The Effect of Increasing Minimum Wage at a City-Wide Level on the Enrollment in Public Assistance Programs.

by Amy Lim

under the Direction of

Professor M. Gretchen Lay

Professor James Hartley

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Dedication

To my advisors, Professor Gretchen Lay and Professor Sarah Adelman who have opened up the academic world of economics to me. Their support and encouragement in the last two years of my undergraduate career have changed the direction of my life forever, and I am truly thankful for having them in my life. This work is also dedicated to my mother and sister, Lisa and May, who have taught me to work hard for the things that I aspire to achieve.

Abstract

This study examines the effect of increasing minimum wage at a city-wide level on the enrollment in means tested public assistance programs. I exploit San Francisco's minimum wage increases in 2011 and 2012 and use data from IPUMS-CPS to estimate the effect on welfare programs. Using a linear probability model and a difference-in-difference estimation, my analysis suggests that San Francisco's minimum wage increases have a positive effect on the enrollment of welfare programs like Temporary Assistance for Needy Families (TANF) and Medicaid and is statistically significant.

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Introduction

For many people around the United States, money in the form of wages is earned through work. In 1938, President Roosevelt enacted the first federal minimum wage as a part of the Fair Labor Standards Act. According to the History of Minimum Wage, the purpose of a minimum wage was to protect workers from being exploited by employers, but today, its purpose is to establish a “living wage” for workers (History of Minimum Wage, 2016). In this paper, I investigate whether minimum wage increases in San Francisco increase or decrease enrollment in means-tested public assistance programs like TANF and Medicaid.

In 2014, California passed a law that would increase the minimum wage to $9.00 an hour (California Department of Industrial Relations, 2018). In the same year, San Francisco’s minimum wage was $10.74 and hour, 19% more than the state minimum. In the 21st century, more and more cities have taken it upon themselves to increase their minimum wage, rather than waiting for the state legislature to do so (City and County of San Francisco, 2018). As of January 2018, 17 cities in California have passed minimum wages above the state minimum wage (California Department of Industrial Relations, 2018). A motivation to increase city-level minimum wages above state-wide minimum wages could be because the cost of living in metropolitan cities like Los Angeles, Berkeley, and Oakland has become too expensive. Therefore, voting residents of these cities would support higher minimum wages to manage rising costs of living.

In these urban areas, the tax burden on residents is also rising to support means-tested public assistance programs. One reason why a higher minimum wage would be beneficial to society is that it would potentially decrease the number of participants in means-tested public assistance programs. With fewer participants, the tax burden to support these programs would be lower. However, there is evidence that minimum wage increases are both ineffective and effective in reducing net participation in means-tested public assistance programs (Sabia Nguyen, 2017; West and Reich, 2015). This study further investigates at a city-level.

In this study, I employ a difference-in-difference estimation and find that minimum wage increases in 2011 and 2012 in San Francisco increased the enrollment by 5.5 and 8.0 percentage points respectively in means-tested public assistance programs. The annual increases of San Francisco's minimum wage in 2011 and 2012 allow it to be the treatment group and the constant minimum wages in nearby cities like Oakland and San Jose control for heterogeneity. This study uses the 2009-2012 Current Population Survey (CPS) ACES supplement to measure the effect of the minimum wage increases in San Francisco on means-tested public assistance programs, like Temporary Assistance for Needy Families (TANF) and Medicaid.

The paper is organized as follows. The first section contains the literature review surrounding economic theory of labor markets, previous minimum wage empirical studies, and means-tested program models. The second section describes the data sources used and the outcomes of interest. The third section contains the model and methodology used to investigate the effect of city-wide minimum wage increases on enrollment of means-tested public assistance programs. Section four offers results and analysis from the model. The final section contains my concluding remarks.

Chapter 1

Literature Review

To create the foundation for my study, I examine previous theoretical and empirical research with respect to minimum wage, labor markets, and public assistance programs. Like many topics in economics, minimum wage is divisive and conclusions regarding its effects are contingent on the models and methods used to study them.

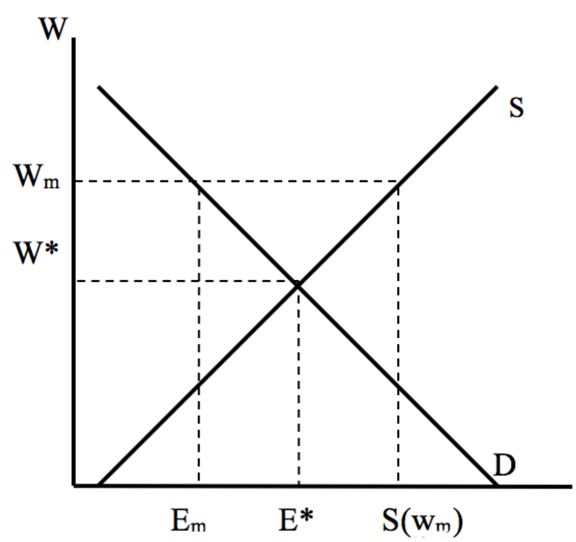
1.1 Theoretical Models of Minimum Wage and Public Assistance Enrollment

1.1.1 Labor Effects Under Perfect Competition

Charles Brown (1999) in the Handbook of Labor Economics describes the basic model of labor under perfect competition with the addition of a minimum wage. Figure 1 shows his model is one with homogenous labor where demand of labor D(w) is downward sloping, and supply of labor S(w) is upward sloping. Instead of an equilibrium wage where D(w) equals S(w) at the equilibrium wage w* and employment E*, a binding minimum wage (w_m>w*) leads to demand driven employment E_m=D(w_m). The minimum wage floor above the market equilibrium creates an excess supply of labor S(w_m)-D(w_m) because firms lay off workers whose productivity is lower than the minimum wage w_m.

There are several predictions that arise from the assumptions of this model. One prediction is that minimum wage has undesirable outcomes in terms of unemployment. In a competitive labor market without minimum wage, there was no shortage or excess supply of labor, however, an addition or increase of minimum wage would generate unemployment. Unemployment could be a reason why individuals sign up for public assistance because, without a source of income, they rely on government assistance to make ends meet.

Figure 1.1
Labor Effects in a Perfectly Competitive Market with Minimum Wage.



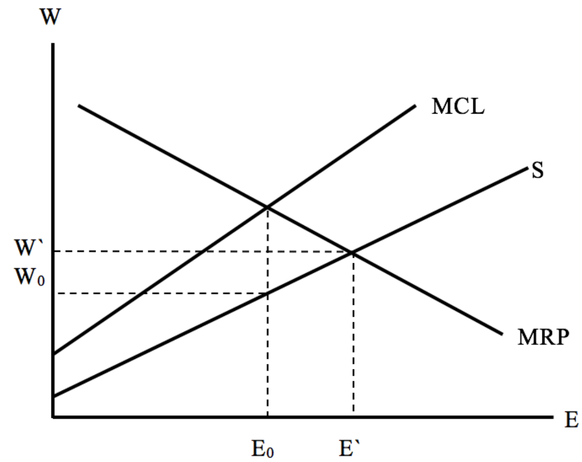
Source: Handbook of Labor Economics, Brown (1999)

1.1.2 Labor Effects Under a Monopsony

An alternative labor model that might explain a different employment outcome is a monopsony labor market. In the monopsony labor model, firms face an upward sloping supply curve for labor and seek profit. Unlike the competitive labor market, firms have the power to set the wage level where they maximize their profits. Brown's (1999) equation for firms to maximize profits is $\pi = R(L) - w(L)L$. In Brown's model, firms choose the profit maximizing level of employment where $R'(L) - w(L) - w'(L)L = 0$ which implies that the marginal revenue product of labor, R', is equal to $w(1+1/\varepsilon)$ where ε is the elasticity of labor supply. If the government sets a minimum wage that is higher than the firm's wage but lower than the point where marginal revenue product equals marginal cost of labor, it moves the equilibrium up along the supply curve. The minimum wage can leave employment higher as long as $(w_m/w_0) < 1+(1+1/\varepsilon)$, but there is still a chance that employment falls or does not change depending on the elasticity of labor supply. If there is an abundance of minimum wage firms in the labor market, each firm faces a more inelastic labor supply curve. If the labor supply curve is approximately perfectly inelastic, employment could not increase as Brown (1999) illustrates because labor supply will not be affected by the addition of minimum wage.

