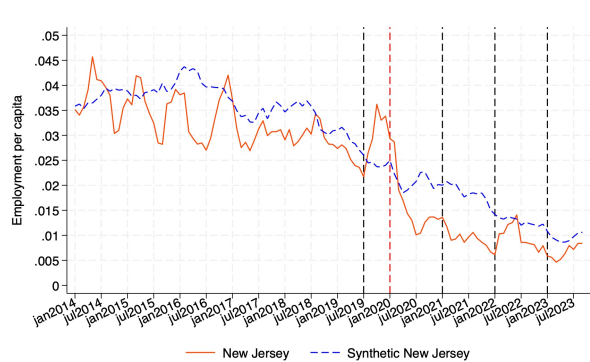


(a) Employment per capita over time

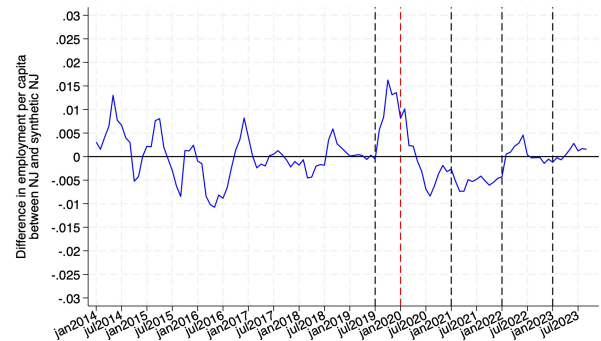


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 4: Employment Estimates in Bin -5 (\$10.00 - \$10.99)



(a) Employment per capita over time



(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

workers to be in compliance with the new law. However, this bin is treated just six months later, and I see a dramatic drop in employment as a result which does not recover to pre-treatment levels. Similar to before, employment in the counterfactual also falls over time, so there is no employment effect in bin -5 after January 2022. This implies that the minimum wage increases caused a temporary boost then a temporary decrease in employment, but no discernible longer term effects. Bin -5 is placed in excess jobs between July 2019 and December 2019, then moves to missing jobs (joining bins -6 and -7) as of January 2020 when it becomes treated.

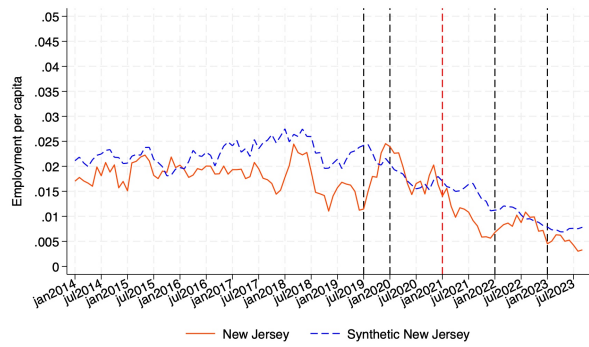
Turning to bin -4, shown in Figure 5, I observe a bunching of jobs through the first two wage increases, then a decrease in jobs when this bin becomes treated in January 2021. Interestingly, the decrease in employment is not as pronounced as the previous two bins, and I do not see strong evidence of a decrease in jobs relative to the counterfactual. As a result, the two earlier wage increases caused a temporary boost in employment in bin -4, but the third wage increase did not cause a detectable relative decrease in employment compared to the counterfactual.

Figure 6 displays results for bin -2. I want to highlight the sizeable degree of excess jobs in this bin. Four wage increases take effect before bin -2 is treated. As a result, there is clear evidence of a bunching of excess jobs building up in this bin as jobs are pushed up from previous wage increases. Additionally, I do not see evidence of a negative employment effect in bin -2 after treatment in January 2023. Panel A shows that employment in New Jersey does indeed decrease after treatment, but so does employment in the counterfactual.

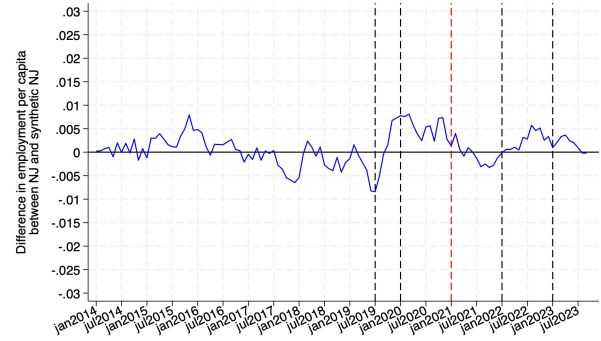
The final bin I want to highlight individually is bin -1, shown in Figure 7. Curiously, I see a large but fleeting bunching of jobs immediately following the first wage increase in July 2019. This bin includes jobs earning \$15, so it's possible that there was some confusion about the phased-in nature of the wage increase and some employers increased wages to \$15 immediately. Additionally, I observe another spike in jobs preceding the January 2023 wage increase which provides more evidence of bunching.

Appendix Figures 20 through 40 display employment results for bins not discussed in this section. I do not see strong evidence of differences in employment between New Jersey and synthetic New Jersey over time in bins outside of the -7 to 2 range. This evidence is reassuring as we would not expect to see employment changes in these bins resulting from the minimum wage changes. This provides further evidence supporting my research design and identification strategy.

Figure 5: Employment Estimates in Bin -4 (\$11.00 - \$11.99)

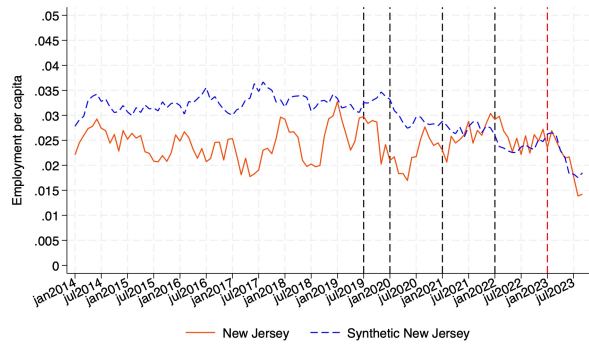


(a) Employment per capita over time

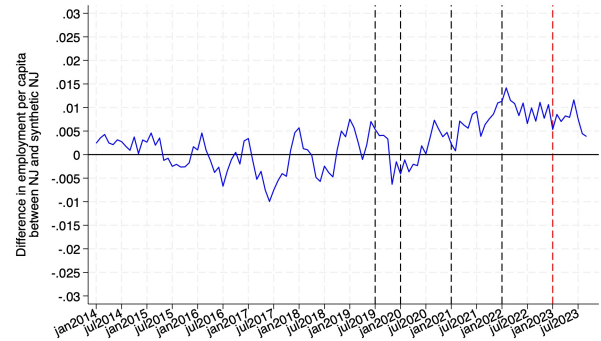


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 6: Employment Estimates in Bin -2 (\$13.00 - \$14.12)

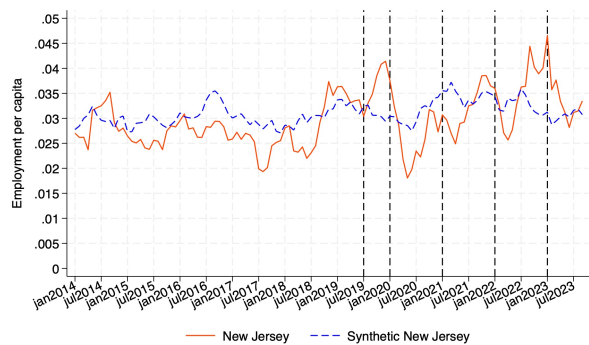


(a) Employment per capita over time

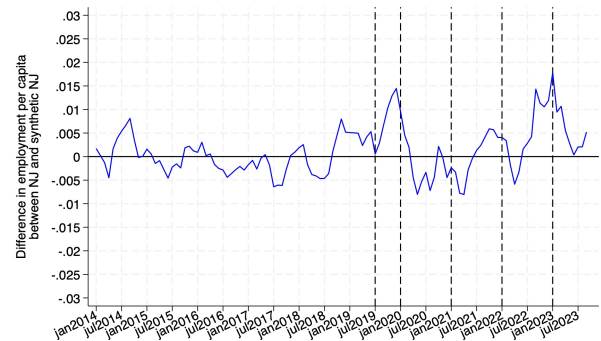


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 7: Employment Estimates in Bin -1 (\$14.13 - \$15.12)



(a) Employment per capita over time



(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

5.2.2 Missing Jobs

Figure 8 shows the magnitude of missing jobs in New Jersey over time. First, missing jobs mostly fluctuates around zero during the pre-treatment period. The pre-treatment mean of missing jobs is -1×10^{-9} which suggests a lack of pre-existing trends. However, there is a clear change in pattern in the post-treatment period. Immediately after each of the first three minimum wage increases, there is a loss of jobs in affected bins. However, this loss in jobs does not persist, and the estimated percentage change in employment in affected bins recovers back towards zero prior to the next wage increase. This trend breaks after the fourth wage increase. After this point, I do not detect any decrease in jobs in affected bins. Rather, there is some evidence of an increase in jobs relative to the counterfactual. This lack of persistence in missing jobs can be explained by the fact that employment in synthetic New Jersey falls over time in treated bins. As can be seen in Figures 3, 4, 5, and Appendix Figure 23, the minimum wage increases create an initial gap in employment between New Jersey and synthetic New Jersey in treated bins, but this gap shrinks over time as employment in the counterfactual falls relative to New Jersey. This finding suggests that the policy intervention only served to speed up employment trends that would have unfolded in the absence of treatment.

5.2.3 Excess Jobs

Figure 9 plots excess jobs in New Jersey over time. Similar to missing jobs, excess jobs mostly fluctuates around zero prior to treatment. The pre-treatment mean of excess jobs is -1.75×10^{-9} which suggests a lack of pre-existing trends. However, this pattern changes after the first wage increase. There is a clear emergence of excess jobs coinciding with each wage increase, but these excess jobs do not persist. The percentage increase in employment for bins above the minimum wage falls back towards zero prior to the next wage increase. An emergence of excess jobs following or shortly preceding an anticipated wage increase suggests that, at least at first, firms are responding by bumping up wages of affected workers to be in compliance with the new wage. However, the lack of persistence of these excess jobs means that firms are not maintaining these heightened levels of employment. This could be because firms are proceeding with layoffs after initially bumping up wages. Alternatively, firms could be pausing hiring and allowing quits to reduce employment to pre-intervention levels. These two hypotheses warrant further investigation.

