5-2021

The Demographic Effect of Minimum Wage: Evidence from San Francisco County

Poorya Mehrabinia
Utah State University

The demographic effect of minimum wage: Evidence from San Francisco County

Poorya Mehrabinia

December 2020

Abstract

The minimum wage in San Francisco was increased from $6.75 to $8.5 per hour in November 2003. This was primarily aimed to improve low-income workers' well-being, especially racial and ethnic minorities. This paper conducts a difference-in-difference model using a synthetic control group for San Francisco, looking into a possible change in employees' demographic composition in Accommodation & Food Services, and Manufacturing industries. The results indicate that the ratio of white employees increased significantly, suggesting that a labor-labor substitution happened in the following years of the minimum wage increase.

Introduction

A new minimum wage floor is believed to have different effects on employment in various industries. Several articles highlight the adverse effects of an increase in the minimum wage on low-wage workers. These workers may experience hourly wage gains, but the hours of work and employment typically decrease.[1] These studies are consistent with the theoretical standpoint that has been discussed in almost any principle of economics textbooks. However, Card & Krueger (1994) do not find an adverse effect of increasing the minimum wage on employment. There are numerous papers that contribute to this debate, and the studies use a broad host of different methods and case studies.

Based on another famous paper, the binding minimum wage would not have a statistically significant effect on employment; instead, this increase in the minimum wage might result in higher employment of the younger workforce.[2] This paper and a variety of other studies also contribute to the debate mentioned above. They can help reconcile the apparent discrepancies between the papers backing the employment decrease and the ones that do not – with identifying labor-labor substitution instead of a significant effect on employment levels. In the case of Los Angeles County, Fairrais and Bujanda (2008), for example, finds evidence of a labor substitution toward more males, high-skilled Hispanics and Blacks workers. Another explanation for weak evidence of minimum wage affecting employment is that the mentioned impact does not happen

[1] Neumark, Schweitzer and Wascher (2002)
[2] Giuliano (2013)

immediately after the minimum wage policy, but instead, it happens over time through changes in growth.[3]

Motivated by this literature on labor-labor substitution, it is possible that employers facing the minimum wage increase might become selective in whom they are hiring based on employees' races and ethnicities. This effect should also be examined over a significant period rather than immediately after the minimum wage binding. The results from our analysis, which uses a synthetic control method, suggest that the demographic composition of workers in the "Accommodation and Food Services" and "Manufacturing" industries significant change in San Francisco County – relative to a pool of control counties both in and outside of California – during the post-wage-increase period.

Background

The San Francisco County's minimum wage bill was passed in November 2003 and became effective in February 2004. The 26% rise in the minimum wage, from $6.75 to $8.5, was the first substantial county-level minimum wage increase relative to federal or state norms. As inserted in the San Francisco County's report, the primary mindset behind this minimum wage increase was to help low-income employees with San Francisco's high living costs. The San Francisco Board of Supervisors commissioned a report to determine how a local minimum wage would affect workers, businesses, and the local economy. According to this report, reinforcement of minorities as the

[3] Meer & West (2015)

majority of low-wage workers was also the stated aim of this minimum wage policy. Policymakers intended that this demography of people get paid more by increasing the minimum wage. However, for the policy to remain successful in achieving its goal, a fixed or even higher employment proportion among these demographic groups needs to be observed. Suppose by any means like displacing these people from the area, this policy results in a significantly lower proportion of minorities working in San Francisco. In that case, we can assert that the policy was a failure.

As mentioned before, there are lots of publications around a local minimum wage increase. But this question of the impacts of these increases on the demographic discrepancy of employment has remained unanswered. Dube, Naidu & Reich (2007) studied San Francisco's 2003 minimum wage with a difference-in-difference method using Almeida County as the control group. Their analysis looked at employment change and wages in restaurants and found no statistical evidence of the policy's effect on employment rates. However, they did not analyze the labor-labor substitution and the employment rate changes among different races and ethnicities. This paper has tried to motivate a framework to examine the minimum wage's demographic effect on employment by looking at the relative change in workers' demography – see if the minimum wage floor has a long-run impact on employment composition.

