The Effects of the Minimum Wage on Social-Safety-Net Dependence Over Time

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Abstract

Although there is much research on the effects of minimum wage increases on workers and low-income families, there is little that investigates how these effects persist or dissipate over time. Using an event-study specification, I investigate how minimum-wage changes affect family incomes at various multiples of poverty, as well as eligibility for and participation in the Supplemental Nutrition Assistance Program (SNAP). I compare the latter effect to that obtained from a state panel regression approach used in previous literature. I find evidence that minimum-wage increases reduce the prevalence of low family income and SNAP participation, but that these effects dissipate by 5 quarters post-increase. At its peak, the effect on SNAP participation is similar in size to that obtained from a state-panel specification.[1]

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1 Introduction and Literature Review

The question of raising the minimum wage is hotly debated in politics today. On its face, the effect of a higher minimum wage is simply to increase the hourly wage of the low-wage workers for whom it is binding. However, some fear that minimum-wage increases may have harmful effects on labor demand, ultimately reducing income and increasing poverty among those the minimum wage is intended to help.

The question of how the minimum wage affects the income distribution is relevant not only in itself, but because of how it may affect the social safety net. Eligibility for social safety net programs is typically based on income, among other factors. Thus, to the extent that increases in the minimum wage boost income for needy households, we should expect them to reduce participation in social safety net programs. If the minimum wage does increase income for low-income households, therefore, the reduction in government expenditures on the social safety net could represent a further benefit of increasing the minimum wage.

A further important consideration regarding this question is the time span of the effects of minimum-wage increases. If minimum-wage increases produce long-term gains in income, and this leads to independence from the safety net, that may be considered cause to prioritize the minimum wage from a policy standpoint. If, however, its effects quickly dissipate – or worse, have long-term harmful effects on income and safety-net dependence by accelerating the automation of low-wage workers' jobs – that could be a serious flaw in the minimum wage as a policy.

Despite the importance of the potential dissipation of effects over time, there is little research on the impact of minimum-wage increases over time – and none that focuses on the income distribution or social safety net programs. To fill this gap, I use an event-study approach to examine the effects of a minimum wage increase over time in the period following the increase.

In a typical event study at the state level, the level of the dependent variable in a state is measured at each time increment before and after that state experienced an event (in this case, a minimum wage increase). These trends are combined for states that experienced events at different times (with event times aligned such that, for example, states 1 quarter post-increase are all considered together), and compared to those that did not experience an event. This helps to eliminate omitted variable bias that may occur if we study time trends within a single state. In the case of the minimum wage, one obstacle to the use of event studies is that multiple minimum-wage increases may occur in the same state or region in quick succession. To overcome this, I use Sandler and Sandler's (2014) multiple event study methodology (described in more detail below) to account for the possibility of multiple minimum-wage changes in a single state. This allows me to take advantage of all changes in the binding minimum wage of one or more states, whether from a state- or federal-level law change.

I further examine how changes in the income distribution may affect social safety net program participation by running the same specifications to measure the effect on participation in one particular safety-net program. Because of its widespread usage and broad eligibility standards, my chosen program is the Supplemental Nutrition Assistance Program (SNAP). I find that, while increasing the minimum wage reduces poverty and near-poverty for about a year after the change, it does not affect SNAP participation.

1.1 Overview of SNAP

SNAP, historically known as food stamps, is a federally-funded, state-administered program that provides households with benefits that they can spend on most kinds of food at grocery stores. In 2017, roughly 9.2% of US households were on SNAP for at least part of the year; these households included about 16.7% of US children. On average, each household received about $250 in monthly benefits from the program (Watson, 2019).

A household is eligible for SNAP if its income is below a certain cutoff specific to the number of people in the household. Households containing an elderly or disabled person face a more inclusive cutoff. These income limits are set each year by the federal government at 130% of the poverty line. However, states can set higher limits (up to 200% of the poverty line) through a process called broad-based categorical eligibility (BBCE), where households are automatically eligible for SNAP if they qualify for other designated programs with higher income limits. BBCE can also be applied to other state-level programs aimed at specific populations. For example, in Minnesota, the income limit for SNAP is set to 165% of the poverty line (Table 1a); in the 40 total states that use BBCE, income limits range from the minimum 130% to the maximum 200% (Table 1b).

Households eligible for SNAP must submit an application to the state government, and interview by phone or in person with a case worker who instructs applicants on supplying the proper documents to prove they qualify. Once accepted, the amount of benefits a household receives is based on its income; the closer it is to the cutoff, the lower the benefit amount. Households must re-apply for benefits each year.

1.2 Overview of Minimum Wage Effects

The most basic and direct impact of the minimum wage is to increase wages for those earning below it – thereby increasing income for them and their families. However, the minimum wage may also affect the markets for low-wage labor and the goods and services it produces. This may produce downsides: firms reducing the number of workers or labor hours they hire; lower corporate profits; or increases in the prices of goods produced by minimum-wage workers. In particular, a reduction in labor hours or employment may counteract some or even all of of the income-boosting effects of the wage increase itself; or cause some families to lose income while others gain it. Thus it is not clear *a priori* how many families will move out of poverty or SNAP eligibility in the aftermath of a minimum-wage increase; or how many others may move into these categories instead.

Another incentive that may change in response to a minimum-wage increase is on the labor supply side. A concern in designing social-safety-net programs is the possibility of creating a "welfare cliff". That is, if gaining a little bit of earnings decreases benefits received from social-safety-net programs by a large amount, it may actually decrease overall income, incentivizing recipients to keep their earnings low (potentially by working fewer hours). The federal eligibility requirements for SNAP include the requirement that SNAP recipients not voluntarily reduce their working hours. However, SNAP recipients affected by the welfare cliff may keep their hours lower through other means. For example, a worker may not seek out additional hours or shifts when the opportunity arises; may not look for a new job if their current employer cuts their hours; or may seek fewer hours when starting a new job. On the other hand, since SNAP benefits decrease steadily as household income approaches the maximum cutoff, rather than abruptly dropping to zero, this effect may not play a meaningful role in the case of SNAP.

Because of these possible factors, the effect of a minimum-wage increase on poverty or SNAP may not reflect the simple "mechanical" effect of the increase – that is, the change in poverty or SNAP that we would predict if we increased the hourly wages of minimum-wage workers while holding all else constant, including hours worked. In real life, hours worked may change in response to a minimum-wage increase, affecting total income. Moreover, not everyone who is eligible for SNAP receives it – some may be unaware that they have moved into eligibility, or the application process may act as a burden. Thus even a change in the income distribution in response to the minimum wage may not fully translate into a corresponding change in SNAP participation. Understanding these effects can help us evaluate minimum wage increases both in terms of the welfare impact on people at the margin of SNAP eligibility, and in terms of money potentially saved by the government on SNAP.