According to this model, firms can only retain the most qualified and skilled workers and will have to let go of workers who are not as skilled or qualified. In monopolistic labor markets, a higher minimum wage would decrease enrollment in public assistance programs by increasing wages without increasing unemployment.

Figure 1.2
Labor Effects Under a Monopsony



Source: Handbook of Labor Economics, Brown (1999)

1.1.3 Criteria for Enrollment in Means-tested Public Assistance Programs

In 1935, President Franklin D. Roosevelt proposed federal social relief programs and federally sponsored retirement programs to help citizens who were affected by the Great Depression (Social Security Administration, 1935). In the 1960s, programs expanded when President Lyndon B. Johnson introduced programs like Medicaid and Aid to Families with Dependent Children (AFDC), eventually replaced by Temporary Assistance to Needy Families (TANF) in 1996 (Moffitt, 2003). Medicaid provides health insurance to low-income populations and pays for a variety of medical services for children and adults who have limited resources. TANF provides cash assistance to low-income families with dependent children.

In the next section, I describe two primary enrollment criteria for TANF and Medicaid. I address the criteria of means-testing specifically on TANF and Medicaid in California.

A. Means-Testing:

TANF eligibility is dependent on income and assets, hence it is considered a means-tested public assistance program. In addition, TANF receives federal funding, but individual states are able to determine how to use these funds. TANF eligibility is determined by each state because the federal government distributes block grants for states to determine benefits and time limits (Moffitt, 2003). The program specifically provides financial support to families with dependent children, who are defined as those who were deprived of the support or care of one's biological parents by reason of death, disability, or absence from the home, and where under the care of the parent of another relative. Although the language of the legislation is intended to be gender neutral, an overwhelming majority of participating families are families where the father is not present (Moffitt, 2003). States are free to set their benefit levels, tax rate, income limits, asset requirements, time limits, and cash assistance. For example, in California, the minimum basic standard of adequate care (MBSAC) is used to determine a family's TANF eligibility. As of April 2018, California's disabilities homepage listed maximum income levels to receive TANF. Below is the MBSAC table listing the countable income maximums for California residents per month to qualify for TANF in 2018:

Table 1.1
Minimum Basic Standard of Adequate Care (MBSAC)
Per Month Maximums

Family Size	Region 1	Region 2
1	$660	$626
2	$1,082	$1,029
3	$1,342	$1,274
4	$1,592	$1,514
5	$1,817	$1,730
6	$2,044	$1,944
7	$2,246	$2,131
8	$2,444	$2,327
9	$2,652	$2,514
10	$2,878	$2,738
More than 10	Add $26 for each extra person	Add $26 for each extra person

Source: ca.db101.org (2018).

California's Department of Social Services has different income limits for different regions as cost of living varies vastly in rural and urban areas. Region 1 refers to the more urban counties in California like San Francisco, Alameda, and Santa Clara county where the cost of living is significantly higher, and region 2 includes more rural counties.

Medicaid is also a means-tested program that was introduced in 1965 (Gruber, 2003). The eligibility was very strict as it was restricted to those who already received welfare payments and who were medically needy. In 1987, eligibility was expanded to cover families, and the income cut-off was set at 185 percent of poverty. Similar to TANF, states have the discretion to spend the funds how they see fit, but instead of receiving block grants, the federal government matches dollar per dollar whatever the state spends on Medicaid (Gruber, 2003). Today, the program eligibility is mostly based on income and those determined to be medically needy. Most states define income similarly to TANF including sources of cash income and does not have a time limit. The United States benefits homepage lists the general prerequisites to enroll in Medicaid in California. The general prerequisites to enroll in Medicaid require participants to be either pregnant, blind, have a disability or family member in your household with a disability, be responsible for children under 19 years of age, or be 65 and older (California Medicaid, 2018). Medicaid is also means-tested and the household income requirements before taxes for California are listed below:

Table 1.2
Income Requirements for Medicaid in California

Household Size*	Maximum Income Level (Per Year)
1	$15,800
2	$21,307
3	$26,813
4	$32,319
5	$37,825
6	$43,331
7	$48,851
8	$54,384

*For households with more than eight people, add $5,533 per additional person. Source: Benefits.gov (2018).

Medicaid has a higher maximum income limit compared to TANF, but that is because it does not differentiate between rural and urban counties. In both programs, the eligibility and funding is the same across my entire sample as each city is in region 1 of the MBSAC determination table.

Minimum wage can have a direct effect on means-tested programs like TANF and Medicaid. If it increases, and the maximum income levels for these programs do not change, enrollment in these programs could decrease because the increased earnings from a higher wage raise their total countable income to a point where they exceed the maximum income for their household size. Furthermore, minimum wage could have an indirect and positive effect on enrollment if it generates unemployment. If an individual is unemployed, they might not have any means to financially support themselves and need financial support from welfare programs.

B. Participation in Human Capital Programs.

TANF replaced AFCD for a number of reasons, but the main objective was to increase labor force participation rates of those enrolled. TANF requires recipients to participate in human capital programs that require an investment of time, if they do not participate in any of these programs, they will stop receiving benefits (Moffitt, 2003). For example, schooling, job training, and searching for work will allow them to yield a rate of return in the form of higher wages to eventually transition out of TANF. TANF is unique in the sense that it is the only means-tested public assistance program that requires participation in human capital programs. According to TANF legislation, the employment goal was to reduce "dependency" on welfare benefits amongst needy families. Furthermore, the maximum time limit of 60 months would eventually force participants to find another source of income to substitute the supplemental income they received from TANF.

In the event that minimum wage increases, the opportunity cost of participating in human capital programs defined by TANF also increases. Depending on the minimum wage increase, the new minimum wage could be enough for a current participant in TANF in a human capital program to consider working full-time earning minimum wage, which would decrease enrollment. Alternatively, for individuals who are unemployed, if the minimum wage increases, it also increases the potential gain from enrolling in TANF. In this scenario, the minimum wage increase could encourage more unemployed individuals to participate in human capital programs, thus, increasing TANF enrollment.

Robert Moffitt's (2003) Economics of Means Tested Transfer Programs presents a two-period model that measures the net present value (NPV) of participating in a human capital program. An individual will participate in TANF if the NPV is positive:

$$NPV = -W_1(1-t)I + (1/(1+r))\{P_2[(W_1 - W_2)(1-t)H_2] + (1 - P_2)[(W_1 - W_2)H_2 - (G - tW_1H_2)]\}$$

where W_1 is the wage if the recipient does not undergo the program, W_2 is the higher wage in period two if the participant does, I is the amount of time required in the program in period one, H_2 is the hours worked in period two, and P_2 is a welfare participation dummy in period two if the recipient undergoes the program.

For the purpose of my research, we will look at W_1 as a function of minimum wage. The opportunity cost of forgone earnings is $W_1(1-t)$ where the individual gives up the present value of time cost and money cost if they were to participate in a human capital program in order to receive TANF benefits. The wage differential $(W_1 - W_2)$ is the increase in wage you would receive by participating in the program. The wage differential could also demonstrate whether or not wages are raised sufficiently to induce in the participant go off of welfare all together.

If minimum wage increases, the opportunity cost of participating in TANF increases, therefore decreasing the wage differential. In the case of the two-period model, the overall effect of increasing minimum wage on the net present value of TANF would be negative and more participants would feel inclined to leave the program because the cost of spending time in a human capital program also increases.