Data

For the purpose of this paper, I used quarterly county-level panel data for the period 2001 to 2010 as the data for our control group states are just available for this period. The data obtained from different sources have been merged and cleaned into one panel data. For the variable under study, employment, data come from the United States Census Bureau intercensal population estimates, using the quarterly workforce indicator (QWI). The employment data estimate the total number of jobs on the first day of the reference quarter. Beginning-of-quarter employment counts are similar to point-in-time employment measures. The data contains county-level demographic shares for black, white, Asian, and Native American groups, each broken down by Hispanic and non-Hispanic groups. I categorized the data into eight different groups for all combinations of race and ethnicity. This paper targets the low-income workforce using the employment data for the Accommodation and Food Services and the Manufacturing industries.

The data for the unemployment rate, one of our predictor variables, is gained from the US Bureau of Labor Statistics database.[4] I reorganized the monthly county-level data into a quarterly format to match our predicted variable format. I made the same arrangement for the multi-unit residential construction data, the other predictor variable of this study. The multi-unit residential construction is chosen because additional residential construction is likely to affect the county's low-skill labor supply. Below, the summary statistics of our working variables are reported in Table 1.

Table. 1: Summary Statistics of working Data

Variable	Mean	Std. Dev.	Min	Max
emp white	16288	26774	0	196981
emp minorities	18518	38419	0	393571
ue	7.79	3.60	2.167	31.233
Multi-unit rescons	166.48	515.7	0	5374

I merged all the eight race-ethnicity groups into two groups of white employment and minority employment because this study focuses on finding the difference between these categories.

[4] Bls.gov

Synthetic Control Method for Case Study

For conducting a comparative case study, we generally examine the effect of some intervention or policy on the exposed unit and determine the difference caused by that event with the unexposed units. With this in mind, what we need is some control units similar to our desirable unit. Finding these unexposed units in some cases is almost impossible. However, in case studies on a city, researchers tend to find one or more cities with the same characteristics as their area of study. In this case, the intervention is one policy or treatment specifically imposed for the region of their research while it does not impact the control group. For all the deficiencies of finding suited regions for the control group, an approach to build a synthetic control group is introduced by Abadie, Diamond, and Hainmuller (2010). This method, which is used in this paper, enables us to assemble a control group from a pool of counties. This synthetic group is constructed as a weighted average of our pool of counties in such a way that the synthetic San Francisco best resembles the values of the predictor variables of San Francisco. For the aim of this analysis, the packages *synth* from Abadie, Diamond & Hainmueller (2010) and *synth_runner* from Galiani & Quistorff (2016) were used in STATA 16 to produce the synthetic control estimates and to complete the comparative analysis.

Methodology and Empirical Analysis

In this paper, I followed Abadie, Diamond, and Hailmueller (2010), to build a synthetic San Francisco from a pool of 76 counties. This pool of counties consists of all available California State counties alongside 20 other counties from all over the United States which had not faced a drastic minimum wage increase.

I used this synthetic San Francisco in our Difference-in-Difference (DiD) model to identify the change in the demographic shares of San Francisco employees following the minimum wage increase in 2003. The demography of employment is categorized into two groups of white people and minorities (or non-white). The demographic share of white employees, for example, is calculated as the number of white employees divided by the total employees - for each specific county.

In our DiD estimate, I used the data from the first quarter of 2001 to the third quarter of 2003 as the pre-intervention period. Since we use quarterly data, the pre-intervention period is where $1 \leq t \leq 11$, and t = 12 is where the intervention happens. Also, the post-intervention period would be $13 \leq t \leq 40$, ending in the last quarter of 2010.

Following Abadie et al.'s (2010) notation, let Y_{it}^{N} be the demographic share of employees for county i at time t, in the absence of treatment, namely the minimum wage increase.[5] Let Y_{it}^{I} be the same variable after the county is exposed. We assume in our model that the implantation of the minimum wage did not influence the demographic shares in the previous periods. We further assume that the treatment does not have cross-county effects on the dependent variable. Let $\alpha_{it} = Y_{it}^{I} - Y_{it}^{N}$ be our parameter of interest, which is the effect of an increase in the minimum wage on the demographic

[5] We assume in our model that the implantation of the minimum wage did not influence the demographic shares in the previous periods.