1.3 Employment, Hours, and Wage Spillover Effects of the Minimum Wage

Economic theory predicts that, if the labor market is competitive, imposing a binding minimum wage will decrease firms' demand for labor. If, however, firms have monopsony power in the labor market, it is possible to construct a theoretical framework in which a binding minimum wage will not reduce labor demand. Much of the empirical research on minimum wage laws, therefore, focuses on which of these scenarios more closely matches real-world markets – i.e., whether the minimum wage causes employers to reduce the labor they hire (e.g., Neumark, Schweitzer, and Wascher, 2004; Dube, Lester, and Reich, 2010). Other research focuses on related questions, such as the minimum wage's impact on poverty and the income distribution (e.g., Addison and Blackburn, 1999; Dube, 2019).

Early empirical minimum-wage research relied mostly on time-series methods, regressing a dependent variable (e.g., employment) on the national-level minimum wage before and after a change while controlling for macroeconomic trends. Neumark and Wascher (1992) provide a full review of this early literature. Time-series methods like this are used occasionally in more recent studies (e.g., Wolfson and Belman, 2004), but since the 1990s, researchers have mostly focused on more sophisticated strategies exploiting variation across space as well as time. One early example is Card and Krueger (1994), who use a "case study" difference-in-differences approach, comparing employment trends in nearby regions in New Jersey and Pennsylvania before and after New Jersey's minimum wage increased (while Pennsylvania's remained constant).

They find no significant effect. Similar results are found by Card (1992), who uses a similar case-study approach to study the minimum wage's effect on teen employment by comparing California (whose minimum wage increased) to a group of other states. Neumark and Wascher (1992) provides an early example of another now-common approach, the state-level panel regression with time and state fixed effects. They find that the minimum wage has a negative impact on hours worked (not people employed).

Since then, many studies have examined the employment and hours effects of the minimum wage using many strategies, and have found mixed results. Most studies find negative employment and hours elasticities with respect to the minimum wage. However, these are typically between 0 and -0.5, suggesting that reductions in employment and hours do not fully cancel out wage increases. Some studies (Neumark, Schweitzer, and Wascher, 2004; Clemens and Strain, 2017) exploit multiple state-level minimum wage changes to run difference-in-differences specifications with minimum-wage increases as treatments. Neumark, Schweitzer, and Wascher (2004) find employment elasticities of -0.12 to -0.17 immediately following a minimum-wage increase; they find no initial effect on hours conditional on remaining employed, but an elasticity of -0.2 to -0.25 one year later. Dube, Lester, and Reich (2010), meanwhile, obtain an overall labor demand elasticity of about -0.48. Sabia (2009) estimates a state-level panel regression with fixed effects; he finds that a 10% increase in the minimum wage leads to a 1% average decrease in both employment and hours. Clemens and Strain (2007) estimate employment effects for various age-and-education groups, finding employment reductions ranging from zero to about 2 percentage points in response to typical minimum-wage increases. Cengiz et al. (2019), however, using a bunching estimator approach based on the number of jobs above and below a new minimum wage, find no significant employment effects.

Some research disaggregates the employment and hours effects of the minimum wage by worker group. These studies generally find that those workers with the least education and experience see the greatest reductions in employment and hours. This is of particular importance in evaluating the welfare effects of the minimum wage, since these workers may be more or less likely to account for a large percentage of their families' income. Neumark, Schweitzer, and Wascher (2004) find that the employment and hours elasticities of the minimum wage vary widely across groups, and for the least educated groups, may have magnitude greater than 1 (indicating a reduction in earned income). Clemens and Strain (2017) run a triple-differences specification of the minimum wage's effects on employment and hours over skill level, and find that lower education and experience are associated with larger effects. In particular, the typical minimum-wage increase reduces employment by 1.6 to 2.1 percentage points for those under 25 without a high school diploma. Sabia (2008) finds no effect of a minimum wage increase on hours for single mothers in general, but for the least educated ones, a significant negative effect on hours that fully cancels out the increase in wages. A later study by Sabia (2009) finds an overall hours elasticity of -0.1 with respect to the minimum wage, but finds that this effect is largely driven by the effect on the least experienced workers. Similarly, in Meer and West's (2016) study of minimum wage increases and slowing job growth, they find that growth slows most dramatically in employment of younger workers and in low-wage industries.

The effects of the minimum wage extend beyond just minimum-wage earners. Many studies (Neumark, Schweitzer, and Wascher, 2004; Cengiz et al., 2019) find evidence of a spillover effect: when the minimum wage increases, the wages of those earning slightly more than the previous minimum wage also increase. Neumark, Schweitzer, and Wascher (2000) find that the spillover effect extends only to those near the minimum wage; higher earners' wages are not affected. Phelan (2019) also finds evidence of a spillover effect, and proposes a mechanism: a minimum wage increase is equivalent to a decrease in the compensating differentials for more undesirable jobs available to minimum-wage workers, reducing labor supply for those jobs and causing equilibrium wages to rise.

1.4 Effects on Income, Poverty, and Program Participation

The extent to which the effects of the minimum wage on individual earners will affect families depends whether affected workers' earnings represent a large portion of their families' income. If many minimum-wage earners are part-time teen workers whose parents earn substantially more money than they do, the effect on families may be negligible. However, the literature shows that these groups form the minority of all minimum-wage earners. 56% of workers earning at most the minimum wage are adults over 25, along with 60% of those earning at most 1.25 times the minimum wage. 9% of both groups are single mothers (Belman, Wolfson, and Nawakitphaitoon, 2015). One in every three minimum-wage workers is the only worker in their household (Leigh, 2008). This suggests that family earnings and income could be meaningfully impacted by minimum-wage increases.

Given the wide range of findings on employment and hours effects, it is not obvious how – and by how much – the minimum wage should affect income and poverty. If the employment elasticity for a particular worker group is -1 (that is, quantity scales down by exactly as much as wage scales up), then an increase in the minimum wage will have zero effect on overall earned income for this worker group, since the reduction in hours will exactly cancel out the higher wage. However, if this effect is primarily in the form of an employment effect (some workers lose their jobs and the remaining ones keep the same number of hours), it could nevertheless affect the poverty rate if those who lose their jobs enter poverty while those whose income increases stay out of it. These effects may be smaller or larger depending on if the employment elasticity with respect to the minimum wage is elastic or inelastic.

Compared to employment and hours effects, there are relatively few empirical studies that directly address the effect of the minimum wage on income, poverty, and the overall income distribution. Addison and Blackburn (1999) note that most previous work simply simulates the effect of the minimum wage on poverty by evaluating the effect of increasing workers' wages, without taking into account the possibility of other labor-market effects that may affect income. They run a state-level panel regression on logged minimum wage with time and state fixed effects, and find that raising the minimum wage by 10% reduces poverty by 5%; this result holds for teens as well as adults with low education.