1.2 Empirical Studies of the Minimum Wage and Public Assistance Enrollment

My study builds on the myriad of minimum wage and public assistance research. Minimum wage has been extensively studied at the state and federal level, but few studies have been done at the city-level. Most minimum wage studies are concerned with how increases will effect employment levels.

Empirical evidence from several studies describe various outcomes from minimum wages. Contrasting results from each study could be supported theoretically with different assumptions about the labor market. Furthermore, results can vary depending on the data sources.

Card and Krueger (1994) preformed the landmark study on minimum wage and its effect on labor. The authors study the effect of increasing minimum wage in the fast-food industry and its effect on employment. They exploit New Jersey's minimum wage increase and compared it to Pennsylvania where minimum wage did not change. To estimate the effects, they used a difference-in-difference estimation and found that an increase in the minimum wage increased employment. The differences of the price changes in New Jersey and Pennsylvania refute the competitive labor market's assumptions regarding labor. Fast-food restaurants in this study did not lay off workers, but they increased prices for consumers in order to compensate for the higher cost of labor.

However, Card and Krueger's findings are challenged. Neumark and Wascher (2000) and Sabia et al. (2016), apply a difference-in-difference estimation similar to Card and Krueger (1994). Neumark and Wascher (2000) examine New Jersey's wage change with a dataset based on payroll and find that Card and Krueger's (1994) results do not hold using this alternative dataset. They find that employment in New Jersey declines compared to Pennsylvania in the long run as a result of wage increases. The estimated elasticities range from -0.2 to -0.1. Neumark and Wascher (2000) confirm the assumptions of the competitive labor market model and the negative employment effect of minimum wage. Sabia et al. (2016) findings are consistent with Neumark and Wascher (2000) where minimum wage increases in New York city have a negative effect on employment.

Dube et al. (2007) take a similar approach to Card and Krueger (1994) and use a difference-in-difference estimation to study minimum wage in the restaurant industry, but use city-wide minimum wage increases instead of state-level increases. They study San Francisco's adoption of a city-wide minimum wage set at $8.50 in 2004 and its effect on employment compared to similar sized restaurants in Alameda County. They found that the policy increased worker pay and compressed wage inequality, but did not create any unemployment. Considering the balanced sample that they created, the treatment group exhibits an 2.79% increase in employment. This growth exceeds that of the control group which was about 1.10% increase, but was not statistically significant. Dube et. al. (2007) also state that their research suffers from few measurement errors as the treatment effect itself is a function of initial employment. Schmitt and Rosnik (2011) extend Dube et al. (2007) research in several dimensions as they expand their research to other cities like Washington D.C. and Santa Fe that have implemented a city-level minimum wage increase. Their findings are consistent with Dube et al. (2007) where minimum wage increases do not have systematic effects on employment. As Dube et al. (2007) is the first to research the effect of minimum wage at a city-level, it was one of the studies that motivated my curiosity to study San Francisco's minimum wage increase in 2011.

Allegretto and Reich (2017) recently researched the extent to where businesses increased their prices in order to adjust for higher labor costs that are associated with increasing minimum wage. To test this, the authors exploit San Jose's 25 % minimum wage increase in 2013. They use a difference-in-difference estimation and panel data from Quarterly Census of Employment and Wage to compare restaurant wage and employment trends. They address issues associated with studying city-wide minimum wage increases like whether or not a firms in the city faces increased competition from firms outside the city's borders. They concluded that an estimated elasticity of .058 implies that restaurant owners in San Jose responded to the 25% increase in the minimum wage by increasing prices. Their estimated price elasticities fall with restaurants that have larger workforces, suggesting the presence of more adjustment margins among larger businesses. The higher prices individuals face as a result of minimum wage increase compelled me to study its effects on public assistance programs. If the prices for consumers are higher as a result of minimum wage, they could be more inclined to enroll in these programs to help cover the higher cost of living. Other studies that are similar to Allegretto and Reich (2017) include Jardim et. al. (2017) where they study minimum wage increases of the restaurant industry in Seattle.

While my study considers short-run impact of minimum wage increases, Meer and West (2013) Clemens and Wither (2014) investigate the long-run effects of increasing the federal minimum wage. Meer and West (2013) find that minimum wage does not have much of an effect immediately, but higher minimum wages decreases job growth in the future. Using data from the Business Dynamics Statistics, the Quarterly Census of Employment, and Wages, and the Quarterly Workforce Indicator across multiple states to test their hypothesis. They used a panel fixed-effect specification to create a benchmark and then they employed a long-differences specification to examine whether there is a dynamic effect of minimum wage on employment. Specifically, they find that a 10% increase in the real minimum wage is associated with a 0.30 to 0.53 percentage point decrease in the net job-growth rate. Clemens and Wither (2014) investigate the effects of increasing the federal minimum wage on employment of low-skilled workers after the Great Recession in 2008. From 2005-2009, the federal minimum wage increased from $5.15 to $7.25 per hour. To test the effect, they use panel data from CPS and SIPP and use a difference-in-difference estimation. They found that over the course of the late 2000s, the average minimum wage rose by 30% and reduced the national employment-population ratio by 0.7 percentage points and employment by about .6 percentage points. Their research confirms that minimum wage increases have a significant effect on employment in the long run. Moreover, they have developed a framework that highlights minimum wage’s effect depends on the economic factors underlying low-skilled individuals’ wages.

Several studies look at the effect of minimum wage and its effect on poverty, wage distributions, and public assistance programs. Autor, Manning, and Smith (2016) reassess the impact of minimum wage on wage distribution using a longer panel from 1979-2012 and an econometric approach that eliminates many of the biases that exist in earlier estimates. They employ an ordinary least squares estimation as well as two-stage least squares estimation using CPS data and instrumental variables. They estimate that between 1979-88, the decline in the real value of minimum wage is responsible for 30-55% of growth for the wages of those in the lower end of the wage distribution. Furthermore, 33 of their calculations indicate that the declining minimum wage made only a modest contribution to growing lower tail inequality between 1988 and 2009. From 1979–2012, the declining minimum wage made a meaningful contribution to female inequality, a modest contribution to pooled gender inequality, and a negligible contribution to male lower tail inequality. The predictions from their results can indicate that minimum wage increases after 1988 may not be strong enough to contribute to income inequality.

As previously stated, a policy incentive to increase minimum wage could be directed towards reducing poverty. Neumark and Wascher (2002) research how minimum wages increase the probability that poor families break away from poverty. They find evidence supporting the view that minimum wages help in the fight against poverty. Using matched March CPS data and a logit probability model over a 2-year period where minimum wages increase, they found that poor families escape poverty and non-poor families fall into poverty. The various tradeoffs created by minimum wage increases resemble income redistribution among low-income families than income redistribution from high- to low-income families. Given these findings, it is difficult to make a distributional or equity argument for minimum wages.

Another study by Sabia and Nielsen (2015) examine the effect of minimum wage increases between 1996 and 2007 on alleviating poverty. Using data from Survey of Income and Program Participation (SIPP), they find little evidence that raising the minimum wage is an effective anti-poverty tool among individuals of working-age. Theoretically, the wage gains that reduce hardship among some low-skilled workers will be paid for by others, but what is the cost of these wage gains and who will pay for them? According to Aaronson (2011), minimum wage increases could increase output prices for goods and services produced by businesses that employ relatively larger shares of minimum wage workers. If minimum wage workers consume these goods and services, the effect of the minimum wage increase in alleviating poverty might be reduced. Furthermore, the gain in earnings for those members of the working poor who previously qualified for means-tested public benefits may lose their eligibility or see a reduction in benefits, thus offsetting any hardship gains.