5.2.4 Total Change in Employment

Figure 10 plots the total change in employment in New Jersey over time, found by taking the sum of missing and excess employment in each month as shown in Figures 8 and 9 above. The mean total change in employment in the pre-treatment period is -2.76×10^{-9} , so there is little evidence of pre-existing trends. As

Figure 8: Missing Jobs Over Time

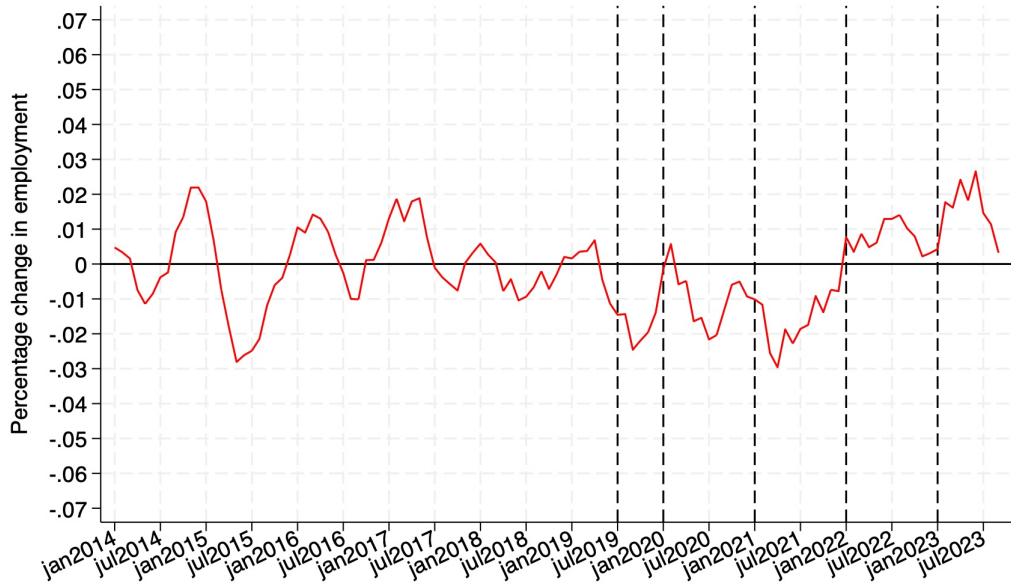
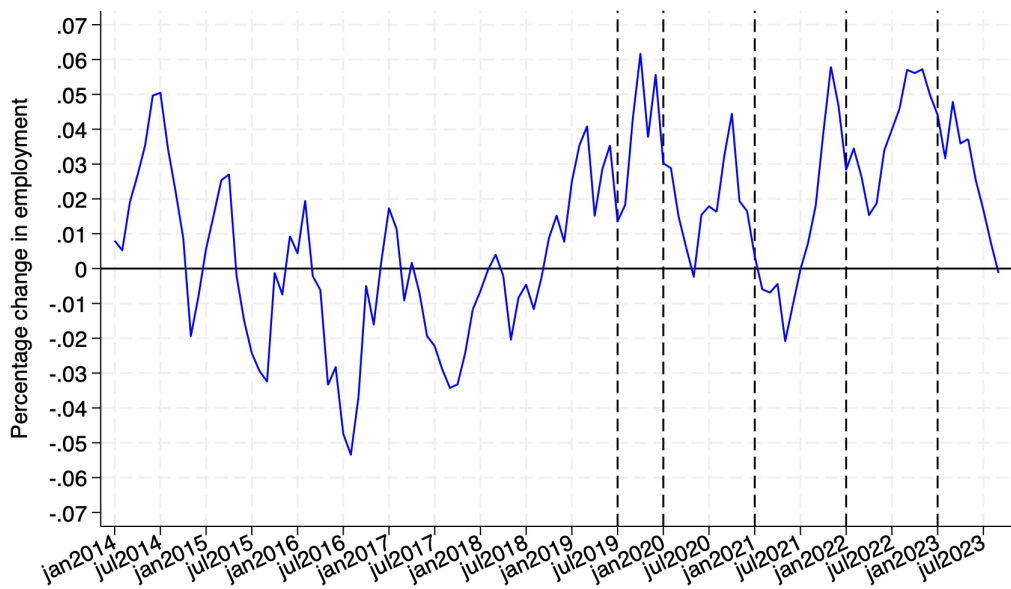


Figure 9: Excess Jobs Over Time



before, total change in jobs fluctuates around zero prior to treatment, but there is a change in pattern after treatment. I observe boosts in employment coinciding with each wage increase. However, these employment boosts do not persist. After peaking, these employment increases fall back towards zero. It is interesting to note that there is some evidence of heightened employment between August 2021 and September 2023, a time period coinciding with the post-COVID pandemic era. [Autor et al. \(2023\)](#) show that the pandemic increased the labor supply elasticity to firms in the low-wage labor market. This finding could explain why I observe much larger employment boosts in the post-pandemic era and could also explain why I find the emergence of excess jobs which outnumber missing jobs. An increase in labor supply elasticity would cause minimum wage increases to induce more workers to seek work than would otherwise be the case.

5.3 Placebo Tests and Inference

To evaluate the validity of my findings, I execute a series of “in-space” permutation tests. For each of the 20 states in the donor pool, I assign a placebo minimum wage treatment, calculate a new set of synthetic control weights using the remaining 19 donor states as the new donor pool, and re-estimate equations (1), (4), (5), and (6). Permutation tests reveal if the results observed in New Jersey are unusually different compared to the placebo results observed in control states. I can then calculate p-values by measuring the fraction of states with results as large or larger than in New Jersey ([Abadie et al., 2010](#)). In other words, these p-values report the probability of obtaining results as large or larger in New Jersey when applying the treatment at random in the data. Table 4 reports employment estimates and p-values for each quarter post-treatment. Quarterly employment estimates are found by averaging the monthly estimates.

Figure 11 shows results for the permutation placebo test for missing jobs, with New Jersey in red and donor states in gray. Here, the p-value measures the fraction of states with a greater percentage decrease in jobs in bins below the minimum wage than New Jersey ($H_0 : \Delta b \geq 0$ vs. $H_1 : \Delta b < 0$). In the two quarters following the first minimum wage increase, I see that New Jersey had the greatest magnitude of missing jobs out of all control states, yielding a p-value of < 0.05 , a test level typically used in tests of statistical significance. I can conclude that there is a statistically significant magnitude of missing jobs in this period. The only other time period in which I can detect a statistically significant magnitude of missing jobs is during 2020q3.

Figure 12 shows results for the permutation placebo test for excess jobs, with New Jersey in blue and donor states in gray. Here, the p-value measures the fraction of states with a greater percentage increase in jobs in bins above the minimum wage than New Jersey ($H_0 : \Delta a \leq 0$ vs. $H_1 : \Delta a > 0$). Immediately following the first wage increase in July 2019, I see that New Jersey had the second greatest magnitude of excess jobs and