Many other studies, however, have found less encouraging results. Vedder and Gallaway (2002) use a state panel approach, controlling for macroeconomic variables and federal transfers, to estimate minimum-wage effects on poverty for a number of sub-populations as well as the population as a whole. They find no significant effects in either direction. Leigh (2008) simulates the effect of a minimum wage increase on income, but takes into account employment effects by taking plausible numbers from existing literature; he also finds no significant effect. Neumark and Wascher (2002) provide a more detailed examination of these effects, using CPS microdata to estimate a model of individuals' probability of moving from poor to non-poor status or vice versa. They find that increasing the minimum wage produces about the same amount of movement in each direction, producing a zero effect in aggregate (although incomes do increase for those who remain poor). In a later study, Neumark, Schweitzer, and Wascher (2005) use CPS data following families over consecutive pairs of years, and run a difference-in-differences specification comparing those who lived in states that saw a minimum-wage increase to those in other states; they find no general trend toward increasing or decreasing incomes for treated households. They also run a state-level version of this specification studying changes in the fraction of people below a certain multiple of poverty. They find that minimum-wage states have more people overall below poverty in year 2, but fewer below 50% of poverty.

These results are contradicted by a recent paper by Dube (2019), who runs several state panel regressions of the proportion of families at several different multiples of the poverty line, with leads and lags of the minimum wage as well as time and state fixed effects and state-specific linear trends. Additionally, he runs an unconditional quantile regression of the income distribution using that same specification. He finds that the elasticity of the non-elderly poverty rate with respect to the minimum wage is between -0.22 and -0.46, and the elasticity of the tenth and fifteenth quantiles of family income are between 0.15 and 0.43, indicating that raising the minimum wage reduces poverty while boosting the tenth and fifteenth quantiles of income.

There is very little literature on the effects of the minimum wage on social safety net programs for low-income people. Only one paper (Reich and West, 2015) focuses on the impact of minimum wage on SNAP. Using a standard state panel approach including Census-division-specific year fixed effects, they find that a 10% increase in the minimum wage is associated with a 2.4-3.2% reduction in SNAP enrollment.

1.5 Event Study Methodology

The event study approach, which I use in this study, has been rarely used in existing minimum-wage literature. An NBER working paper by Adams, Meer, and Sloan (2018) provides one of the only examples of a minimum-wage study using an event-study specification with a full set of pre- and post-event dummies. In this paper, they study the effect of minimum-wage increases on labor-market search effort, using individual-level panel data. Their specification includes dummy variables representing, for each observation in their data, whether it is n months from a month in which the minimum wage goes up, where n ranges from -5 to 5 (the largest number they could choose without allowing event windows to overlap within states). They also include month and state-month fixed effects. They find large positive effects on search intensity immediately following an increase, but find that these effects quickly dissipate after the first month post-event.

One major advantage of an event-study specification in minimum wage research is that some literature points to the importance of the time scale over which the effects of the minimum wage take place. Neumark, Schweitzer, and Wascher (2004) find negative employment effects immediately following increases in the minimum wage, but find effects on hours only at a one-year lag. Moreover, they find that individual earned income increases immediately after an increase, but has decreased by a year later. Meer and West (2016), in a local-level panel regression studying employment effects of the minimum wage, find that the effects lessen over time but are still present as far as eight years post-increase.

Another benefit of event studies is that they provide a natural way of checking for pre-trends; that is, the possibility that one's dependent variable tends to trend upward or downward in the time leading up to events (indicating potential endogeneity). Multiple studies (Dube, Lester, and Reich, 2010; Allegretto et al., 2017) find evidence that this may bias results of minimum wage studies. Dube, Lester, and Reich (2010) address this by using a difference-in-differences estimator on border-county pairs; they find a labor demand elasticity of about -0.48, compared to an elasticity of -1 obtained from a traditional state panel regression. Event studies provide another way of addressing this issue (by yielding coefficients for the time periods leading up to events), while also providing information about effects over time.

1.6 Literature Gap

In this paper, I provide the first evidence on the effects of minimum-wage increases on the income distribution as those effects progress over time, rather than in a single period relative to the minimum wage increase. I also provide a link between the literature on income and poverty effects of the minimum wage and its effects on social safety net participation, by evaluating its effects on income at the margin of SNAP eligibility.

Measuring the progress of effects over time is important both from a policy perspective and an empirical measurement perspective. The benefits and costs of the minimum wage depend heavily on whether it produces long-term income increases for those at the low end of the income distribution, or whether it produces only immediate benefits that quickly fade (or become harmful). It is plausible, moreover, that the magnitude of the effect may differ depending on the time frame we choose to study. Labor markets may take time to adjust to the imposition of a minimum wage, as firms make and implement different decisions about factors of production to use. Thus measuring the contemporaneous effects of MW increases, or the effects lagged by a particular amount, may not fully capture a full picture of the effects. In this paper, I provide evidence on the effects of a minimum wage increase as they unfold over time.

Finally, my method allows for comparison between the effects of an increase on the income distribution and the effects on SNAP participation (which should theoretically be linked). Most previous studies on the minimum wage's effect on the income distribution have not addressed the subsequent effects on social safety net programs like SNAP. Meanwhile, studies that focus on SNAP (e.g., Reich and West, 2015) do not address the underlying changes in the income distribution that may produce the effect they find.

2 Economic Theory

2.1 The Minimum Wage and Workers' Income

My theoretical model begins with a model of how minimum-wage increases may affect workers' income, and thus poverty rates. This is loosely adapted from the model proposed by Fields and Kanbur (2007). They begin with a competitive labor market in which labor is a homogeneous input to production initially provided by identical workers at a market wage $w*$. There is a downward-sloping labor demand curve $D(w)$, defined such that $D(w*) = 1$. Suppose a minimum wage $\hat{w}$ is put into place, and we have $D(\hat{w}) = x$. Since D is downward sloping, we have $x < 1$, and a fraction $1 - x$ of the population is unemployed.

For poverty threshold z, a poverty index P_α is defined as

$$P_\alpha = \frac{1}{n} \sum_{i=1}^{q} \left(\frac{z - y_i}{z} \right)^\alpha$$

where there are n individuals in the population, of whom individuals 1 through q have income below the poverty line; and y_i is the income of individual i. When $\alpha = 0$, this simplifies to the so-called "headcount ratio" used to define the poverty rate in the United States and many other countries.

I expand this model to one including multiple time periods, where the labor market takes one period after a minimum-wage increase to respond to it.

- In period 0, the minimum wage is at w_1, and we have $D(w_1) = 1$. Each individual's earnings are w_1.