West and Reich (2015) using data from the 1990 to 2012 from March CPS study the effect of increasing minimum wage on the enrollment of Supplemental Nutrition Assistance Program (SNAP). They estimate a difference-in-difference model with controls for state-specific linear time trends and census division-specific year effects. They obtain SNAP participation elasticities with respect to the minimum wage of -0.24 and -0.32. Then, drawing data from the National

Income and Product Accounts (NIPA) and an identical identification strategy, they estimate a SNAP expenditure elasticity with respect to the minimum wage of -0.19. Their results demonstrate that that minimum wage increases are associated with a reduction in program participation in the long run. The findings by West and Reich (2015) have been extremely influential in recent policy debates over the minimum wage as an effective welfare reform. However, Sabia shows that the models which these results are based fail a number of falsification tests due to their identification strategies.

Sabia and Nguyen (2017) research the direct effect of a minimum wage increase on means tested government programs like WIC, SNAP, TANF, Housing Assistance programs and Medicaid. Their research examines over 35 years of data across several datasets like CPS and SIPP. Using a difference-in-difference estimation and CPS data, they find no evidence that minimum wage increases are associated with reductions in SNAP/Food stamp use, housing assistance receipt, TANF/AFDC use, or WIC receipt. In another test, Sabia and Nguyen (2017) also use the same specification as West and Reich (2015) and find that using the West and Reich specification, minimum wage increases are associated with very large declines in means-tested program participation, however, this result only holds when the sample is restricted to one-person working in the household or participating households without any workers. West and Reich (2015) specification fails an important falsification test and likely overstates minimum wage-induced reductions in program participation.

Chapter 2

Analysis

2.1 Policy Experiment: Minimum Wage Increases in San Francisco

San Francisco's minimum wage increases in 2011 and 2012, and the lack of minimum wage increases in surrounding cities like Oakland and San Jose, provide the foundation to this study to examine whether San Francisco's minimum wage increases affected enrollment in means-tested public assistance programs. The study treats the minimum wage increase as the exogenous variation in my model.

To find information about each city's minimum wage, I used their respective government or county websites and news releases. During our time period of interest, the minimum wage in San Francisco, Oakland, and San Jose remained the same from 2009-2010 at $9.79/hour, $8.00/hour, and $8.00, respectively. San Jose and Oakland's minimum wage remained at $8.00/hour until 2012, whereas San Francisco's minimum wage increased in 2011 to $9.92/hour and $10.24 in 2012 (Table 2.1). New minimum wage ordinances in all three cities went into effect in the first month of the year.

Table 2.1
Minimum Wages

	San Francisco	Oakland	San Jose
2009	$9.79	$8.00	$8.00
2010	$9.79	$8.00	$8.00
2011	$9.92	$8.00	$8.00
2012	$10.24	$8.00	$8.00

Source: City and County of San Francisco (2018), California Department of Industrial Relations (2018).

2.2 Data Description

2.2.1 Data Source

My study uses repeated cross sections of data from the 2009-2012 Current Population Survey (CPS) ASEC supplement, formerly known as the March Supplement in microdata format from IPUMS-CPS. The sample that I extract from IPUMS is a 1% sample of the population. The CPS is a monthly U.S. household survey conducted by the U.S. Census Bureau and the Bureau of Labor Statistics. The U.S. Census Bureau defines a household as all persons who occupy a dwelling unit, a dwelling unit is a room or group of rooms intended for occupation as separate living quarters and having either a separate entrance or complete cooking facilities for the exclusive use of the occupants (Flood and Pacas, 2016). CPS samples are multi-stage stratified samples. The first stage divides U.S. states into primary sampling units that are comprised of metropolitan areas, a large county, or a group of smaller adjacent counties. The second stage, a systematic sample of housing units is drawn from each primary sampling unit. The CPS is designed so that it is a rotating panel. This means that households are interviewed for four consecutive months are not in the sample for the next eight months, and then are interviewed for four more consecutive months. This method allows for 50% of households are in the CPS during the same month one year earlier and the other 50% of households are in the CPS in the same month one year later (Flood and Pacas, 2016).

The ASEC stands for Annual Social and Economic Supplement, which is the source of timely official national estimates of poverty levels and rates and of widely used measures of income. It provides annual estimates based on a survey of more than 75,000 households (Flood and Pacas, 2016). The ASEC supplement has been used by many economists when studying minimum wage and poverty; however, using the ASEC supplement has a few limitations in my study. Sabia and Nguyen (2017) also used the supplement and noted that there is an underreporting problem with individuals reporting whether or not they received public assistance.

2.2.2 Sample

I manipulate the CPS data to contain the sampling units, observations, and variables to test the effects of increasing minimum wage. I restrict my data set to only include my cities of interest, San Francisco, San Jose, and Oakland, and years 2009-2012. In addition, I also restrict the population to that of working age individuals between 16-65. The outcome variable of interest is enrollment in means-tested public assistance programs, which I will call welfare programs from this point on. The dependent binary variable is equal to 1 if the household is enrolled in either TANF or Medicaid and 0 otherwise. The regression estimates a linear probability model to predict the likelihood of an individual enrolling in welfare programs when the minimum wage increases.

Table 2.2 shows the descriptive statistics of the variables that I will use in my specification. Using independent t-tests to compare the means of the same variable between the treatment and control groups, I conclude that individuals who live in San Francisco are less likely to be married and have children, whereas the control group has more families. They are also more likely to be more educated and identify as Asian compared to the control group where more individuals identify as Black. Furthermore, we can see that 7% of the sample in San Francisco is enrolled in welfare programs compared to the control group which has 13% percent of the sample enrolled. The independent t-tests indicate that there are some systematic differences across treatment and control groups along these dimensions that I control for in my main specification.

Table 2.2
Descriptive Statistics

	San Francisco	Oakland & San Jose	P-Value
Welfare	0.0708 [0.00753]	0.134 [0.00753]	0
Percent Married	0.392 [0.0143]	0.5 [0 .011]	0
Children in Household	0.267 [0.0130]	0.491 [0 .011]	0
No Education	0.006 [0.00227]	0.0044 [0.0014]	0.524
High School Diploma	0.117 [0.009]	0 .197 [0.008]	0
Bachelor's Degree	0.339 [0.0139]	0 .244 [0.009]	0
Race: White	0.563 [0.015]	0 .554 [0.0109]	0.612
Race: Asian	0.333 [0.0138]	0 .298 [0.010]	0.037
Race: Black	0 .035 [0.005]	0.107 [0.006]	0
Percent Male	0.558 [0.014]	0 .497 [0.011]	0.0009
Age	39 [0.30034]	38 [0.380]	0.2331
Employment	0.703 [0.0134]	0.645 [0.0106]	0.0009
Median Income	$30,415 [2,246]	$23,000 [1,251]	0

Note: Means and standard errors in parentheses calculated from IPUMS-CPS.

Econometric Specification:

To analyze the effects of increasing minimum wage in San Francisco and to determine the effect it has on the enrollment in the public assistance programs of interests, I will employ a linear probability model using a difference-in-difference estimation. This estimation allows me to identify whether San

Francisco's minimum wage increases have a direct effect on the enrollment in welfare programs.

A difference-in-difference estimator is a quasi-experimental design used to evaluate the impact of a program or treatment on a population (Stock and Watson, 2011). A stylized version of the model I use in my study is:

1) $Welfare_{it} = \alpha + \beta_1 San\ Francisco_{it} + \beta_2 Year_i + \beta_3 (San\ Francisco * Year = 2011)_{it} + \beta_4 (San\ Francisco * Year = 2012)_{it} + \varepsilon_i$

The outcome $Welfare$ is a binary dependent variable that measures the enrollment in welfare programs and equals 1 if the individual *i* is enrolled in either TANF or Medicaid in year *t* and 0 otherwise. $\beta_1 San\ Francisco_{it}$ identifies the average difference in enrollment between those who live in San Francisco, the "treated group", and those that live in San Jose or Oakland, the "control group". The binary variable $San\ Francisco_{it}$, distinguishes the treatment group from the control group: it equals 1 if the individual lives in San Francisco and 0 if they live in San Jose or Oakland. The individuals are observed over two time periods, $\beta_2 Year_i$ where 0 indicates that the year is 2009 or 2010, the time before the treatment group receives the treatment. Conversely if it is 2011 or 2012, after the treatment group receives the treatment it equals 1. Finally, ε_i is the error term.