Figure 10: Total Change in Employment Over Time

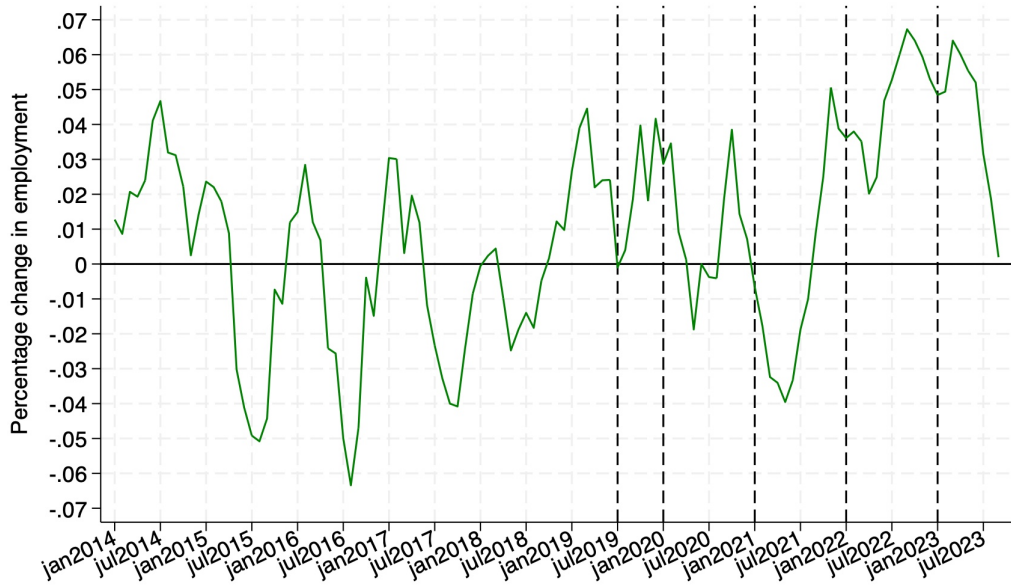


Figure 11: Permutation Test - Missing Jobs in New Jersey and Donor Pool

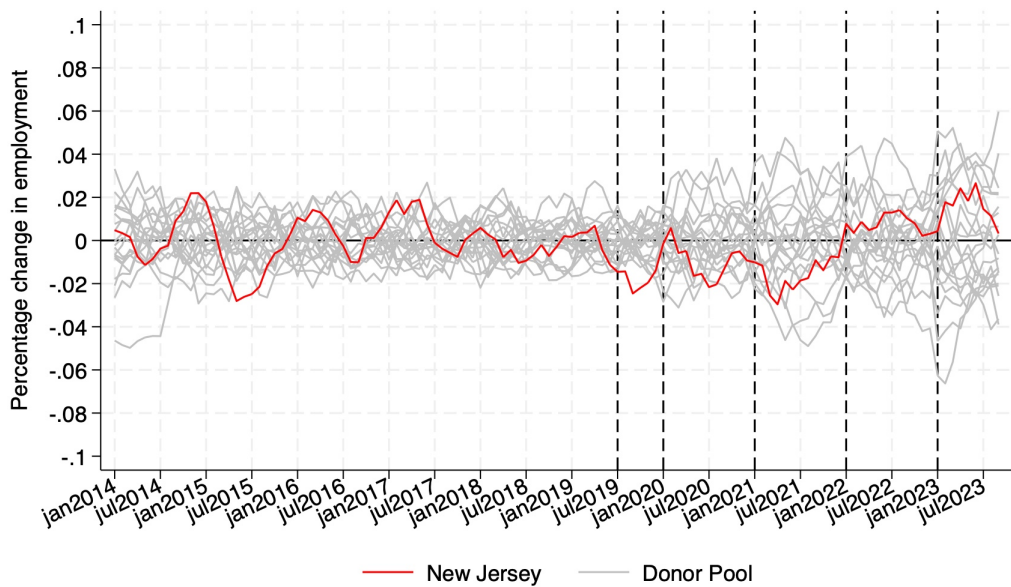


Table 4: Employment Estimates and P-Values Over Time

Year	Quarter	(1)		(2)		(3)	
		Missing Jobs		Excess Jobs		Total Change	
		Estimate	p-value	Estimate	p-value	Estimate	p-value
2019	3	-1.78%	< 0.05	2.49%	< 0.1	0.71%	0.81
	4	-1.85%	< 0.05	5.16%	< 0.05	3.31%	< 0.1
2020	1	-0.05%	0.57	2.46%	0.14	2.41%	0.28
	2	-1.22%	0.19	0.63%	0.47	-0.58%	0.9
	3	-1.83%	< 0.1	2.21%	0.23	0.37%	0.76
	4	-0.67%	0.28	2.67%	0.14	1.99%	0.28
2021	1	-1.57%	0.23	-0.30%	0.61	-1.88%	0.28
	2	-2.37%	0.14	-1.19%	0.76	-3.56%	< 0.1
	3	-1.50%	0.19	0.83%	0.38	-0.66%	0.61
	4	-0.96%	0.28	4.78%	< 0.05	3.81%	0.19
2022	1	0.66%	0.76	2.97%	0.19	3.64%	0.19
	2	0.79%	0.76	2.26%	0.19	3.06%	0.14
	3	1.24%	0.85	4.76%	< 0.05	6.00%	< 0.1
	4	0.44%	0.61	5.44%	< 0.05	5.88%	< 0.05
2023	1	1.27%	0.66	4.12%	< 0.05	5.39%	0.14
	2	2.29%	0.76	3.28%	< 0.05	5.58%	< 0.1
	3	0.97%	0.71	0.76%	0.42	1.74%	0.57

Notes: Quarterly estimates are found by averaging the three monthly estimates in a quarter. Column 1 reports p-values of the test $H_0 : \Delta b \geq 0$ vs. $H_1 : \Delta b < 0$. Column 2 reports p-values of the test $H_0 : \Delta a \leq 0$ vs. $H_1 : \Delta a > 0$. Column 3 reports p-values of the test $H_0 : \Delta e = 0$ vs. $H_1 : \Delta e \neq 0$.

greatest magnitude of excess jobs in the first and second quarter, respectively. This yields a p-value of < 0.1 in the first quarter following treatment and < 0.05 in the second quarter following treatment. Additionally, I am able to detect statistically significant magnitudes of excess jobs in 2021q4 and from 2022q3 through 2023q2.

Figure 13 shows results for the permutation placebo test for the total change in jobs, with New Jersey in green and donor states in gray. P-values measure the fraction of states with a greater absolute total change in employment than New Jersey ($H_0 : \Delta e = 0$ vs. $H_1 : \Delta e \neq 0$). I am able to detect a statistically significant total increase in jobs in 2019q4, 2022q3, 2022q4, and 2023q2, and a statistically significant decrease in jobs in 2021q2.

6 Robustness

6.1 Sensitivity to Inclusion of Bin 16

First, I test the sensitivity of my results to the inclusion of bin 16 when calculating the synthetic control weights. Appendix Figure 41 graphs employment per capita in bin 16 over time for New Jersey and each state in the donor pool. New Jersey has the highest proportion of employment in bin 16 out of all control states. Given that the difference in employment between New Jersey and the rest of the donor states is greatest in this bin, I am potentially concerned that the synthetic control could be placing heavier weight on states with employment in this bin closest to New Jersey. New Hampshire (graphed in blue) has employment most similar to New Jersey in bin 16, and New Hampshire receives the second highest weight.

I recalculate the synthetic control, but this time I exclude bin 16. Appendix Table 7 reports the new set of synthetic weights. New Hampshire loses just under half of its weight importance, with most being redistributed to Alabama. Additionally, Texas no longer receives weight while South Carolina and Wyoming receive new weight.

Figures 14, 15, and 16 below graph missing, excess, and total change in jobs for my benchmark specification and excluding bin 16. My results are largely robust to the exclusion of bin 16, but the new estimates are slightly more negative than the benchmark estimates.

6.2 Leave-one-out Permutation Tests

To test the sensitivity of my results to the inclusion of certain donor states, I conduct a series of leave-one-out permutation tests (Abadie et al., 2015; Andersson, 2019). I iteratively eliminate one of the seven control

Figure 12: Permutation Test - Excess Jobs in New Jersey and Donor Pool

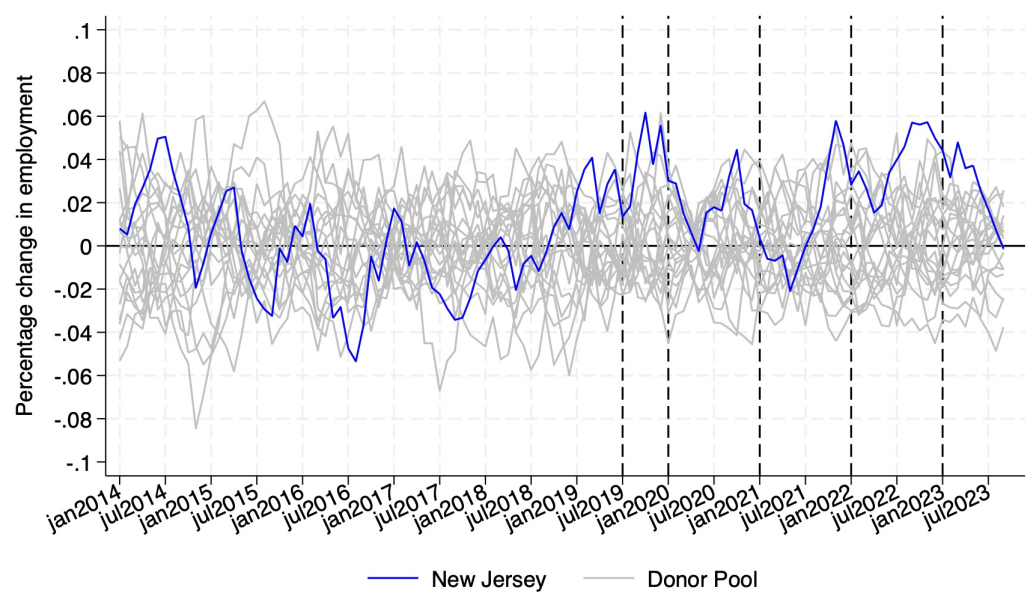


Figure 13: Permutation Test - Total Change in Employment in New Jersey and Donor Pool