- In period 1, the minimum wage is increased to w_2, such that $D(w_2) = x < 1$.

However, the labor market does not respond in period 1; the same number of people are employed, and their earnings are w_2.

- In period 2, the labor market responds, and the quantity of labor demanded is x. Firms reduce labor partially by firing workers and partially by reducing the hours of the workers they keep. The parameter p represents what proportion of that is accomplished through hours reductions: the number of employees is multiplied by x^{1-p}, and hours for the remaining employees are multiplied by x^p.[2]

  This means $1-x^{1-p}$ of workers' income drops to zero. For the rest, their income becomes $w_2 x^p$. If the elasticity of demand for labor is less than x^{-1+p} at this point, this will represent an increase in income; otherwise, a decrease.

  Thus, depending on the poverty line and elasticity, multiple scenarios are possible. In one scenario, only the $1 - x^{1-p}$ fraction of unemployed workers enter poverty, and the rest face hours reductions that cancel out their increased wages and remain as they are. If labor demand is inelastic or hours reductions for remaining employees are small, the workers who remain employed may be lifted out of poverty. However, if labor demand is elastic and the demand response consists primarily of hours reductions, we may see all low-wage workers enter poverty. There could also be a scenario, for high poverty thresholds, where everyone begins and ends in poverty (or, for low poverty thresholds, where

[2] For example, if $p = 0.9$, then the number of employees is multiplied by $x^{0.1}$, which is only slightly less than 1; and hours are multiplied by $x^{0.9}$. Thus total labor hours are reduced to $x^{0.1}x^{0.9} = x$, and the reduction is mostly driven by reducing employees' hours.

everyone begins and ends above poverty).

- In period 3, inflation progresses to the point that the real minimum wage is once again w_1. If the previous minimum-wage increase caused firms to make permanent changes to production (e.g., incentivized the development of technology that makes more capital-intensive production optimal even now that the higher wage is gone), the quantity of labor demanded may be less than 1, and income may be less than the w_1 it was in period 0. However, if this did not happen, income will return to w_1.

Thus, with respect to a headcount-ratio measure, this model predicts that the effect of the minimum wage on incomes below a given poverty threshold depends on the labor demand response to the higher wage. If most low-wage workers remain employed and those workers see little reduction in their hours, the prevalence of low incomes will decrease on the margin of the incomes employed workers are earning. If many workers lose their jobs, the prevalence of very low or zero incomes will increase; if workers remain employed but with fewer hours, the prevalence of low incomes will increase on the margin of employed workers' incomes. Regardless, after some time, the effect should shrink; and eventually poverty rates should return to their prior levels if the production process has not been changed in the interim.

These predictions should apply to income-based SNAP eligibility rates as well as standard poverty-headcount measures. However, they may not fully extend to SNAP participation itself. The following subsection explains how this may occur.

2.2 Factors in SNAP Participation

A household's decision to participate in SNAP in a period t is a function of three things:

(1) The household's financial situation, including wage earnings (as well as any other income sources, a disabled or elderly household member, or anything else that's taken into account).

(2) The eligibility rules in that state, including where it sets the cutoff (between the required 130% and 200% of poverty), and any other programs it chooses to designate for broad-based categorical eligibility (i.e., anyone eligible for that program would automatically be eligible for SNAP).

(3) The costs of applying for and being approved to receive SNAP (including the opportunity cost of the time and mental energy used to fill out forms, set up a meeting, and collect documentation; as well as the disutility of the application process itself).

Together, (1) and (2) determine if a household has the option of applying for SNAP. Assuming the household is eligible, it decides whether to apply or not based on (3), by comparing the amount of benefits to the perceived time/effort cost.

For a simple example, consider a minimum-wage worker (earning a wage of w_1) in a SNAP-eligible household who works h_1 hours per month. Income from sources other than this worker's earnings (either the earnings of other family members, or nonwage income) is constant at I, meaning total income is $w_1 h_1 + I$.

A household of this size is eligible for SNAP if and only if its monthly income is less than the cutoff X. The household's exempt income (that which is deducted from the total income when determining benefit amount) is constant at E, and the maximum benefit is B_{max}. Thus the benefit amount is $B_{max} - (w_1 h_1 + I - E)$, or $B_{max} + E - (w_1 h_1 + I)$.

If the costs of applying for and receiving SNAP (given that you're eligible) is C, then the household will receive SNAP if and only if

$$w_1 h_1 + I < X \quad \& \quad B_{max} + E - (w_1 h_1 + I) > C$$

$$w_1 h_1 + I < \min[X, B_{max} + E - C]$$

If the minimum wage increases from w_1 to w_2, but hours remain at h_1 and all other variables remain constant, the left-hand side of this inequality will grow. This means that for some households, the inequality will no longer hold, and they will either no longer be eligible for SNAP or no longer find it worth it to apply. Thus SNAP participation will decrease. Moreover, even for households that remain, the benefit amount $B_{max} + E - (w_1 h + I)$ will decrease. Thus, if we assume all other variables remain constant, we predict that a minimum-wage increase will decrease SNAP participation at the extensive level, and reduce benefits for those who remain on the program.

Now consider the possibility that hours will change in response to the minimum-wage increase. Assume that, in the presence of a binding minimum wage, labor demand is the binding constraint on hours worked, even if the worker may wish to work more hours at the new wage. Thus, for small wage changes, the new hours worked are approximately

$$h_2 = h_1 + \epsilon_D^w(w_2 - w_1)\frac{h_1}{w_1}$$

where ϵ_D^w is the own-wage elasticity of labor demand. Therefore, after the minimum-wage increase, the households receiving SNAP will be the ones for which the following inequality holds:

$$w_2\left(h_1 + \epsilon_D^w(w_2 - w_1)\frac{h_1}{w_1}\right) + I < \min[X, B_{max} + E - C]$$

When $\epsilon_D^w = 0$ (perfectly inelastic labor demand), the left-hand side of the inequality equals w_2h_1, and the observed change is the same as the mechanical change. When $\epsilon_D^w = -1$ (unit-elastic labor demand), the left-hand side of the inequality is approximately $w_1h_1 + I$. That is, things are the same as they were before the minimum wage change, and the behavioral change exactly cancels out the mechanical change, and the observed change is zero. When $-1 < \epsilon_D^w < 0$ (inelastic labor demand), the behavioral change will be nonzero but smaller than the mechanical change, and the overall observed change will be negative.

The results may also be affected if we consider the possibility of imperfect information. We can account for this by assuming instead that a household will apply for SNAP if and only if

$$w_1h_1 + I < \min[X', B'_{max} + E' - C']$$

where X', B'_{max}, E', and C' represent the household's beliefs about, respectively, the SNAP cutoff, the maximum benefit, the amount of their income that is exempt when calculating benefit amount, and the cost of applying.