The first coefficient of interest, β_3, is the coefficient on the interaction between $San\ Francisco_{it}$ and an indicator variable equal to 1 in year 2011, which is the true effect of the treatment of the 13 cent minimum wage increase in 2011. The second coefficient of interest, β_4, is the coefficient on the interaction between $San\ Francisco_{it}$ and an indicator variable equal to 1 in year 2012, which is the true effect of the treatment of the 45 cent minimum wage increase in 2012.

Let $\bar{Y}_0^{SF}$ and $\bar{Y}_1^{SF}$ be the sample averages of the outcome for the treated group before and after treatment, and let $\bar{Y}_0^{SJ\&OAK}$ and $\bar{Y}_1^{SJ\&OAK}$ be the corresponding sample of the outcomes for the control group. The difference-in-difference estimator is defined as the difference in the average outcome in the treated group before and after the treatment, minus the difference in the average outcome in the control before and after the treatment (Stock and Watson, 2011):

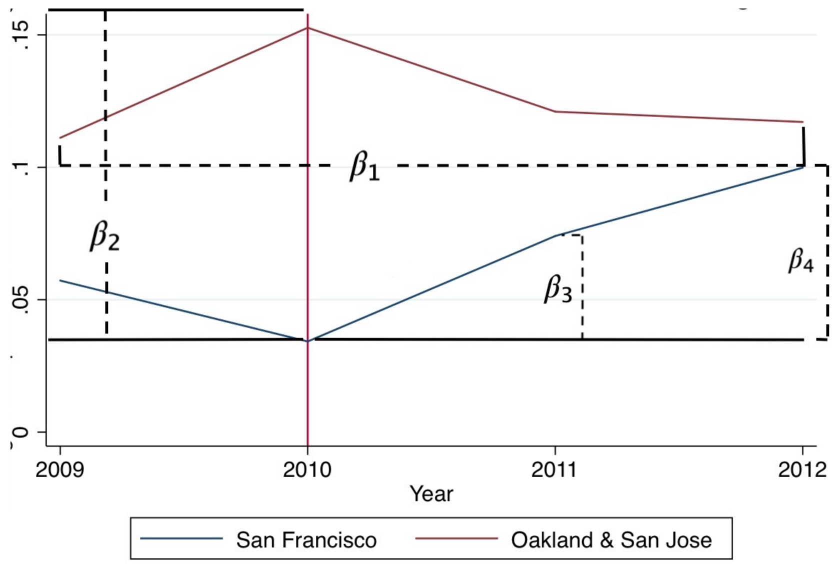
2) $\beta_3 or\ \beta_4 = \bar{Y}_1^{SF} - \bar{Y}_0^{SF} - (\bar{Y}_1^{SJ\&OAK} - \bar{Y}_0^{SJ\&OAK})$

The estimator is understood as the difference between two estimators, one before the treatment and one after the treatment is in effect (Stock and Watson, 2011). The stylized estimator above subtracts the control group's estimator, which captures the time trend β_2 in equation 1, from the treatment group's estimator to get β_3 and β_4 for each respective year that the minimum wage increased in San Francisco. In Figure 1, we can see the difference in San Francisco over time between the two estimators captured in β_3 and β_4.

The difference-in-difference estimator is reliant on a key assumption called the parallel trends assumption to ensure that the estimator is not biased (Stock and Watson, 2011). In the absence of treatment, the difference in the outcome variable, enrollment in welfare, between the treatment and control group are constant over time.

Figure 2.1

Average Participation in Means-tested Welfare Programs



Note: Average enrollment in treatment and control groups from 2009-2012, authors calculations using IPUMS-CPS.

To ensure that my estimator is unbiased, the parallel trends assumption must hold. Figure 1 demonstrates the parallel trends assumption where in the absence of the treatment, the difference between the treatment and control group must be constant, but is not in the case of welfare participation. This is a clear threat to my identification. Later in the paper, I discuss potential reasons that this assumption may not hold.

A further assumption is uncorrelated errors. To control for the systematic differences across my sample, I will be adding controls such as race, sex, education, age, marital status and fixed-effects. The complete model with the controls is as follows:

3) $Welfare_{it} = \alpha + \beta_1 San\ Francisco_{it} + \tau_t + \beta_3(San\ Francisco * Year = 2011)_{it} + \beta_4(San\ Francisco * Year = 2012 + \delta Demographics_{it} + \eta_l + \varepsilon_i$

The vector $Demographics_{it}$ includes an individual i's age and age squared, dummy variables that identify race, educational attainment, sex, marital status, and parental status at time *t*. Race is a sociopolitical construct and is not scientific or anthropological, therefore, I only created dummies for White, Black, and Asian and do not include Hispanic or Latinx in this study. I breakdown educational attainment into three dummies: no education, high school education, and college education where each one indicates the highest level of education attained according to the dummy that is defined. Marital status is a binary variable equal to 1 if an individual is married, and 0 otherwise. Parental status is a binary variable equal to 1 if the individual has any children in their household and, and 0 otherwise. Previous studies like Sabia and Neilson (2015) and Lopresti and Mumford (2016) find that males who are White, single, obtain a college degree, and have no children are the least likely to enroll in means-tested public assistance programs.

In an additional step that I take to ensure that my model is unbiased, I also include year and county level fixed effects, to control for any unobserved heterogeneity similar to Dube et al. (2010). Year fixed-effects, τ_t, control for variation in enrollment across years between 2009-2012, and can help rule out biases associated with legislation passed in the time period of my sample. They control for anything that changes over time, but affects the treatment and control groups the same, such as legislation. The addition of county fixed-effects, η_l, will also help control for variation across enrollment across San Francisco, Oakland and San Jose that is consistent over time.

There are contradicting predictions that arise from my empirical specification and theoretical models described earlier in this paper when measuring the effect of minimum wage increases on the enrollment in means-tested public assistance programs. On the one hand, theoretical models predict that minimum wage increases would steer more individuals away from public assistance programs by increasing wages or the incentive to work. On the other hand, other theoretical models predict that minimum wages would increase participation in public assistance programs by increasing unemployment. Prior empirical research suggests that minimum wage increases do not reduce employment which would increase enrollment (Neumark and Wascher, 2000 and Sabia et al.,2015).

Chapter 3

Results and Analysis

Table 3.1 shows the difference-in-difference estimation on welfare and the effect of increasing minimum wage at city-wide level in San Francisco. The results in Table 3.1 are from a linear probability model of how enrollment in welfare programs is affected by the increase of minimum wage in 2011 and 2012 in San Francisco compared to Oakland and San Jose. The standard errors in all the regressions in Table 3.1 are clustered around household ID and are robust.

Column (1) estimates the treatment effect of the minimum wage increase in San Francisco in 2011 and 2012, on the enrollment of welfare programs. The first coefficient of interest estimates the treatment effect of the 2011 minimum wage increase in San Francisco where the probability of enrolling in welfare increases by 4.5 percentage points and is insignificant at the 5% level. The second coefficient of interest estimates the treatment effect of the 2012 minimum wage increase in San Francisco where the probability of enrolling in welfare increases by 7.6 percentage points and is significant at the 5% level. On average, if the individual lives in San Francisco they are 9.4 percentage points less likely to be enrolled in a welfare program compared to Oakland and San Jose. This difference is statistically significant at the 1% level.