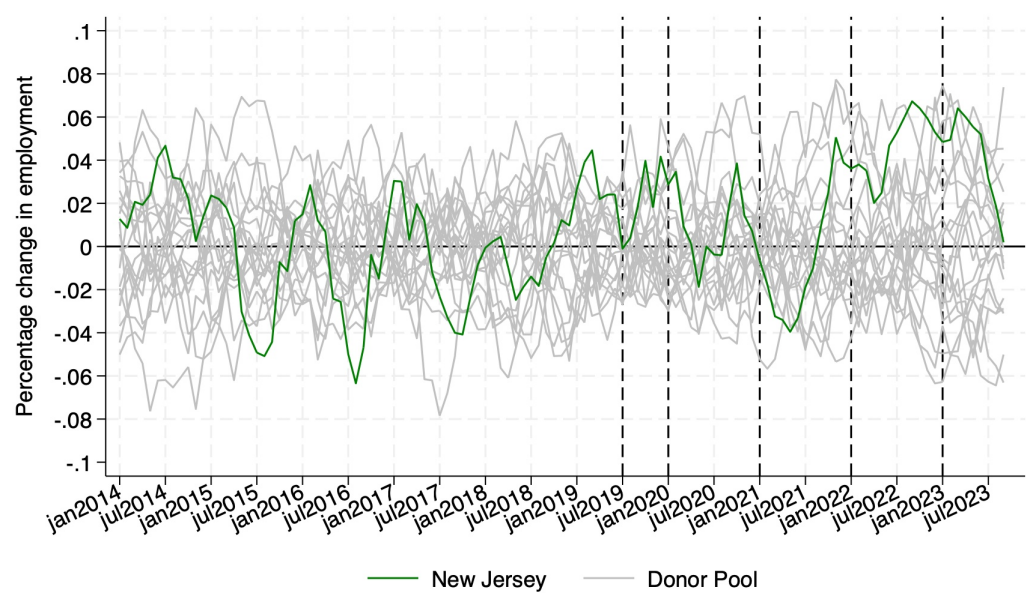


Figure 14: Missing Jobs - Sensitivity to Inclusion of Bin 16

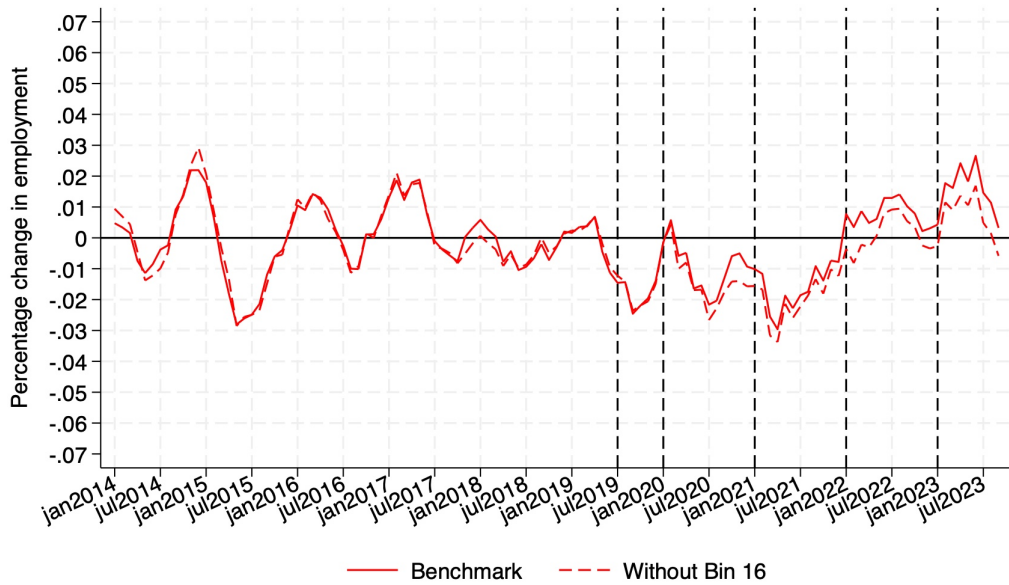
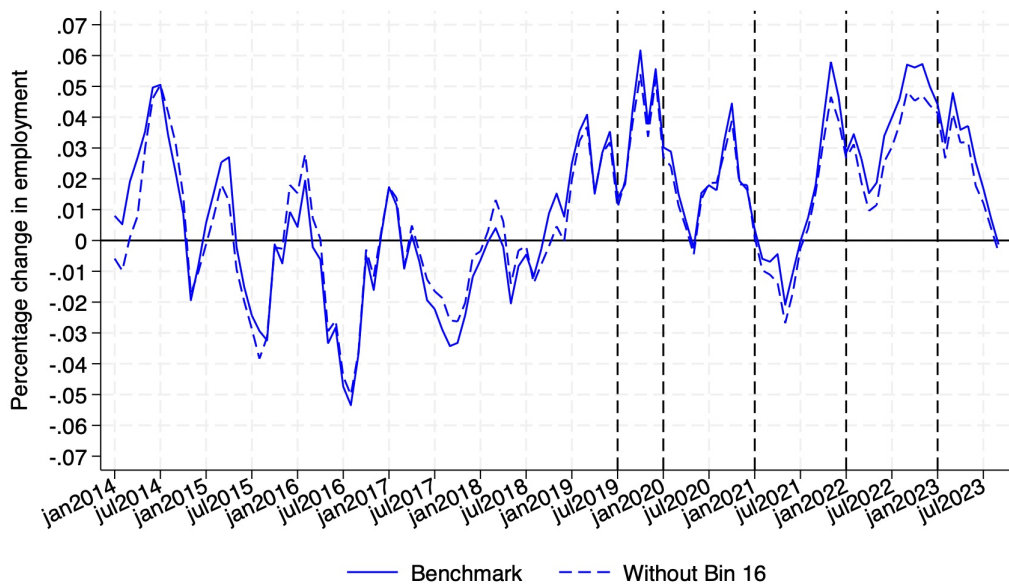


Figure 15: Excess Jobs - Sensitivity to Inclusion of Bin 16



states that received a positive weight in my benchmark specification, find a new set of synthetic weights, then recalculate missing, excess, and total change in jobs. Figures 17, 18, and 19 below display results for these leave-one-out permutation tests. Overall, my results are robust to the exclusion of certain controls states. However, my estimates for excess jobs and total change in employment show slight sensitivity to the exclusion of New Hampshire.

7 Discussion

In this paper, I estimate the employment effects of New Jersey’s \$15 minimum wage phase-in by observing changes in the distribution of hourly earnings. I use a synthetic control to create a counterfactual wage distribution, then estimate the number of missing and excess jobs to infer the total change in employment local to the minimum wage.

Appendix Table 6 reports estimated employment elasticities w.r.t. the minimum wage for each wage event. Averaging over these five wage increases, I estimate an elasticity of 0.248. My estimates are on the high side of aggregate employment elasticities found in the literature. Cengiz et al. (2019) find an elasticity of 0.024, and Meer and West (2016) find an estimate of -0.074. Additionally, my results are not aligned with Cengiz et al. (2019)’s finding of missing and excess jobs that match each other and persist over the medium run. In contrast, I find the emergence of excess jobs greater than missing jobs, and both disappear fairly quickly. Finally, my results support Jardim et al. (2022)’s finding of non-linear responses to Seattle’s two-phase minimum wage increase. They find an employment elasticity of -0.88 for the first phase which grew to -2.63 after the second phase. Interestingly, I find elasticities which decrease through the third wage increase, then positive elasticities after.

The main argument against minimum wage increases is the anticipated disemployment effects, but my results largely rule out this concern. Even after sizeable and persistent increases in the minimum wage, I fail to find consistent negative employment effects. This paper provides suggestive evidence that New Jersey’s phased-in \$15 minimum wage created temporary boosts in employment without any medium run disemployment effects. These findings support additional minimum wage increases in New Jersey.