If $B'_{max} > B_{max}$ or $E' > E$, or if $C' < C$, the household may apply for and receive SNAP even if its benefit amount does not justify the cost in terms of utility. If $X' > X$, the household may apply for SNAP thinking it is eligible and be rejected.

Meanwhile, if $B'_{max} < B_{max}$, $E' < E$, or $X' < X$, or if $C' > C$, the household may choose not to apply for SNAP even if doing so would increase its utility. This could be a potential cause of low takeup.

If any of these inequalities are more or less likely to hold for the marginal households who leave SNAP eligibility when the minimum wage increases (relative to eligible people in general), it may result in a change in SNAP participation that is higher or lower than we might expect.

3 Empirical Strategy

The theoretical models above suggest that increasing the minimum wage will increase family incomes at a particular level (in particular, at the margin of SNAP eligibility) if those incomes are supported by minimum-wage workers who face inelastic demand for their labor. However, incomes will stay the same or decrease if labor demand is more responsive to the higher wage. Even if families move out of (or into) SNAP eligibility, moreover, participation may not change if the families affected tend not to take up SNAP. All these effects will tend toward zero over time as inflation cancels out a minimum-wage increase.

To test these predictions, I use an event-study specification to measure the effects of minimum-wage increases, over time, on the fractions of families earning below each of several different income cutoffs. I also use the same specification to evaluate the effects on a simple measure of simulated SNAP eligibility, and on SNAP participation rates. I then compare the results of these regressions to those of a state panel regression replicating that used by Reich and West (2015).

The main specification is as follows:

$$Y_{s,t} = \sum_{q} \beta_q (QuartersFromEvent = q)_{s,t} + \beta_c Controls_{s,t} + \alpha_s + \gamma_q + \epsilon_{s,t}$$

where α_s represents state fixed effects and γ_q represents quarter-within-year fixed effects (i.e., fixed effects for whether a particular quarter is the first, second, third, or fourth of the year). In addition to these fixed effects, I variously control for the year in two different ways: with a linear year term in the control vector, and with year fixed effects; as well as running a version without year effects. (I elaborate more on this below.)

In different versions of this regression, $Y_{s,t}$ stands for various different dependent variables, described in more detail below. The time-to-event dummies $\sum_q \beta_q (QuartersFromEvent = q)_{s,t}$ run from n quarters before the event to n quarters after, for multiple different values of n. These ranges sometimes overlap for different minimum-wage increases in a particular state. To address this, I use the method proposed by Sandler and Sandler (2014) of allowing more than one time-from-event dummy variable to equal 1 for the same state and quarter.

The number of leads and lags around each event is informed by the theoretical prediction that the effects of a minimum-wage increase will dissipate after inflation causes the real minimum wage to return to its pre-increase value. The inflation rate over the period studied was roughly constant at about 2%. The typical minimum wage increase, meanwhile, was about 5-8%; it would take about 3 years for such an increase to be canceled out by inflation. Thus for the longest-time-scale version, I use a maximum of 12 quarters for the time frame.

I run several versions of this regression:

- I use four different ways of defining an event. In one version of the regression (Tables 3a-b), every minimum-wage change of at least 5 percent (relative to the mean minimum wage for that state and quarter) is treated as an event. In two other versions (Tables 4a-4b and 5a-5b), the thresholds are instead 7.5% and 10%. In a final version, following Sandler and Sandler (2014), I include pre- and post-event "dummies" for every minimum-wage change, which are equal to the percent increase in the minimum wage. Because these measures are defined in terms of the existing minimum wage rather than absolute amounts, there is no bias introduced by inflation rendering the definitions less exclusive over the time period studied. (Meanwhile the poverty measures are defined in terms of the federal poverty thresholds, which are adjusted to account for inflation.)

- For each of the four approaches above, I run the regression with seven different dependent variables: the fraction of a state's families at or under 75%, 100%, 125%, 150%, and 200% of the poverty threshold for their year and family size; for the fraction of families estimated to be eligible for SNAP; and for the fraction of families who received nonzero SNAP benefits in a particular quarter.

- To generate the measure of simulated eligibility that forms one of my dependent variables, I use federal poverty thresholds for each year to determine the SNAP income cutoff for each state in each year if the multiples of poverty used by each state as its BBCE threshold for eligibility were the same as their 2019 levels. This measure relies on the assumption that, while the generosity of SNAP requirements may have changed over time (resulting in this measure over- or underestimating true SNAP eligibility in past years), the relative generosity of states within a given year has remained constant. If this assumption holds true, any bias in the measure should be state-invariant, and is therefore accounted for by year controls.

Some of my robustness checks involve different ways of accounting for the calendar year. There is evidence (e.g., Dube, Lester, and Reich, 2010) that minimum-wage increases may be endogenous to state and national macroeconomic trends. Moreover, minimum-wage increases, and particularly the largest ones, are not evenly distributed across the time period of study; many of the largest ones occurred in the late 2000s (Figure 2), with the periods afterwards characterized by economic downturn. Controlling for fixed effects for each individual year in the period of study, therefore, may eliminate some identifying variation, possibly obscuring a true effect. For this reason, I run my main specification using a linear term for the year; in alternate specifications, I instead include year fixed effects, or no year term at all.

Another set of robustness checks involve including and excluding each of a number of control variables used in past literature on the minimum wage, the income distribution, and SNAP: logged population (e.g., Dube, 2019); real median family income, mean family size, unemployment rates, and Census-division-specific year fixed effects (e.g., Reich and West, 2015). I also run these regressions using different numbers of leads and lags for the event dummies.

4 Data

My main data sources are the Survey of Income and Program Participation (SIPP) and the minimum wage data from the Washington Center for Equitable Growth (Vaghul & Zipperer, 2016). I also use US Census Bureau data provided by FRED (US Census Bureau, 2020a) for state-level annual population estimates. These datasets are described below.

4.1 SIPP Data

I use SIPP data from January 1996 to October 2013, which includes monthly data on family-level income and SNAP participation. Using the family weights provided in the dataset, I generate several state-level variables, each for the fraction of families that, given their size, falls below a particular multiple of the federal poverty threshold for the relevant year and family size. The multiples of poverty used, as listed above, are 75%, 100%, 125%, 150%, and 200%. I then aggregate each variable to the state-quarter level by generating weighted means over the three months in each quarter.

I also generate similar variables for the fraction of families estimated to be eligible for SNAP, and that of families participating in it. The formula for simulated SNAP eligibility is as described in the empirical strategy section above.