shares of employment for county i at time t. Finally, let SF_{it} be a dummy variable indicating whether county i is exposed to the treatment at time t. From the definition of α_{it} we have:

$$Y_{it} = Y_{it}^N + \alpha_{it} SF_{it} \qquad (1)$$

Where Y_{it} is the actual demographic share of employment, which is observable in the data. Notice that San Francisco is the only county that is exposed to the treatment. Therefore, we have:

$$SF_{it} = \begin{cases} 1 & for\ i = 38\ and\ t > 12 \\ 0 & otherwise \end{cases} \qquad (2)$$

Our goal is to estimate the vector of after-treatment parameters $(\alpha_{38,13}, \alpha_{38,14}, \dots, \alpha_{38,40})$. In order to do so, we can rearrange (1) to get:

$$\alpha_{38,t} = Y_{38,t}^I - Y_{38,t}^N = Y_{38,t} - Y_{38,t}^N \qquad (3)$$

Notice that $Y_{38,t}$ on the right-hand side of equation (3) is observable in the data, but $Y_{38,t}^N$, the counterfactual demographic share of employment without treatment in San Francisco, is missing.

Now suppose that $Y_{i,t}^N$ behaves, according to the following model:

$$Y_{i,t}^N = \delta_t + \theta_t Z_i + \lambda_t \gamma_i + \epsilon_{it} \qquad (4)$$

Where δ_t is the time fixed effects, $\lambda_t \gamma_i$ is allowing for time-county fixed effects, and Z_i is a vector of observable characteristics for county i, In our model, Z_i consists of the unemployment rate and multi-unit residential reconstruction unit.

Abadie et al. (2010) show that $\alpha_{38,t}$ can be estimated by $\widehat{\alpha_{38,t}} = Y_{38,t} - \sum_{\substack{i=1 \\ i \neq 38}}^{76} w_i^* Y_{i,t}$ where $w_i^*$is derived from minimizing $[(X_{38} - X_0 W)' V (X_{38} - X_0 W)]^{\frac{1}{2}}$, where X_{38} itself is a vector consisting of the unemployment rate, multi-unit residential reconstruction, as a weighted average of dependent variables before the treatment.

Intuitively, we can estimate the counterfactual demographic share of employment in San Francisco at time t by a weighted average of the same variable in other counties. These weights are calculated by minimizing Euclidian (or some other) distance between the dependent variable and the predictor variables in San Francisco and other counties before the treatment. Then, I use these weights for the post-treatment period and calculate the differences for demographic shares.

The advantage of using synthetic control for the estimated differences of the employees' share is that it enables us to vary over time and evaluate the minimum wage's dynamic long-run demographic effect. A traditional differences-in-differences model, as used in Dube, Naidu & Reich (2007), fails to capture these effects and may underestimate the minimum wage's long-run dynamic effects. The same is true for the mean comparisons used to estimate labor-labor substitution in Farrais & Bujanda (2008).

Table 2 shows the predictor means for San Francisco and synthetic San Francisco for the Accommodation and Food Services industry. I also added Alameda county's values, the control group for Dube, Naidu & Reich's (2007) paper. We can see that the synthetic control group resembles San Francisco better than the Alameda county.

Table 2: White Employment's Percentage, Predictor means

Variables	San Francisco	Synthetic	Alameda
Unemployment	6.22	6.22	6.57
multi-unit rescons	308.17	308.34	451.72
White emp percentage 2001 Q2	36.34%	36.29%	39.65%
White emp percentage 2002 Q3	36.30%	36.23%	38.72%
White emp percentage 2003 Q3	36.21%	36.13%	38.72%

After running the synthetic control algorithm, we develop each county's weights, as discussed previously. Table 3 shows the first 16 counties with the most weight in our synthetic San Francisco. These weights are for the Accommodation and Food Services industry. For the Manufacturing sector, the weights would be different as we use different values in our analysis.