Figure 16: Total Change in Jobs - Sensitivity to Inclusion of Bin 16

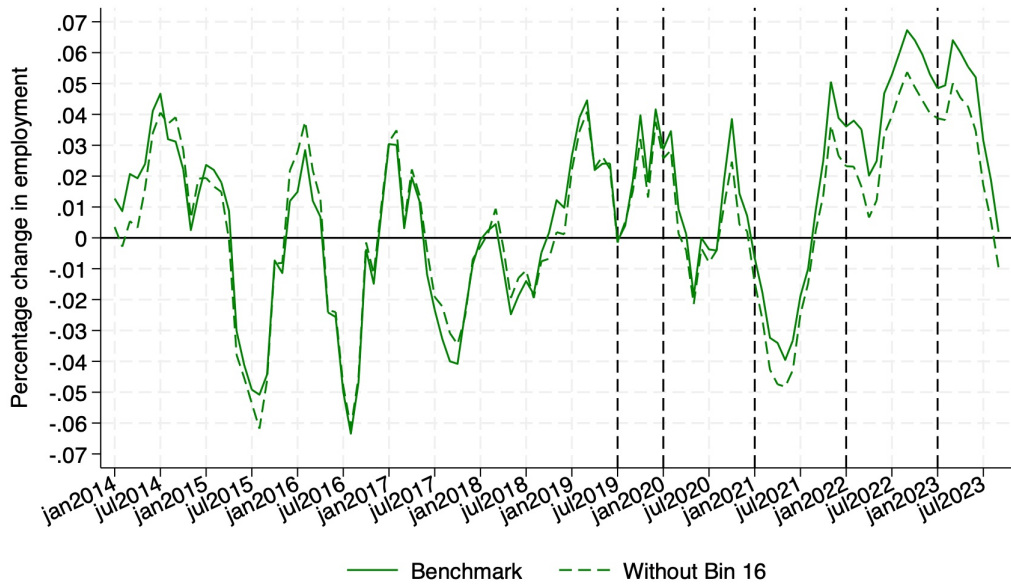


Figure 17: Missing Jobs - Leave-one-out Permutations

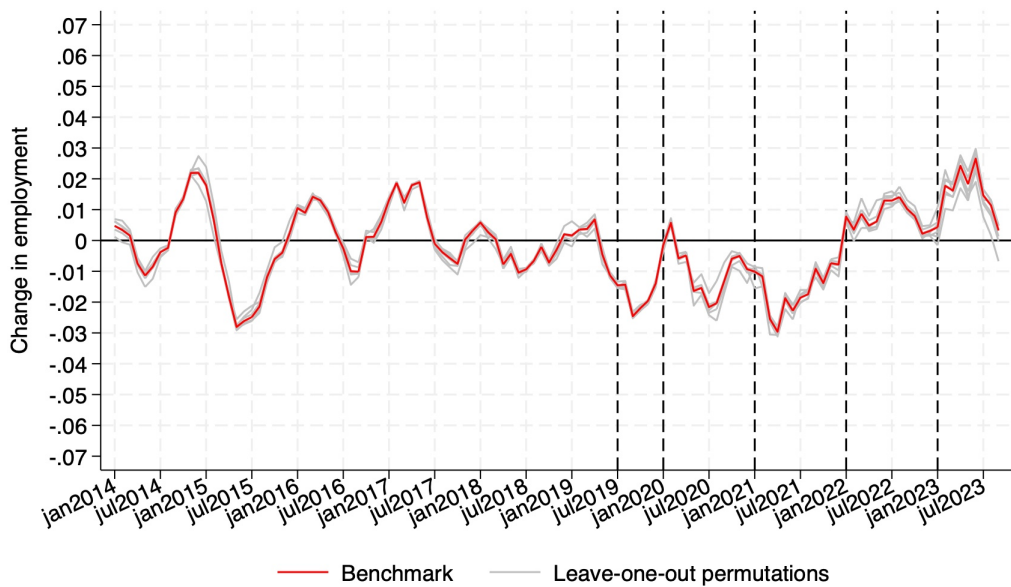


Figure 18: Excess Jobs - Leave-one-out Permutations

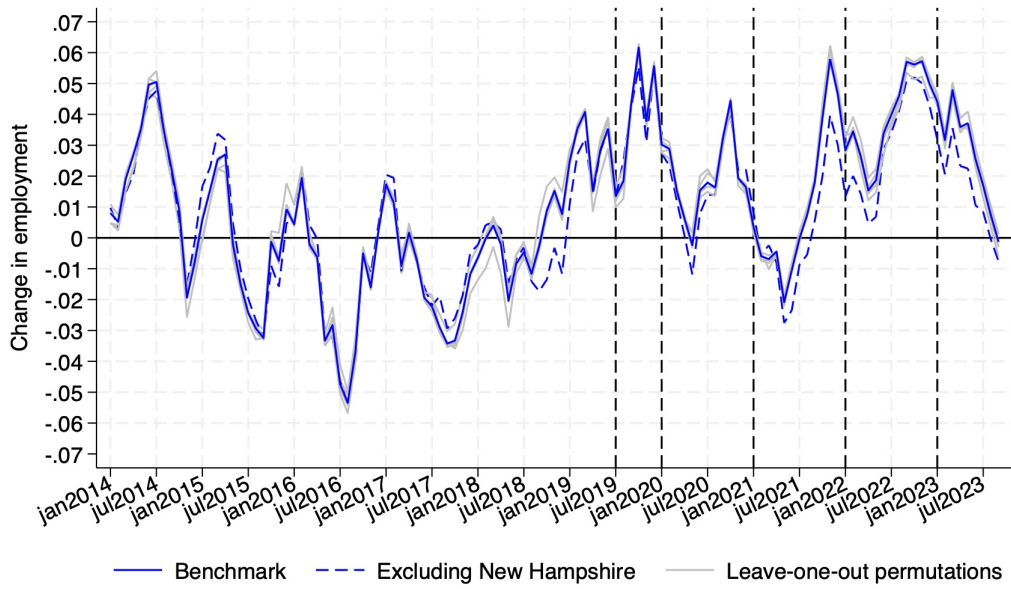
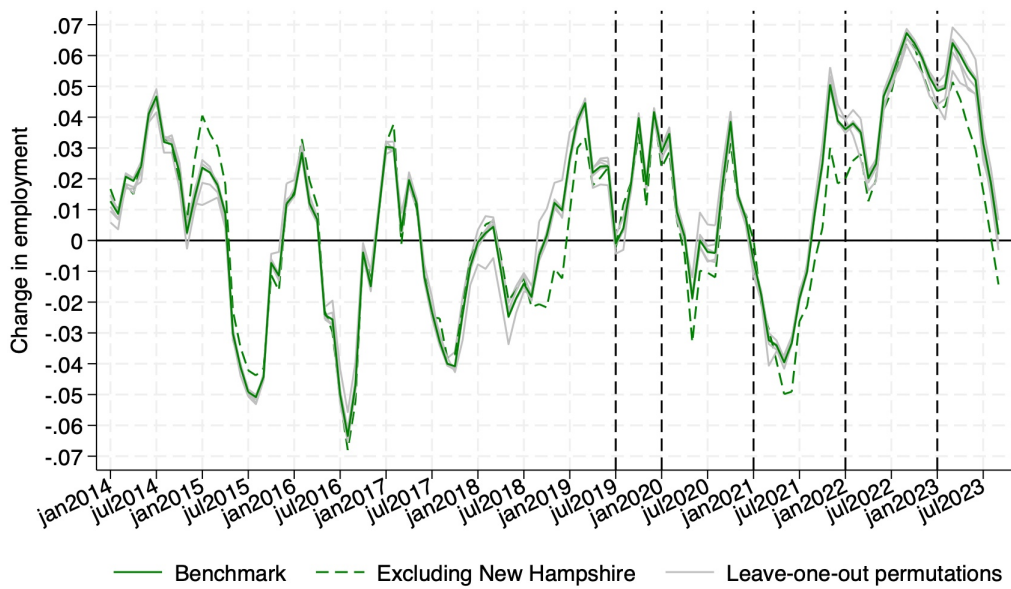


Figure 19: Total Change in Jobs - Leave-one-out Permutations



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Table 5: MSPE by bin

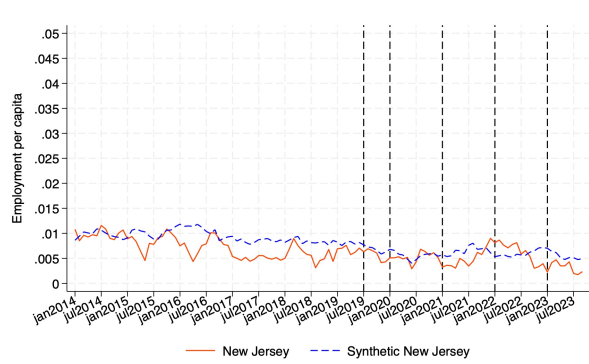
Bin	MSPE	Bin	MSPE
-10	0.00000783	4	0.0000122
-9	0.00000076	5	0.000014
-8	0.0000693	6	0.0000112
-7	0.0000272	7	0.00000911
-6	0.0000321	8	0.0000103
-5	0.0000354	9	0.00000767
-4	0.0000275	10	0.00000659
-3	0.0000257	11	0.000004
-2	0.0000806	12	0.0000038
-1	0.0000184	13	0.00000737
0	0.0000265	14	0.00000425
1	0.000023	15	0.00000249
2	0.0000162	16	0.0031947
3	0.0000151		

Table 6: Employment elasticities w.r.t. minimum wage

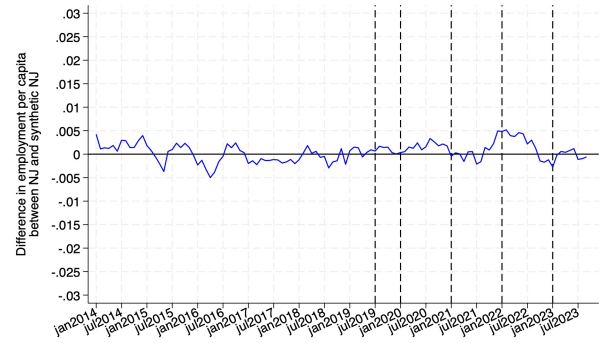
	Total Change in Employment	% Change in Minimum Wage	Employment Elasticity w.r.t. Minimum Wage
Wage Increase #1 \$8.85 → \$10.00	2.01%	12.99%	0.155
Wage Increase #2 \$10.00 → \$11.00	1.05%	10.00%	0.105
Wage Increase #3 \$11.00 → \$12.00	-0.57%	9.09%	-0.063
Wage Increase #4 \$12.00 → \$13.00	4.64%	8.33%	0.557
Wage Increase #5 \$13.00 → \$14.13	4.24%	8.69%	0.487
Average			0.248

Note: Total change in employment reported in column 1 is the average of monthly total change in employment estimates.

Figure 20: Employment Estimates in Bin -10 (\$0.01 - \$5.99)

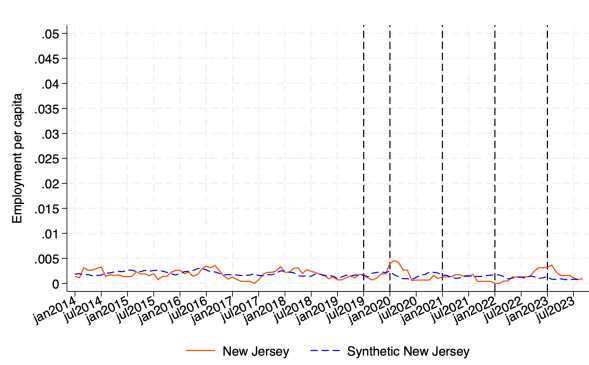


(a) Employment per capita over time

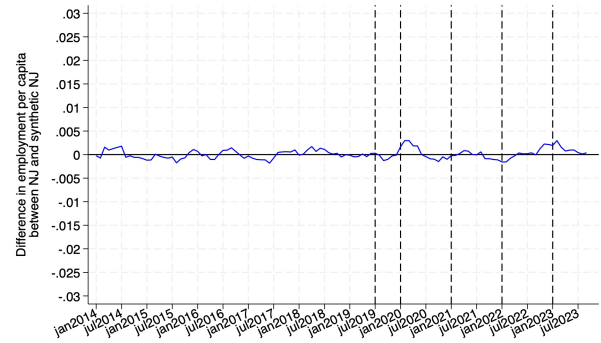


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 21: Employment Estimates in Bin -9 (\$6.00 - \$6.99)

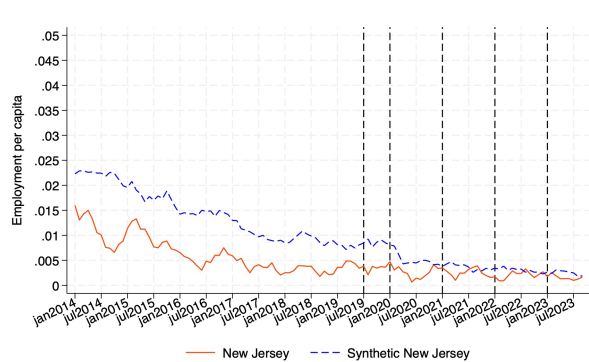


(a) Employment per capita over time

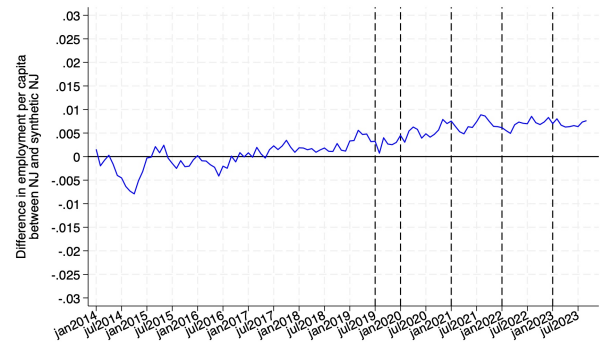


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 22: Employment Estimates in Bin -8 (\$7.00 - \$7.99)