For the first month of my period of study, January 1996, there are a total of

20,142 families surveyed. In the final month, October 2013, there are 14,181 families. Descriptive statistics for these families (as well as families of four, of which there are 2,696 for January 1996 and 1,679 for October 2013) are shown below (all dollar amounts are given in 2019 dollars). In general, the real income distribution has shifted slightly upward, although more so for the upper end of the distribution; and rates of each multiple of poverty have slightly declined. SNAP rates and benefits, however, have increased, likely due to the increased use of BBCE thresholds by states.

	January 1996	October 2013
Median income, all families	$3,529	$3,670
25th pctile income, families of four	$3,290	$3,554
Median income, families of four	$6,024	$6,627
75th pctile income, families of four	$9,396	$10,470
% below poverty, families of four	15.3%	14.3%
$ below 1.5x poverty, families of four	24.8%	23.2%
% below 2x poverty, families of four	33.9%	32.0%
% families of four receiving SNAP benefits	7.11%	11.12%
% Median SNAP benefit per family of four	$355	$377

4.2 Minimum Wage Data

This dataset includes the mean, minimum, and maximum values of the federal and state minimum wage in each quarter for every US state and DC from 1996 to 2013. From this I generate a minimum wage change for each state and quarter, defined as the binding minimum wage for the current quarter (the greater of the federal and state minimum wages) minus that for the previous quarter in the same state.

During my time period (1996 to 2013), there were 45 minimum-wage changes, all increases, each applying to anywhere from 1 to 46 states; or a total of 325 state-quarters in which a minimum-wage change occurred. Changes are distributed roughly evenly over all four quarters of the year, meaning that time-from-event is not strongly correlated with the quarter of the year; this allows me to control for seasonal effects without eliminating valuable identifying variation. The mean increase, weighted by number of states covered, was about 8.3%; the middle 50% of affected state-quarters saw increases between 4.1% and 10.5%.

Some of my regression specifications involve only considering minimum wage increases of at least a certain size. A table of these change sizes and their frequencies is shown below:

Size	State-quarters w/ event	Quarters w/ 1+ state event
All changes	325	45
5+ percent	231	35
7.5+ percent	204	34
10+ percent	117	22

Figure 1 shows the number of events of each size in the data. Figure 2 shows a scatter plot of each change in the data; note that most of the largest changes occurred between 2005 and 2010.

5 Results

Results from the main regression specifications (with a linear year term and logged population term) show negative (that is, poverty-reducing) effects of being after a minimum-wage increase, which are significant at the 0.05 alpha level. In general, these effects tend to begin at the 2nd quarter after an increase, grow until the 4th quarter after, and then fade. These results are generally robust to the use of different numbers of pre-/post-event leads and lags.

In the 5-percent version of the regressions (Tables 3a-3b), the effects are significant and negative for the second, third, and fourth quarters post-event when considering the fractions of families below 75% (Table 3a, column 1), 100% (Table 3a, column 2), 125% (Table 3a, column 3), and 150% (Table 3b, column 1) of the poverty line. The largest effects are seen for the 125% and 150% variables, where we see coefficients of around -0.03. That is, the rates of 125% and 150% poverty are about three percentage points lower beginning one to two quarters after an event and continuing until about a year out. There are no significant post-event effects for 200% of poverty (Table 3b, column 2), or for simulated SNAP eligibility (Table 3b, column 3; threshold ranges from 130% to 200% poverty) or participation (Table 3b, column 4). Only a few pre-event coefficients are significant, suggesting that endogeneity (after accounting for controls) is minimal.

The 7.5-percent version (Tables 4a-4b) yield similar results, with only very slightly larger effects. The 10-percent version (Tables 5a-5b), however, yields no results for the 2nd through 4th quarters post-event, and significant effects in the 7th or 8th quarters for some dependent variables (some are positive and some negative). This may be a result of the limited number of 10-percent-or-greater minimum-wage increases in the period of study.

In the version (6a-6b) where minimum-wage increases are weighted by the percent increase they represent, the same pattern is apparent: significant negative effects in the 2nd to 4th quarters post-event, for the 75%, 100%, 125%, and 150% variables only. Again, the largest effects were found in the 125% and 150% columns (Table 6a, column 3; Table 6b, column 1), with coefficients around -0.004. That is, increasing the size of a minimum-wage increase (as a percent of the existing minimum wage) by a single percentage point – for example, going from $12.00 to $12.12 – reduces the rates of 125% and 150% poverty (within the 2nd-to-4th-quarter period) by about 0.4 percentage points.

5.1 Robustness Checks

The above results are generally robust to changing the number of leads and lags; the inclusion and exclusion of each control variable; as well as different ways of accounting for yearly variation (controlling for year fixed effects and leaving out year controls entirely). However, in the fixed-effects version, the magnitudes of the coefficients are generally smaller (sometimes half or less as large as the corresponding ones in the main tables); and some coefficients are not significant. This is consistent with the idea that year fixed effects may remove some of the identifying variation. Moreover, in the fixed-effects version, the results are sensitive to the number of leads and lags used.

5.2 Comparison to Reich and West (2015)

The results here contradict the findings of Reich and West (2015), who use an annual state panel approach to study the effect of the minimum wage on SNAP participation, and find that a 10% increase in the minimum wage is associated with a 2.4–3.2% reduction in SNAP participation.

To investigate why this may have occurred, I replicate their strategy using the state-quarter-level data used in my event-study approach. I run the following specification:

$$Y_{s,t} = \beta_0 + \beta_1 \log(RealMinimumWage_{s,t}) + \beta_2 Controls_{s,t} + \alpha_s + \gamma_q + \phi_{d,y} + \epsilon_{s,t}$$

where $Y_{s,t}$ is the SNAP participation rate in state s and time t; $Controls_{s,t}$ closely approximates the vector of controls used by Reich and West in their study; α_s and γ_q represent state and quarter-within-year fixed effects as before; and $\phi_{d,y}$ represents year fixed effects that vary by Census division.

The result of this regression is significant and negative, indicating that higher minimum wages are associated with lower SNAP participation. This result (Table 7) holds whether the regression is run on the full quarterly panel (columns 1-2) or an annualized version (columns 3-4); and is robust to the use of either linear or fixed-effect Census-division-specific year controls. Coefficients range from -0.024 to -0.030; these are similar to those found by Reich and West (2015), who obtain a coefficient of -0.031. These results imply that increasing the minimum wage by 10% increase reduces SNAP participation by about 0.3 percentage points – that is, about 3% if the SNAP participation is 10%.

This suggests that my findings contradict those of Reich and West (2015), not due to differences in data or time period, but because of the different empirical strategies used.

6 Discussion, Limitations, and Future Work

Overall, the results indicate that increasing the minimum wage increases income for families below 150% of the poverty line, and particular those below that line but above the poverty line itself; and that this effect persists for about a year after the wage increase. There is some indication that smaller wage increases (around 5%) are about as effective as larger ones (around 7.5% – half again as large); however, there is insufficient evidence to conclude that this holds true across the spectrum of possible wage-hike sizes. There is no evidence that larger or smaller minimum wage increases affect different portions of the income distribution.