There appears to be a positive relationship between San Francisco's minimum wage increase and the enrollment of public assistance programs from the regression in column (1). However, in order to ensure that the estimation is not biased, I add demographic controls such as race, sex, and age to the regression as well as other characteristics like marital status, parental status, and education.

Column (2) of Table 3.1 estimates the same model as column (1), but contains demographic controls. The addition of the controls increases the magnitude of the first coefficient of interest to 5.2 percentage points and is significant at the 10% level. We also see an increase in magnitude of the second coefficient of interest to 8.2 percentage point increase and is significant at the 1% level. The estimated coefficients of demographic controls are also consistent with the results of previous studies regarding minimum wage and welfare programs (Sabia and Neilson, 2015). Males who are older and have bachelor's degrees are less likely to enroll in public assistance programs. Furthermore, marital status, sex, and age are negatively correlated with enrollment whereas education and race are positively correlated with enrollment.

I also add county and year level fixed-effects in order to control for any biases that occur across the cities and years in my sample. Column (3) in Table 3.1 demonstrate that the addition of county fixed-effects do not change the magnitude of the coefficients of interest or their significance levels. Column (4) includes year and county fixed-effects change the magnitudes of the coefficients of interest to some extent. The magnitude of first coefficient of interest suggest that the minimum wage increase increases the enrollment in welfare programs by 5.5 percentage points and is significant at the 10% level, whereas the second coefficient of interest increases the enrollment by 8 percentage points compared to 8.2 percentage points and is now significant at the 5% level. The insignificance of the county fixed-effects can indicate that variation across counties in my sample do not explain the changes in welfare enrollment. Conversely, the addition of year fixed-effects demonstrate that variation across years are significant as the magnitudes and significance levels of my coefficients of interest change. Thus, there is strong evidence that suggests the 2012 minimum wage increase of 45 cents in San Francisco increased enrollment by 8 percentage points, which is almost doubling the enrollment by 2012, and is statistically significant at the 5% level. Furthermore, there is evidence that the 2011 minimum wage increase of 13 cents in San Francisco are not as significant compared to the minimum wage increase in 2012 to affect the enrollment of welfare programs.

3.1 Robustness Checks

The previous section finds a positive impact of minimum wage on enrollment and that the magnitude is stronger if the increase is higher. To further explore the robustness of my estimation, I run additional regressions and Table 3.2 presents those results.

Column (1) of Table 3.2 presents the same model used in Table 3.1 column (4), but the sample is restricted to only San Francisco and Oakland, whereas column (2) of Table 3.2 is restricted to only San Francisco and San Jose. In column (1) the first coefficient of interest suggest that the minimum wage increase, increased the probability of enrollment by 4.2 percentage points in 2011 and is not significant, whereas the second coefficient of interest increases enrollment by 1.4 percentage points and is also not significant. Compared to column (2), the first coefficient of interest increases the probability of enrollment by 5.8 percentage points and is significant at the 10% level, and the second coefficient of interest increases the probability of enrollment by 11.1 percentage points and is significant at the 1% level. Here, it is clear that when the sample is limited to two cities, the effect of increasing minimum wage is stronger and more significant when comparing San Francisco and San Jose than comparing San Francisco and Oakland. The results are striking when comparing San Francisco to each individual city in the control group, but could be explained by the fact that Oakland only has 655 individuals compared to San Jose which has 1,395 individuals.

In the theoretical models described earlier in this paper, minimum wage has ambiguous effects on employment and in terms of public assistance programs. Another analysis that I run to further investigate the effect of increasing minimum wage on public assistance programs is by looking at employment. In Table 3.2 column (3), I run the same regression as I did in Table 3.1 column 4, but employment is the binary dependent variable. In this model, both coefficient of interest of each year that the minimum wage increased, increased the likelihood that the individual is employed by .2 to 1.9 percentage points, but is not statistically different from 0. Theoretically, minimum wage increases might induce unemployment which is evident in the model of minimum wage in a competitive labor market described by Brown (1999). In turn, this could increase enrollment in public assistance programs. However, my results demonstrate that this increase of a minimum wage does not negatively affect employment. The individuals who have at least a college degree are more likely to be employed and is significant at the 1% level, which can be expected from previous empirical studies (Sabia and Neilson, 2015). These results also conform with the predictions from the labor market as a monopsony where firms can only retain the most qualified and skilled workers. Employers in this situation might be more likely to lay off workers who are less educated, but because their supply curve is often close to infinite, the firm may not have to lay off any workers at all.

Next, in Table 3.2 column (4), uses the same model in column (1), but uses logged income as the continuous dependent variable. In this model, both coefficients of interest generate a positive increase, but are not significantly different from 0. The effect of minimum wage increases on income is insignificant which could indicate that the increases are not enough to make individuals wealthier. This could help explain the increase of enrollment in welfare programs, despite the increase in minimum wage. From Moffitt's (2003) model of the net present value of TANF enrollment, we could predict that enrollment would decrease because the wage differential would also decrease when minimum wage increased. The decreasing wage differential would increase the opportunity cost of participating in human capital programs that are required to receive TANF benefits, making it more appealing for individuals to leave the program and work more hours or full time. The model in column (4) of Table 3.2 illustrates that the income of individuals did not increase because of the minimum wage increases, and because these individuals did not see a change in their total income as a result of minimum wage increases, they might be more inclined to enroll in welfare programs.

Table 3.1
Regression Results—Welfare Dependent Variable, CPS Data 2009-2012

	(1) Welfare	(2) Welfare	(3) Welfare	(4) Welfare
SF* Year=2011	0.0453	.0523*	.0523*	.055*
	[.0294]	[.0282]	[.0282]	[.0309]
SF* Year=2012	.0762**	.0826***	.0826***	.08**
	[.0322]	[.0312]	[.0312]	[.0332]
San Francisco	-.0946***	-.0731***	-.0742***	-.0746***
	[.0218]	[.0207]	[.0242]	[.0242]
Year as Two-period Time Trend	-0.0199	-0.0214	-0.0214	
	[.0192]	[.0185]	[.0185]	
Marital Status		-.0444***	-.0445***	-.0443***
		[.0168]	[.0167]	[.0167]
Children in the Household		.055***	.0551***	.0553***
		[.0205]	[.0205]	[.0206]
No Education		.343**	.343**	.344**
		[.144]	[.144]	[.144]
High School Diploma		0.0163	0.0163	0.0162
		[.02]	[.02]	[.0198]
Bachelor's Degree		-.0608***	-.0608***	-.0606***
		[.0131]	[.0132]	[.0131]
Race: White		-0.0459	-0.0458	-0.0464
		[.0398]	[.0399]	[.0402]
Race: Asian		-0.0189	-0.0188	-0.0192
		[.0407]	[.041]	[.0412]
Race: Black		0.0756	0.0751	0.0747
		[.0501]	[.0496]	[.0498]
Sex		-.0294***	-.0294***	-.0294***
		[.00956]	[.00956]	[.00958]
Age		-.0164***	-.0164***	-.0165***
		[.00359]	[.0036]	[.00361]
Age^2		.000193***	.000193***	.000193***
		[.000043]	[.0000431]	[.0000432]
County Fixed-Effects	No	No	Yes	Yes
Year Fixed-Effects	No	No	No	Yes
Constant	.144***	.498***	.499***	.493***
	[.0171]	[.0771]	[.0782]	[.0769]
N	3209	3209	3209	3209
R^2	0.012	0.063	0.063	0.064

Note: Means and standard errors are robust in parentheses calculated from IPUMS-CPS and are clustered around Serial ID

$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 3.2
Regression Results--Robustness Checks, CPS Data 2009-2012