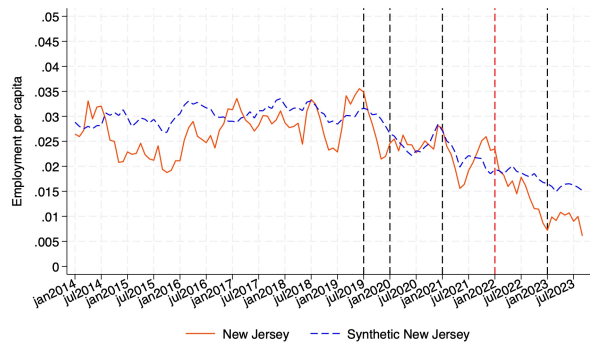


(a) Employment per capita over time

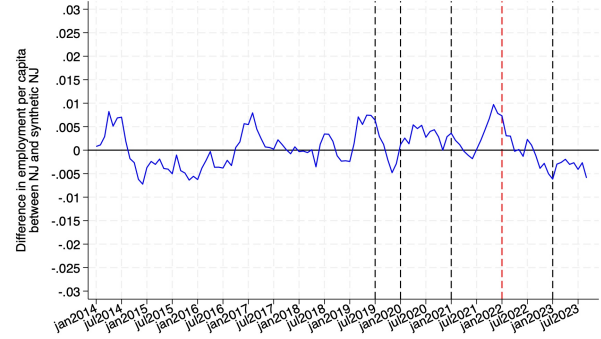


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 23: Employment Estimates in Bin -3 (\$12.00 - \$12.99)

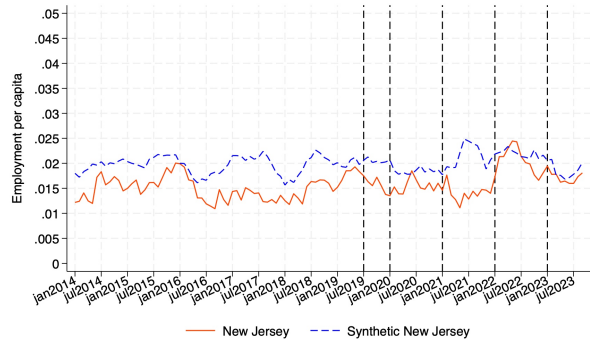


(a) Employment per capita over time

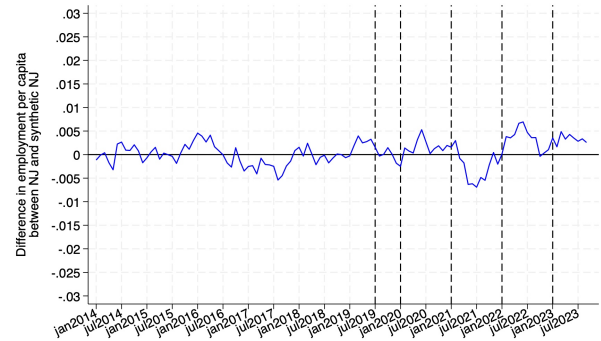


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 24: Employment Estimates in Bin 0 (\$15.13 - \$16.12)

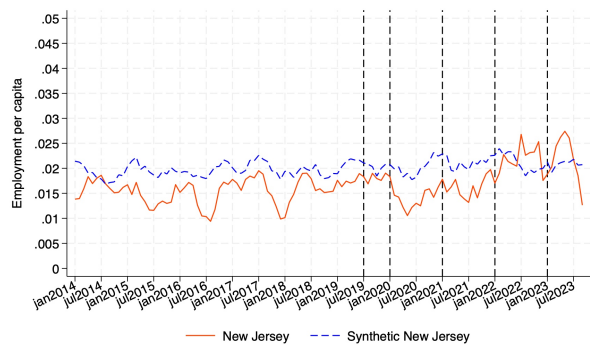


(a) Employment per capita over time

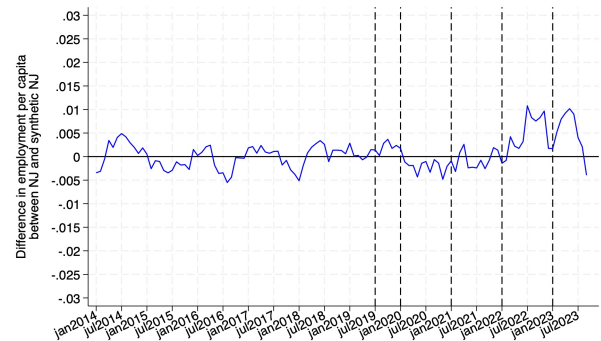


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 25: Employment Estimates in Bin 1 (\$16.13 - \$17.12)

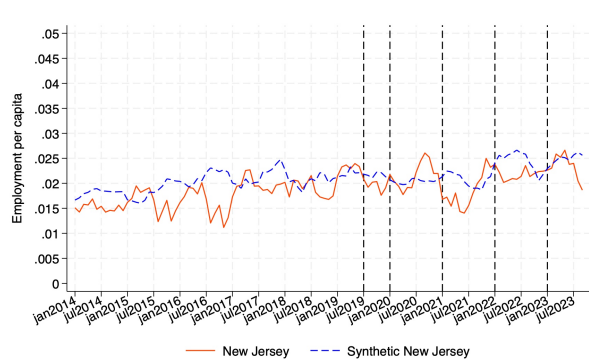


(a) Employment per capita over time

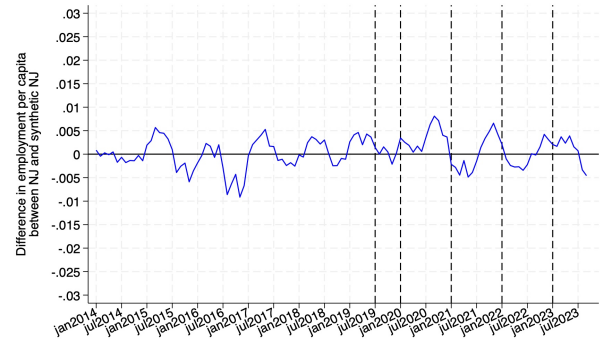


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 26: Employment Estimates in Bin 2 (\$17.13 - \$18.12)

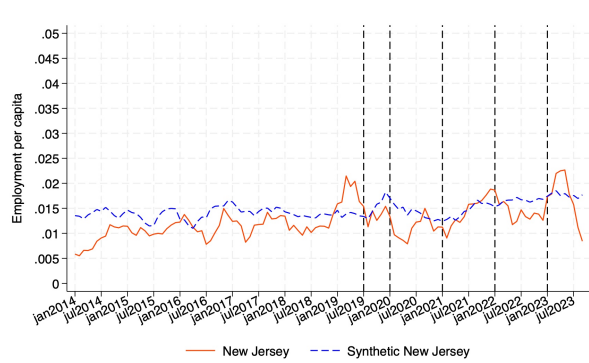


(a) Employment per capita over time

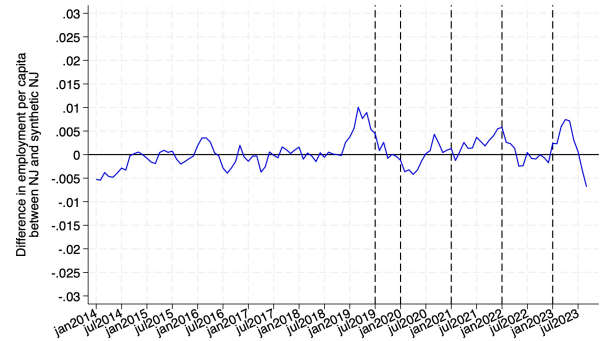


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 27: Employment Estimates in Bin 3 (\$18.13 - \$19.12)

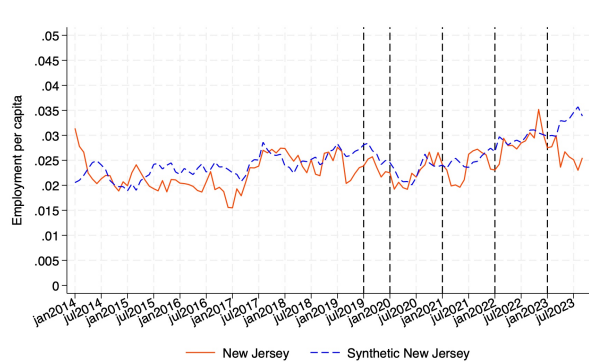


(a) Employment per capita over time

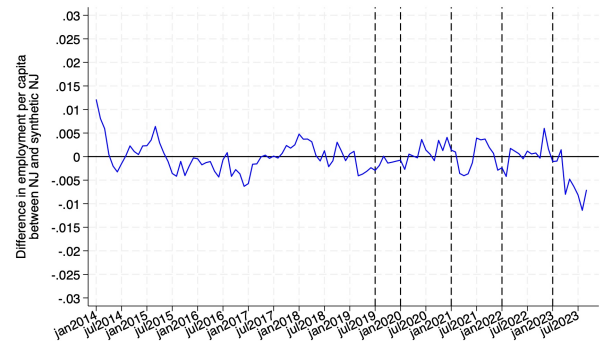


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 28: Employment Estimates in Bin 4 (\$19.13 - \$20.12)

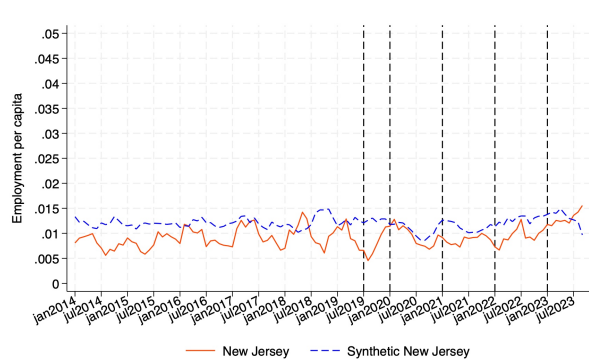


(a) Employment per capita over time

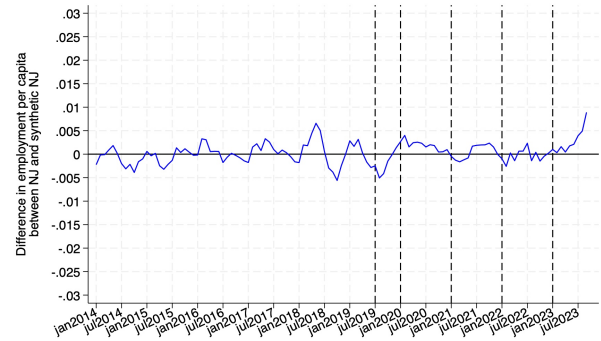


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 29: Employment Estimates in Bin 5 (\$20.13 - \$21.12)