There is consistently no evidence that the minimum wage reduces either simulated SNAP eligibility or participation at any time. This, combined with the fact that SNAP cutoffs fall between 130% and 200% of the poverty line, suggests that families just below the threshold for SNAP eligibility may be above the income range that benefits most from minimum wage increases; and that these increases, although they boost income, do not do so to the point of lifting families out of SNAP eligibility. This contradicts the finding of Reich and West (2015) that higher minimum wages are associated with lower SNAP participation rates. Moreover, replicating their approach with the data used for this study reproduces their finding, indicating that the difference in results arises from differences between the state panel and event study approaches.

The delayed beginning of the effects is counterintuitive, since the theoretical prediction is that the increased wages would boost families' income immediately, and then the effects would be reduced as the labor market responded to the higher costs of labor. The dissipation of the effect over time, meanwhile, could be driven by a number of factors. It could be that, as inflation reduces the value of the minimum wage and eventually makes it equivalent in real terms to its pre-increase value, the effect of the increase goes away. Firms may also take time to substitute toward capital or non-minimum-wage labor – in this case, some of the income-reducing labor demand effects of the minimum wage would take a while to take effect and offset the increase in income that initially comes from a higher wage. Finally, the dissipation may be partially accounted for by the findings of Neumark, Schweitzer, and Wascher (2004), who find that after the first year following a minimum-wage increase, employers are less likely to increase wages, and earned income tends to decrease.

One limitation of this study is in the potential limitations of the SIPP data used to construct state-level variables. Using the family weights provided, the SIPP is capable of producing estimates that are representative at the state level for some but not all states from the year 2004 on (US Census Bureau, 2020b). However, this leaves room for flawed estimates of the rates of low income and SNAP participation in some states and in the earlier years of the time period I consider. If the errors potentially introduced by this are uncorrelated with changes in the minimum wage, then they simply add random noise to my estimates, leading to greater standard errors. If, however, the errors are systematically correlated with minimum-wage changes, they may have also introduced bias in my results. Future work on this topic might rerun the same regressions using data from a source designed to be representative at the state level.

Another limitation is that the measure of simulated SNAP eligibility used is a relatively simplistic one, which does not take into account the possibility of differing state-level trends in SNAP income cutoffs over time, or other state-level criteria beyond income that affect eligibility. Thus this study's results on simulated SNAP eligibility provide only limited information on the effects of the minimum wage on true SNAP eligibility as well as takeup rates. Future research in this area might collect more detailed data on historical state-level SNAP eligibility policies, and use it to construct a more sophisticated measure of simulated eligibility.

Additional possible directions for future research might focus on the mechanisms underlying the dissipation of the effect over time; or use the same event-study strategy to study participation in another social safety net program. Future methodological work might also further examine the differences between the state panel and event study approaches in the context of minimum wage research, and the potential biases to which each approach is subject.

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Tables

# of people	SNAP cutoff	Equivalent wage for full-time worker
1	\$20,040/year	\$9.63/hour
2	\$27,168/year	\$13.06/hour (one worker) \$6.53/hour (two workers)
3	\$35,196/year	\$16.92/hour (one worker) \$8.46/hour (two workers)
4	\$41,424/year	\$9.96/hour (two workers)

Table 1: 2019 SNAP gross income limits in the state of Minnesota (set at 165% of the federal poverty line), and the hourly wage at which one or two full-time workers would earn exactly that limit. Minnesota's minimum wage was \$9.86 in 2019, implying that the minimum wage would keep some families but not others out of SNAP eligibility. Source: Minnesota Department of Human Services (2019).

SNAP income limit set by broad-based categorical eligibility (BBCE) (% of poverty line)	States
130%/no BBCE	Alabama, Alaska, Arkansas, Georgia, Idaho*, Indiana*, Kansas, Kentucky, Louisiana, Mississippi, Missouri, Nebraska*, Ohio, Oklahoma, South Carolina, South Dakota, Tennessee, Utah, Virginia, Wyoming
160%	Iowa, Pennsylvania
165%	Illinois, Minnesota, New Mexico
185%	Arizona, Connecticut, Maine*, New Hampshire, New Jersey, Oregon, Rhode Island, Texas*, Vermont
200%	California, Colorado, Delaware, Florida, Hawaii, Maryland, Massachusetts, Michigan*, Montana, Nevada, New York, North Carolina, North Dakota, Washington, West Virginia, Wisconsin

Table 2: BBCE income cutoffs in each state, as percentages of the poverty threshold below which a family in that state categorically qualifies for SNAP. In states with a *, the higher BBCE income limit only applies to those who fall below a certain asset limit (varies by state). Additionally, the higher limits in New Hampshire and New York only apply to families with dependents. Source: USDA FNS (2019).

VARIABLES	(1) 75% of Poverty	(2) 100% of Poverty	(3) 125% of Poverty
9 before	-0.00542**	-0.00785***	-0.00715**
	(0.00226)	(0.00259)	(0.00344)
8 before	-0.00161	-0.00356	-0.00628
	(0.00452)	(0.00472)	(0.00473)
7 before	-0.000476	-0.00238	-0.00303
	(0.00271)	(0.00381)	(0.00518)
6 before	-0.00245	-0.00437	-0.00765
	(0.00318)	(0.00477)	(0.00674)
5 before	0.00391	0.00518*	0.00314
	(0.00309)	(0.00304)	(0.00373)
4 before	-0.0110	-0.00735	-0.00504
	(0.0111)	(0.00870)	(0.00702)
3 before	-0.0111	-0.0127*	-0.0113
	(0.00697)	(0.00667)	(0.00998)
2 before	-0.00447	-0.000846	0.00111
	(0.00365)	(0.00579)	(0.00865)
1 before	-0.0153*	-0.00959*	-0.00661
	(0.00777)	(0.00486)	(0.00750)
Event time	-0.00191	-0.00440	-0.00285
	(0.00499)	(0.00514)	(0.00866)
1 after	-0.0121*	-0.00635	-0.00498
	(0.00616)	(0.00597)	(0.00481)
2 after	-0.0197***	-0.0228***	-0.0257***
	(0.00595)	(0.00573)	(0.00690)
3 after	-0.0194***	-0.0251***	-0.0304***
	(0.00585)	(0.00613)	(0.0105)
4 after	-0.0104***	-0.00665	-0.0174**
	(0.00306)	(0.00457)	(0.00758)
5 after	0.00582	0.00611	0.00445
	(0.00673)	(0.00731)	(0.00789)
6 after	-0.00369	-0.00301	-0.00728
	(0.00995)	(0.00760)	(0.00680)
7 after	-0.00481	-0.00541	-0.00620
	(0.00657)	(0.00667)	(0.00779)
8 after	-0.0154	-0.0131	-0.0135
	(0.0121)	(0.0107)	(0.0120)
9 after	-0.00841	-0.00947	-0.0107
	(0.00672)	(0.00660)	(0.00741)
Observations	543	543	543
R-squared	0.273	0.306	0.318
Number of statefips	49	49	49

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3a: Results of event-study regressions of the fractions of families that fall below 75%, 100%, and 125% of the poverty line. Events are defined as minimum-wage increases of at least 5%. Significant negative effects for the 2nd through 4th quarters ($p < 0.05$) for all dependent variables.