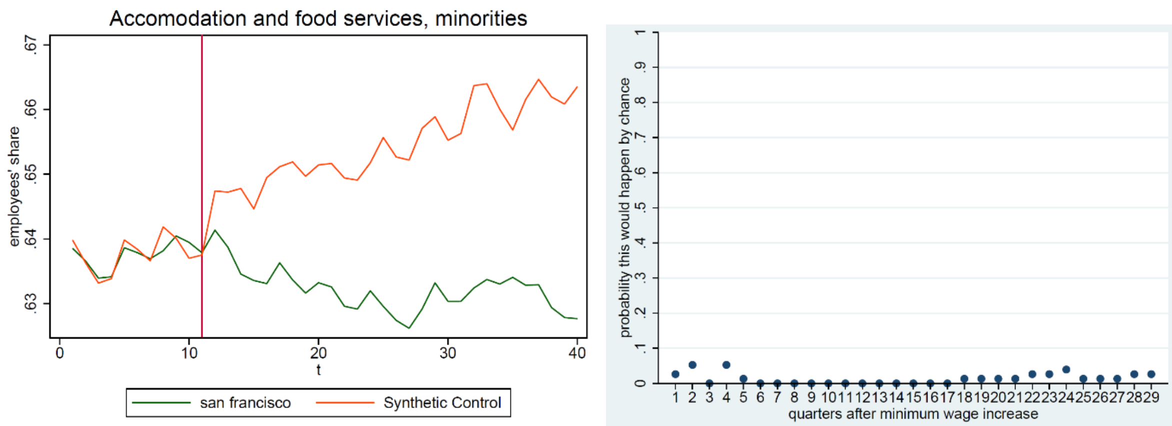
Table 3: County Weights in Synthetic San Francisco

Honolulu, HI	39.2%
Marin, CA	11.2%
Imperial, CA	8.0%
Los Angeles, CA	5.8%
Madera, CA	2.8%
Cook, IL	2.0%
Siskiyou, CA	1.5%
Calaveras, CA	1.4%
Fulton, GA	1.4%
San Diego, CA	1.3%
Alpine, CA	1.2%
Lake, CA	1.1%
Yuba, CA	0.9%
San Mateo, CA	0.8%
Orange, CA	0.7%
Tuolumne, CA	0.6%

Results

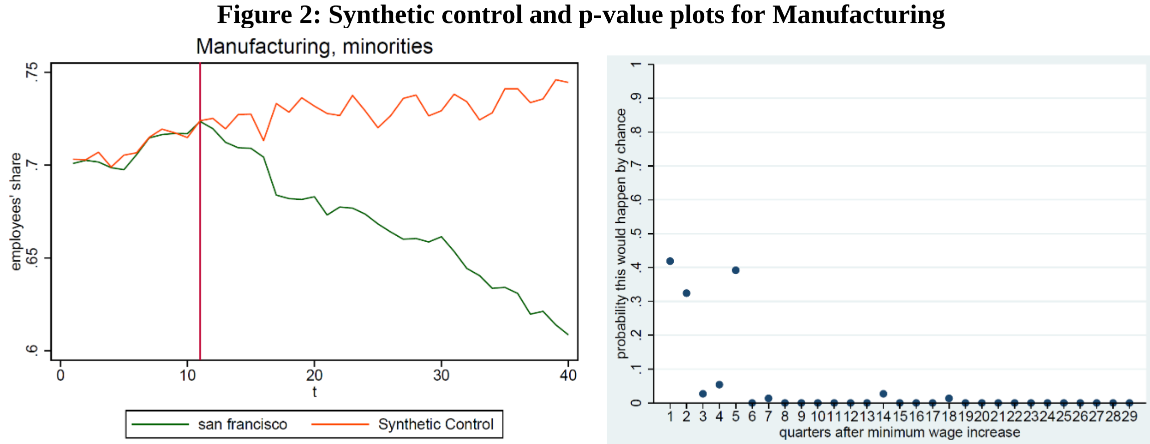
Using the synth_runner package in STATA, the observed results for San Francisco and synthetic San Francisco are as follows. The results are for two different industries, and both employees' share of minorities and whites. I placed the results for minorities here, and by definition, the results for whites are precisely in the other way. I also extracted the corresponding p-values for the difference-in-difference coefficients ($\widehat{\alpha_{38t}}$).

Figure 1: Synthetic control and p-value plots for Accommodation and Food Services



As shown in Figures 1 & 2, the employees' share for minorities dropped in the next years following the minimum wage increase. The p-values support the significance of these results. In other word, with a higher minimum wage, employers tend to hire more white people rather than minorities. That can also be due to higher demand from white people but does not change the employers' selection behavior.