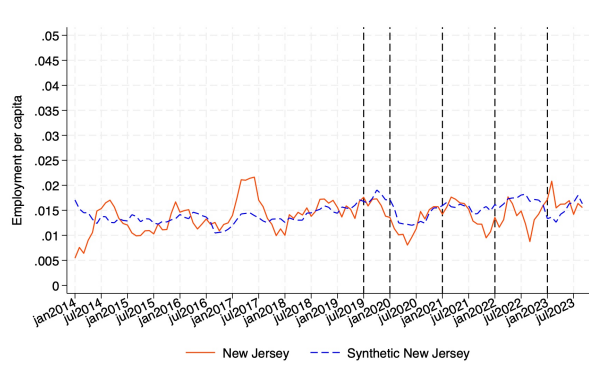


(a) Employment per capita over time

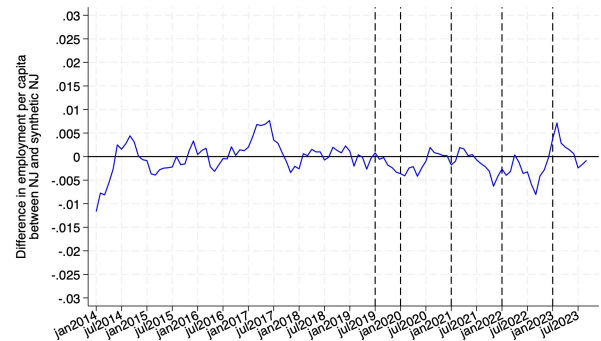


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 30: Employment Estimates in Bin 6 (\$21.13 - \$22.12)

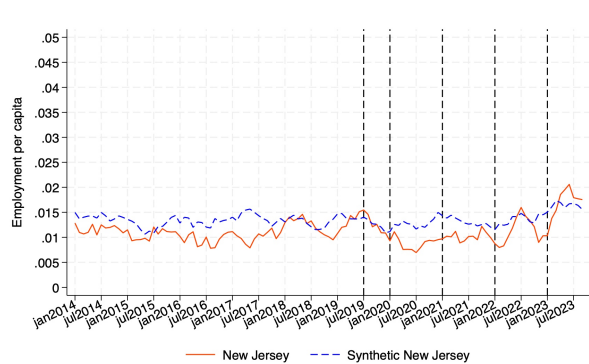


(a) Employment per capita over time

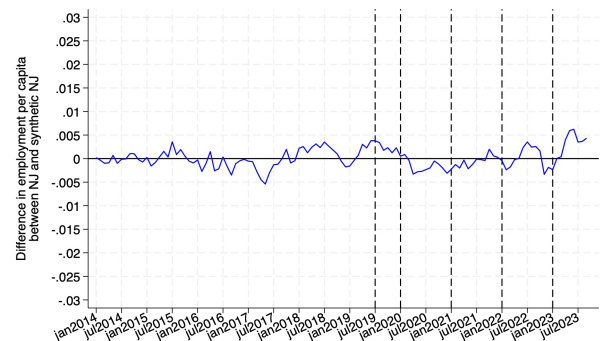


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 31: Employment Estimates in Bin 7 (\$22.13 - \$23.12)

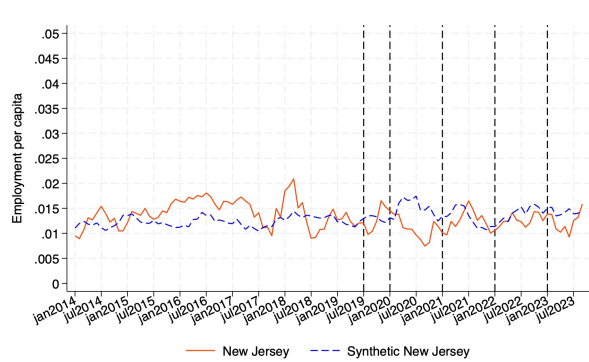


(a) Employment per capita over time

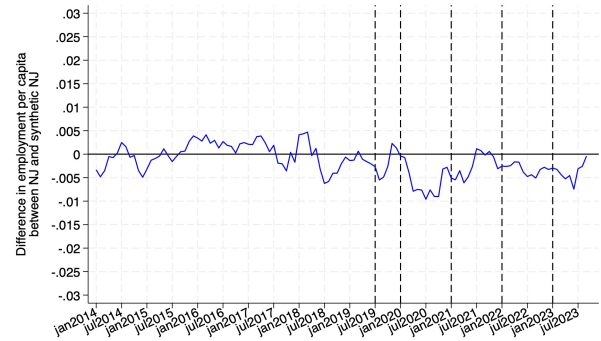


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 32: Employment Estimates in Bin 8 (\$23.13 - \$24.12)

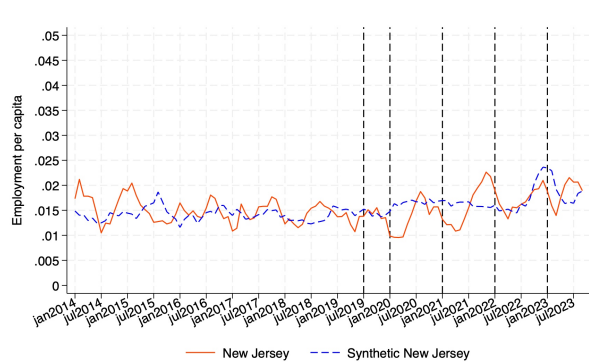


(a) Employment per capita over time

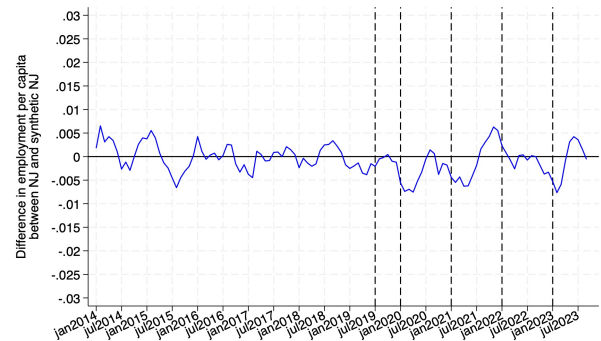


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 33: Employment Estimates in Bin 9 (\$24.13 - \$25.12)

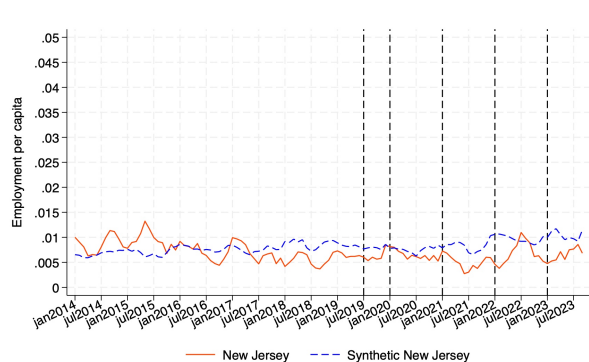


(a) Employment per capita over time

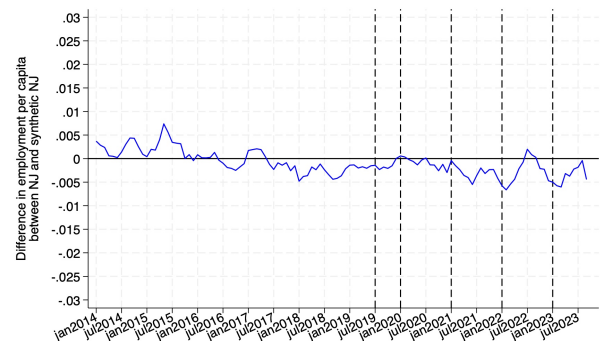


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 34: Employment Estimates in Bin 10 (\$25.13 - \$26.12)

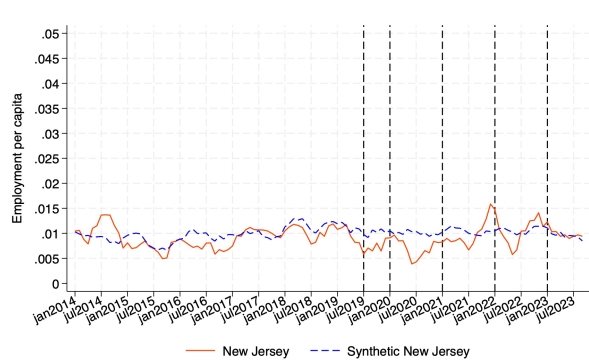


(a) Employment per capita over time

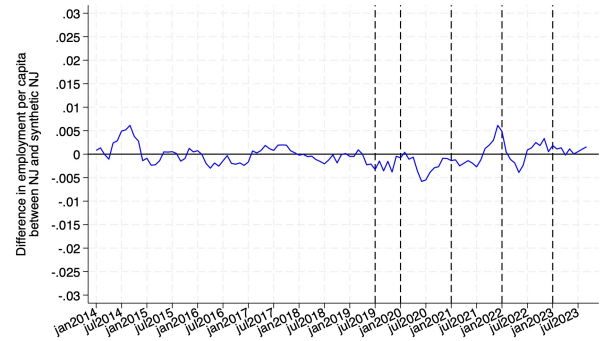


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 35: Employment Estimates in Bin 11 (\$26.13 - \$27.12)