	(1) Welfare	(2) Welfare	(3) Employment	(4) Logged Income
SF* Year=2011	0.0422	.0587*	0.00273	0.0152
	[.0452]	[.034]	[.0391]	[.306]
SF* Year=2012	0.0142	.111***	0.0193	0.227
	[.0478]	[.0348]	[.0431]	[.352]
San Francisco	-.058**	-.0892***	0.0462	.536**
	[.0277]	[.0239]	[.0327]	[.247]
Marital Status	-.0469**	-.0513***	0.0273	0.0532
	[.021]	[.0185]	[.0229]	[.173]
Children in the Household	.0608**	0.0363	-0.0178	-.444**
	[.0267]	[.0228]	[.0243]	[.179]
No Education	.569***	.308*	-.305*	0.598
	[.147]	[.17]	[.159]	[.645]
High School Diploma	0.0176	0.00752	-0.0415	-0.111
	[.0251]	[.0234]	[.0261]	[.192]
Bachelor's Degree	-.0517***	-.0594***	.086***	.951***
	[.0157]	[.0146]	[.0194]	[.152]
Race: White	-0.017	-0.0755	0.053	0.284
	[.0364]	[.0468]	[.0497]	[.312]
Race: Asian	0.0262	-0.0586	0.0226	-0.172
	[.0415]	[.047]	[.0514]	[.337]
Race: Black	.0974*	0.0236	-0.00813	0.21
	[.0508]	[.0653]	[.0621]	[.423]
Sex	-.0243**	-.0291***	.0896***	.958***
	[.011]	[.0111]	[.0193]	[.135]
Age	-.014***	-.0113***	.0586***	.661***
	[.00471]	[.00382]	[.0061]	[.0393]
Age^2	.000158***	.00014***	-.000717***	-.00736***
	[.0000552]	[.0000464]	[.0000724]	[.000477]

Table 3.2
Regression Results--Robustness Checks, CPS Data 2009-2012
(Continued)

	(1) Welfare	(2) Welfare	(3) Employment	(4) Logged Income
County Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
Constant	.41*** [.0957]	.436*** [.0815]	-.51*** [.123]	-5.31*** [.784]
N	1814	2554	3076	3200
R2	0.089	0.053	0.098	0.222

Note: Means and standard errors are robust in parentheses calculated from IPUMS-CPS and are clustered around Serial ID
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2 Commuting Issues

Another reason to have San Jose and Oakland in my control group is to account for mobility. San Francisco is a very commutable city if one lived outside of it, one could easily commute in for work, school, or other opportunities. Highways and public transit like BART (Bay Area Rapid Transportation) or Caltrain could easily get you to San Francisco in a reasonable amount of time. Examining these two other cities is important because they are very similar in regards to size and demographics, but these two cities did not experience minimum wage increases in our time frame of interest. When San Francisco's minimum wage increased, individuals who live in the surrounding area including San Jose and Oakland may to commute to work for higher wages.

To further examine the potential biases that come with commuting, I test the probability of commuting after the minimum wage increase in San Francisco after 2011 using cross-sectional data from IPUMS USA that sources data from the

American Community Survey (ACS). The ACS is an ongoing survey conducted by the U.S. Census Bureau that provides estimates of selected social, economic, and housing characteristics of the population for many geographic areas and subpopulations, which makes the ideal dataset to estimate the probability of commuting in to San Francisco for work (Torreiri, 2014). I limit my sample according to the same restriction I did with CPS. However, as I limit my sample, the observations recorded in 2012 are dropped because the commuting data is missing for 2012. Furthermore, this sample is restricted to who work in San Francisco.

I use a linear probability model using an OLS estimation and the model is as follows:

$$Commuting_{it} = \alpha + \beta_1 Year_{it} + \delta Demographics_{it} + \tau_t + \eta_l + \epsilon_{it}$$

Where $Commuting_{it}$ is equal to 0 if the individual lives in San Francisco and does not need to commute and 1 if the individual lives outside of San Francisco in Oakland or San Jose and commutes to work. The individuals are observed over two time periods, $\beta_1 Year_i$ where 0 it indicates that the year is 2009 or 2010, and 1 if the year is 2011 which indicates the year of the minimum wage increase in San Francisco. The vector $Demographics_{it}$, describes the same demographics that I used in my difference-in-difference estimation from my previous models. I include the same fixed-effects at the year and county, τ_t and η_l, to control for any biases that occur across the cities and years in my sample. Finally, ϵ_{it} describes the error term.

Table 3.3 presents the results from the commuting linear probability model that are robust and clustered around serial IDs. In column (1) of Table 6, the time trend after the minimum wage increase in San Francisco would increase the probability of commuting by 0.008 and is not significant. As I add my controls and fixed-effect, the coefficient of the time trend continues to get smaller and remains insignificant. The insignificance of the time trend indicates that the commuting patterns did not change in response to the minimum wage increase in San Francisco.

Table 3.3
Regression Results—Commuting Dependent Variable, ACS Data 2009-2011

	(1) Commuter	(2) Commuter	(3) Commuter	(4) Commuter
Year Time Trend	.00874	.00577	8.68e-18	
	[.0244]	[.0244]	[1.97e-17]	
Year Fixed-Effect Dummy 2010				3.43e-17*
				[1.80e-17]
Year Fixed-Effect Dummy 2011				2.67e-17
				[1.80e-17]
Marital Status		.0126	5.03e-17**	4.91e-17***
		[.026]	[2.13e-17]	[1.87e-17]
Children in Household		-.0195	-3.16e-17	-2.01e-17
		[.0281]	[2.42e-17]	[2.11e-17]
No Education		-.0693***	-4.94e-17	-2.48e-18
		[.0201]	[5.75e-17]	[4.99e-17]
High School Diploma		-.0169	-3.94e-16***	-3.98e-16***
		[.0287]	[5.96e-17]	[5.58e-17]
Bachelor’s Degree		.0631***	-7.32e-17***	-1.01e-16***
		[.0236]	[1.67e-17]	[1.26e-17]
Race: White		-.0358	-1.28e-17	1.19e-17
		[.0437]	[3.54e-17]	[3.05e-17]
Race: Asian		-.0567	4.12e-18	3.96e-17
		[.0457]	[3.82e-17]	[3.28e-17]
Race: Black		.238***	6.39e-17	5.77e-19
		[.0915]	[5.65e-17]	[5.28e-17]
Sex		-.00825	2.00e-16***	2.03e-16***
		[.0174]	[1.72e-17]	[1.59e-17]
Age		.00581	-4.12e-17***	-4.03e-17***
		[.00595]	[5.52e-18]	[4.83e-18]
Age^2		-.0000558	4.68e-19***	4.53e-19***
		[.0000696]	[6.28e-20]	[5.54e-20]
County Fixed-Effects	No	No	Yes	Yes
Constant	.0949***	-.0303	1***	1***
	[.013]	[.122]	[1.20e-16]	[1.04e-16]
N	931	931	931	931
R^2	0.000	0.051	1.000	1.000

Note: Means and standard errors are robust in parentheses calculated from IPUMS-CPS and are clustered around Serial ID
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3 American Reinvestment and Recovery Act

As previously stated, there are some threats to my identification strategy as the parallel trend assumption does not hold. The difference of enrollment in welfare programs between the control and treatment group are not constant before the minimum wage increase. I account for this threat by considering the American Reinvestment and Recovery Act (Recovery Act) that passed in 2009 that may bias my results.

The Recovery Act was signed into law by President Obama on February 17th, 2009 (American Recovery and Reinvestment Act, 2009). It was the response to the 2008 recession to promote economic recovery and growth. The Act includes measures to modernize infrastructure, enhance energy independence, expand educational opportunities, preserve and improve affordable health care, provide tax relief, and protect those in greatest need (Lav et al., 2009). This legislation extended the time allowed on TANF for those nearing the end of their benefit schedule and extended Medicaid to more Americans. A report by the Center on Budget and Policy Priorities explains how the Recovery Act effectively distributed additional funds from the federal government to state governments to increase spending on Medicaid.