Figure 2: Synthetic control and p-value plots for Manufacturing



Same as the p-values, another way to find out about our results' significance is using the placebo tests, following Abadie and Diamond (2003). These placebo tests are conducted to see if the minimum wage's observed effect in San Francisco is relatively large compared to if we assigned a random county of our donor pool as the treated unit. For that, I apply the synthetic control method to every county in the donor pool, assuming that county is the treated unit, and then plot the differences between predicted and observed values for all counties. By this, I can examine whether the San Francisco minimum wage effect in 2003 is large compared to the distribution of estimated effects for the counties not affected by the minimum wage. Figures 3 and 4, respectively, show the placebo plots for "Accommodation & Food Service" and the "Manufacturing" industries.

Figure 3: Placebo plots for Accommodation and Food services

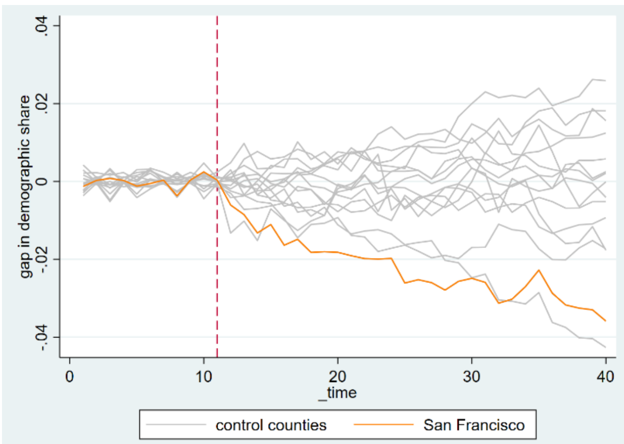
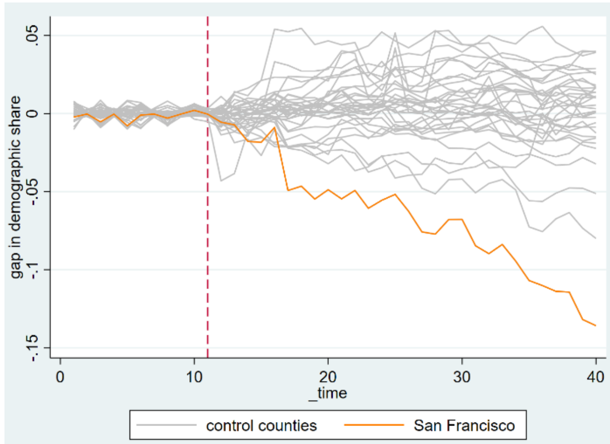


Figure 3: Placebo plots for Manufacturing



Conclusion

Considering all of the results thus far, this study can assert that employees' composition has changed in the following years of the minimum wage increase. Whites' demographic share increased, and minorities have experienced a diminishing share in low-income jobs. Contrary to the opinion that the rise in the minimum wage would improve the economic standard of living of minorities living in San Francisco County, it appears that the opposite occurred as the composition of minority employment within the county significantly decreased – relative to the synthetic control group – after the minimum wage increase took effect.

References

Abadie, A., Diamond, A. & Hainmueller, J. (2010) Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program, Journal of the American Statistical Association, 105:490, 493-505

Neumark, D., Schweitzer, M., & Wascher, W. (2004). Minimum Wage Effects throughout the Wage Distribution. The Journal of Human Resources, XXXIX, 425 - 450.

Card, D., & Krueger, A. (2000). Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania: Reply. The American Economic Review, 90(5), 1397-1420. Retrieved November 30, 2020

Giuliano, L. (2013). Minimum Wage Effects on Employment, Substitution, and the Teenage Labor Supply: Evidence from Personnel Data. Journal of Labor Economics, 31(1), 155–194.

Card, D., & Krueger, A. (1993). Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania.

Addison, J.T., Blackburn, M.L. & Cotti, C.D. On the robustness of minimum wage effects: geographically-disparate trends and job growth equations. IZA J Labor Econ 4, 24 (2015).

Fairris, D., & Bujanda, L.F. (2008). The Dissipation of Minimum Wage Gains for Workers through Labor-Labor Substitution: Evidence from the Los Angeles Living Wage Ordinance. Southern Economic Journal, vol. 75, no. 2, 2008, pp. 473–496.

Meer, J., and West, J. (2015). Effects Of The Minimum Wage On Employment Dynamics. Journal Of Human Resources 51 (2): 500-522. University of Wisconsin Press.

Dube, A., Naidu, S., & Reich, M. (2007). The Economic Effects of a Citywide Minimum Wage. ILR Review, 60(4), 522-543.