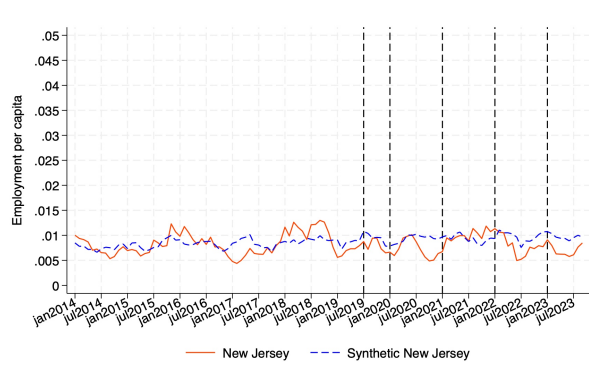


(a) Employment per capita over time

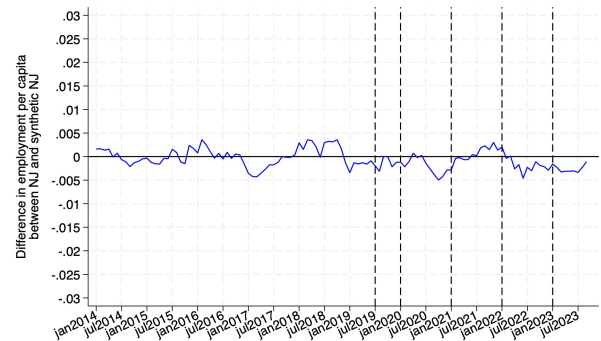


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 36: Employment Estimates in Bin 12 (\$27.13 - \$28.12)

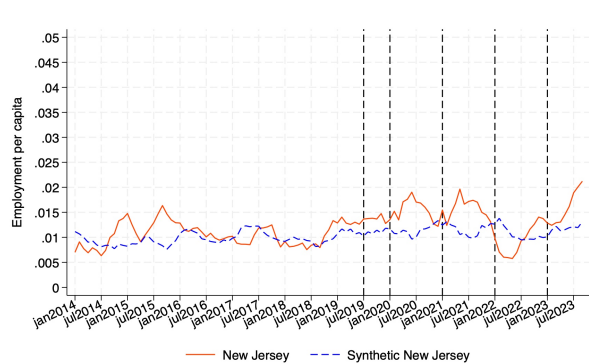


(a) Employment per capita over time

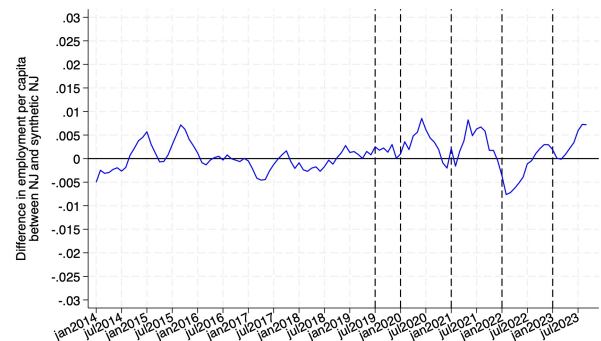


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 37: Employment Estimates in Bin 13 (\$28.13 - \$29.12)

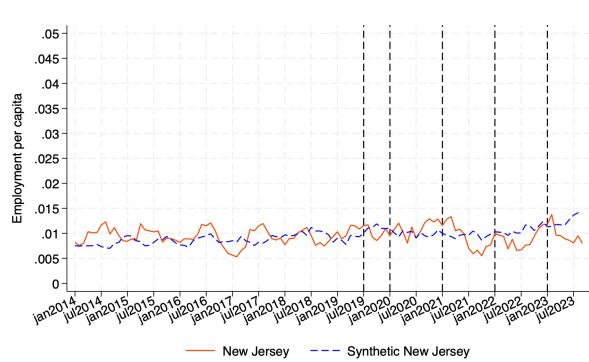


(a) Employment per capita over time

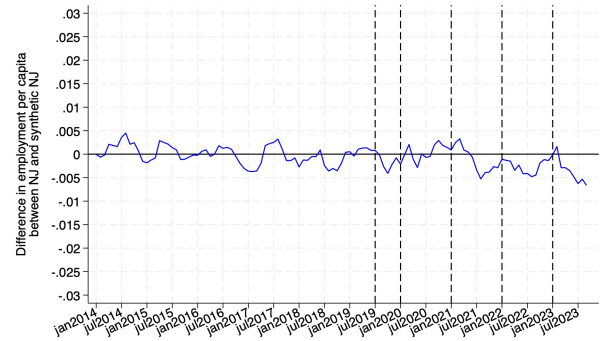


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 38: Employment Estimates in Bin 14 (\$29.13 - \$30.12)

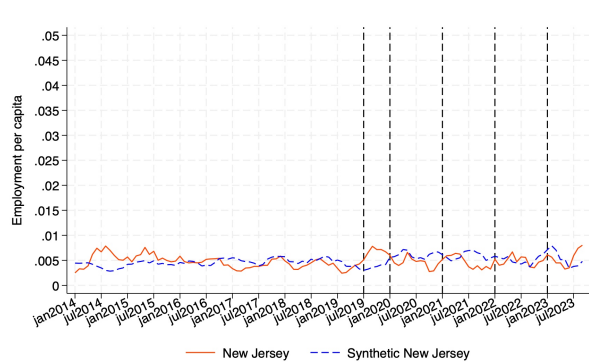


(a) Employment per capita over time

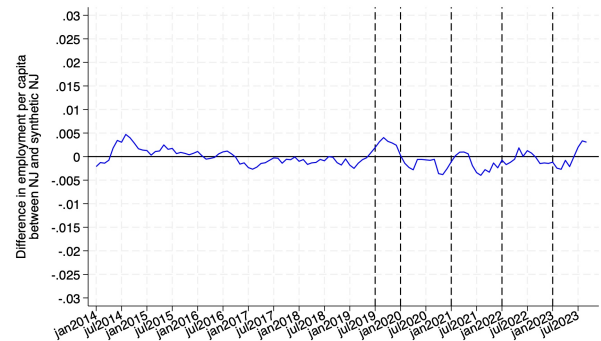


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 39: Employment Estimates in Bin 15 (\$30.13 - \$31.12)

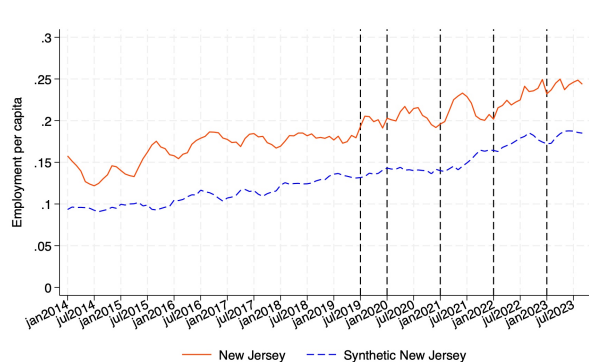


(a) Employment per capita over time

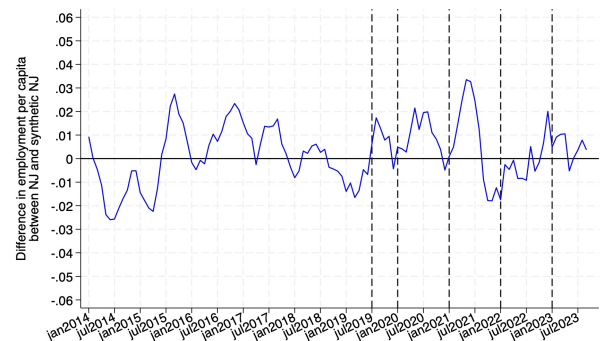


(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

Figure 40: Employment Estimates in Bin 16 (\$31.13 and up)



(a) Employment per capita over time



(b) Difference in employment per capita between New Jersey and synthetic New Jersey over time

8 Appendix

Figure 41: Employment Over Time in Bin 16 (\$31.13 and up)

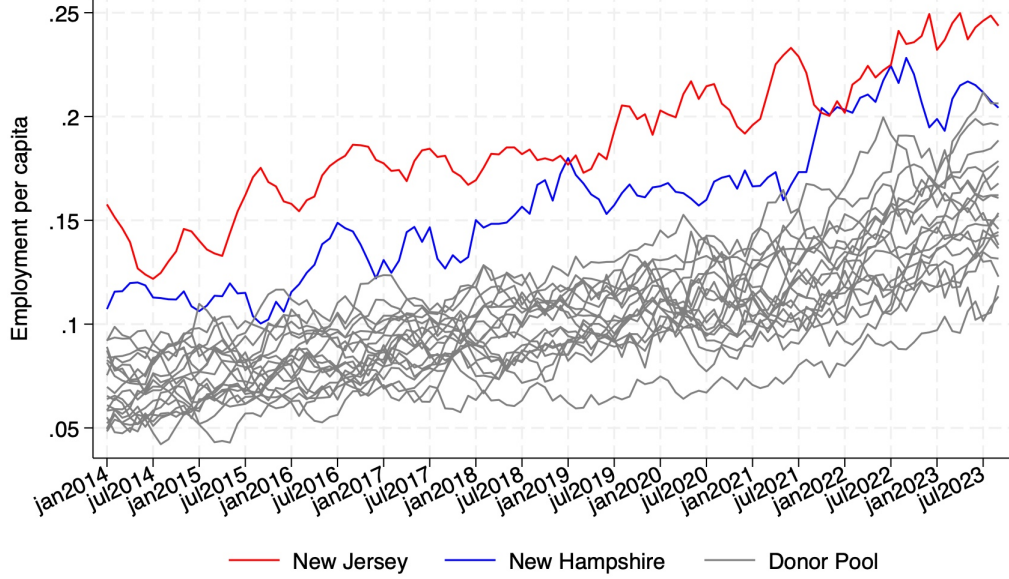


Table 7: State Weights for Synthetic New Jersey - Excluding Bin 16

State	Weight	State	Weight
Alabama	0.165	North Carolina	0.094
Georgia	0.086	North Dakota	0
Idaho	0	Oklahoma	0
Indiana	0	Pennsylvania	0.203
Iowa	0	South Carolina	0.089
Kansas	0	Tennessee	0
Kentucky	0	Texas	0
Louisiana	0.126	Utah	0
Mississippi	0	Wisconsin	0
New Hampshire	0.163	Wyoming	0.074

Note: Synthetic control does not allow extrapolation, so all weights are between $0 \leq w_i \leq 1$ and $\sum w_i = 1$