Lav et al. (2009) explain how states could receive increased Medicaid funding. The federal government reimburses states between 50-83% of their Medicaid expenditures, as determined by the Federal Medical Assistance Percentages (FMAP) (American Recovery and Reinvestment Act, 2009). Each federal fiscal year, states' FMAPs are recalculated based on the three-year average of each state's per capita personal income relative to the national average, with poorer states receiving higher reimbursement rates. Thus, states that have lower average incomes, more recipients of Medicaid per capita, or more generous benefits receive larger per capita matching funds from the federal government.

The Recovery Act made a three changes to the baseline FMAP calculation for October 2008 through December 2010 in order to expand eligibility (Lav et al., 2009). First, the baseline FMAP could not decrease. Second, the FMAP was temporarily increased by 6.2 percentage points above the baseline for every state. Finally, through December 2010, each state received a further increase in its FMAP based on the largest increase in its unemployment rate experienced between the trough three-month average since January 2006 and the most recently available three-month average. To qualify for the Recovery Act provisions, states had to maintain the eligibility standards, methodologies, and procedures of their Medicaid programs that existed on July 1, 2008. The law also forbade states from increasing the share of the non-federally financed portion of Medicaid spending by local governments, in effect extending the fiscal relief to local governments. Lav et al. (2009) point out that assistance is well targeted because the federal government sent more funds to states with greater needs to provide greater assurance that states will spend the funding on the healthcare needs of low-income households and the newly unemployed.

The additional Medicaid funds are given to states to appropriately distribute to municipalities that are in need of additional funds due to the 2008 recession. This could potentially bias my results if San Francisco, San Jose, or Oakland were effected differently by the 2008 recession. If San Francisco was hit harder by the recession in 2009 compared to San Jose or Oakland resulting in higher unemployment rates, the Recovery Act would bias my results downward. Alternatively, if San Francisco was hit harder by the recession in 2011 and 2012, the Recovery Act would bias my results upwards.

A study by Chodorow-Reich et al. (2012) demonstrates the distribution of additional Medicaid and examined the effects of employment after the Recovery Act was enacted. Their research assesses the impact of the Recovery Act's Medicaid match program across different states using an OLS estimation with an instrumental variable. They find that the Recovery Act's transfers to states had an economically large and statistically robust positive effect on employment. Their estimation suggests that a marginal $100,000 in Medicaid transfers resulted in 3.8 net job-years of total employment through June 2010. In a similar study by Dupor (2013) using a similar specification, he finds that the Recovery Act's emergency Medicaid grants were approximately as effective or even less effective than the Recovery Act's broadly-directed spending on jobs.

The results demonstrate that reforms like the Recovery Act affected enrollment in Medicaid and employment after the recession in 2008, which leads me to speculate it impedes my parallel trends assumption. If San Francisco received a larger share of additional Medicaid funds due to higher unemployment rates, my coefficients of interest are underestimating the effects of minimum wage increases on the enrollment of public assistance programs.

Conclusion

My study has examined the effect of increasing minimum wage at a city-wide level on the enrollment of public assistance programs, using a difference-in-difference estimation. The theoretical predictions regarding employment in a labor market where minimum wage is present is ambiguous and depends on the structure of the labor market and the level of the wage floor. Using data from 2009-2012 from CPS's ASEC supplement and exploiting San Francisco's minimum wage increase in 2011 and 2012, this study has found that both years of the minimum wage increase, increased enrollment in means-tested public assistance programs. These results indicate that increasing minimum wage does not the decrease enrollment in welfare programs in previous studies like West and Reich (2015) where increasing minimum wage had the reversed effect of decreasing enrollment of SNAP.

The theoretical model of a perfectly competitive labor market when minimum wage is present or increased predicts an excess supply of labor as firms must hire workers at the minimum wage floor above market equilibrium, generating unemployment in the labor market. Therefore, the minimum wage could positively affect enrollment in means-tested public assistance programs as more individuals would no longer have a source of income and would need to rely on government assistance to make ends meet. In contrast, the theoretical model of a monopsony labor market predicts that firms are likely to hire more workers, depending on their elasticity of labor supply, at the new minimum wage as firms would collect a smaller profit. While minimum wage might increase enrollment in public assistance programs in a competitive labor market due to an increase in unemployment, minimum wage would have the opposite effect in a monopsonistic labor market. As a result of the increase of employment, enrollment in means-tested public assistance programs would decrease as some individuals earn an income that exceeds the income limits for public assistance eligibility.

Using a linear probability model and a difference-in-difference estimation, I find that a 13 cent increase of San Francisco's minimum wage in 2011 generated a 5.5 percentage point increase and is significant at the 10% level. In addition, the minimum wage increase of 45 cents in 2012 generated an 8.0 percentage point increase in enrollment of welfare programs in the short-run and is statistically significant at the 5% level. The effect of the 2012 minimum wage increase suggests that it doubles the number of individuals enrolled in welfare programs.

With additional robustness checks running the same regression with employment and logged income as the outcome, we can see that my results conform with some of the predictions from the assumptions of the monopsonistic labor market. The effect of the minimum wage increase in San Francisco increased employment and income, but the impact is not statistically significant.

These robustness checks are consistent with Card and Kruger (1994) and Dube et al. (2007). The minimum wage increase did not negatively affect employment as the increased costs were absorbed in consumer prices (Allegretto and Reich, 2017; Card and Kruger, 1994). Furthermore, these results also consider any "border effects" like Allegretto and Reich (2017) as the minimum wage increase did not prompt more individuals to commute from outside of San Francisco to work at more competitive wages.

If a motivation to increase minimum wage is to alleviate poverty, my results illustrate that it may not be an effective tool as enrollment in public assistance programs increases (Sabia and Nielson, 2015; Sabia and Nguyen, 2017; Neumark and Wascher, 2002). Neumark and Wascher's (2002) findings from their CPS data that poor families escape poverty and non-poor families fall into poverty make it difficult to confirm that minimum wage can alleviate poverty.

One limitation of my study is that I use repeated cross-sections of the CPS ASEC supplement for my data set, which does not allow me to track the specific individual from year to year. My results cannot point out exactly how much of the increase consist of new enrollees or previous participants that remained in the program. Sabia and Nielson (2015), Sabia and Nguyen (2017) and Neumark and Wascher (2002) all exploit the panel nature of their data sets to specifically find the exact number of individuals leaving and enrolling in welfare programs. Another limitation of my study is that legislation like the Recovery Act may bias my results downward or upward depending on how San Francisco was effected by the recession in 2008. A suggestion for further study is to include a variable in my difference-in-difference estimation that captures the effects of additional Medicaid and TANF funds from the Recovery Act.

An additional area for further study is “border effects”. Allegretto and Reich (2017) mention a crucial question for city-wide minimum wage policies concerns how individuals and firms in surrounding cities respond. Are individuals who live in the treatment city likely to move out because of rising prices that accompany minimum wage increases? Or are more individuals who live in surrounding cities likely to move in because of higher wages? Allegretto and Reich (2017) have provided the only evidence regarding “border effects”, but it would be useful to expand on this topic especially in regards to public assistance.

This study concludes that increasing minimum wage also increases the enrollment of public assistance programs. There are only a handful of studies that research the effect of minimum wage at a city-level and an even smaller number of studies that directly study the effect of minimum wage on enrollment in public assistance programs. A suggestion for further study is to expand the size of the sample using a panel dataset that includes detailed information about employment, public assistance programs, and residency. The panel nature of SIPP would make it an ideal data set, however, it does not have information regarding the city where individual resides. The ideal dataset would be a linked dataset with SIPP to contain information on enrollment of public assistance programs and municipal residency. Furthermore, data on legislation like the Recovery Act would strengthen my results.

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