VARIABLES	(1) 150% of Poverty	(2) 200% of Poverty	(3) SNAP Elig.	(4) SNAP Partic.
9 before	-0.00579*	-0.00508	-0.00658*	-0.00292
	(0.00344)	(0.00432)	(0.00372)	(0.00188)
8 before	-0.00670	-0.0117	-0.0108	-0.00148
	(0.00652)	(0.00713)	(0.00657)	(0.00231)
7 before	-0.00667	-0.0113	-0.0113	0.00167
	(0.00680)	(0.00736)	(0.00675)	(0.00266)
6 before	-0.00988	-0.0125	-0.0161*	-0.00199
	(0.00750)	(0.00948)	(0.00920)	(0.00288)
5 before	-0.000276	0.000177	-0.00252	-0.00116
	(0.00459)	(0.00828)	(0.00869)	(0.00344)
4 before	-0.00743	-0.00902	-0.00952	-0.00148
	(0.00852)	(0.00982)	(0.00956)	(0.00242)
3 before	-0.00798	-0.0137	-0.0114	-0.00506
	(0.00808)	(0.0100)	(0.00926)	(0.00466)
2 before	0.00199	-0.00173	-4.97e-05	-9.98e-05
	(0.00685)	(0.00792)	(0.00762)	(0.00255)
1 before	-0.00575	-0.00348	-0.000165	0.000999
	(0.00720)	(0.00631)	(0.00676)	(0.00218)
Event time	-0.00119	-0.00160	-0.000122	0.00261
	(0.00978)	(0.0126)	(0.0120)	(0.00248)
1 after	-0.00705	0.00348	0.00179	0.00555
	(0.00898)	(0.0123)	(0.0118)	(0.00379)
2 after	-0.0300**	-0.00349	-0.00780	0.00375
	(0.0131)	(0.0156)	(0.0153)	(0.00316)
3 after	-0.0321**	-0.0111	-0.0205	-0.00505
	(0.0122)	(0.0201)	(0.0213)	(0.00600)
4 after	-0.0219***	-0.00954	-0.0111	-0.0107**
	(0.00793)	(0.00978)	(0.00689)	(0.00503)
5 after	0.0111	0.0120	0.0130	-0.00157
	(0.00965)	(0.0108)	(0.0101)	(0.00747)
6 after	-0.00423	0.00279	0.00296	0.00393
	(0.00754)	(0.0109)	(0.00910)	(0.00831)
7 after	-0.00756	-0.00694	-0.00630	-0.00612
	(0.00767)	(0.00961)	(0.00805)	(0.00607)
8 after	-0.0162	-0.0177	-0.0166	-0.00335
	(0.0115)	(0.0124)	(0.0117)	(0.00773)
9 after	-0.0171*	-0.0165	-0.0179*	-0.00658
	(0.00931)	(0.0106)	(0.0102)	(0.00722)
Observations	543	543	543	543
R-squared	0.345	0.262	0.295	0.731
Number of statefips	49	49	49	49

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3b: Results of event-study regressions of the fractions of families that fall below 150% and 200% of the poverty line, as well as simulated SNAP eligibility rate and SNAP participation rate. Events are defined as minimum-wage increases of at least 5%. Significant negative effects for the 2nd through 4th quarters ($p < 0.05$) for 150% of poverty only; and for SNAP participation in the 4th quarter.

VARIABLES	(1) 75% of Poverty	(2) 100% of Poverty	(3) 125% of Poverty
9 before	-0.00391	-0.00599**	-0.00519
	(0.00275)	(0.00297)	(0.00372)
8 before	0.00196	-0.00140	-0.00322
	(0.00469)	(0.00516)	(0.00480)
7 before	0.00102	-0.00133	-0.000334
	(0.00315)	(0.00423)	(0.00564)
6 before	-0.000242	-0.000460	-0.00208
	(0.00342)	(0.00486)	(0.00707)
5 before	0.00533	0.00836**	0.00725*
	(0.00353)	(0.00342)	(0.00406)
4 before	0.00354	0.00417	0.00614
	(0.00338)	(0.00281)	(0.00484)
3 before	-0.00243	-0.00451	-0.00696
	(0.00315)	(0.00368)	(0.00753)
2 before	-0.00670*	-0.00660*	-0.00763
	(0.00353)	(0.00357)	(0.00593)
1 before	-0.0127*	-0.0129**	-0.0135
	(0.00736)	(0.00552)	(0.00874)
Event time	-0.00397	-0.00330	-0.0106
	(0.00409)	(0.00451)	(0.00790)
1 after	-0.00845**	-7.24e-06	-0.00503
	(0.00414)	(0.00411)	(0.00570)
2 after	-0.0262***	-0.0276***	-0.0338**
	(0.00484)	(0.00871)	(0.0147)
3 after	-0.0215***	-0.0272***	-0.0347**
	(0.00555)	(0.00401)	(0.0153)
4 after	-0.0209***	-0.0113***	-0.0312***
	(0.00317)	(0.00333)	(0.00588)
5 after	0.00571	0.00712	0.00524
	(0.00993)	(0.0109)	(0.0118)
6 after	0.00319	0.00346	-0.00108
	(0.0101)	(0.00895)	(0.00925)
7 after	0.00307	0.00233	0.000432
	(0.00899)	(0.00878)	(0.00957)
8 after	-0.000256	-0.0129*	0.00442
	(0.00710)	(0.00679)	(0.00768)
9 after	-0.00302	-0.00588	-0.00793
	(0.00786)	(0.00843)	(0.00812)
Observations	543	543	543
R-squared	0.255	0.292	0.309
Number of statefips	49	49	49

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4a: Results of event-study regressions of the fractions of families that fall below 75%, 100%, and 125% of the poverty line. Events are defined as minimum-wage increases of at least 7.5%. Significant negative effects for the 2nd through 4th quarters ($p < 0.05$) for all dependent variables.

VARIABLES	(1) 150% of Poverty	(2) 200% of Poverty	(3) SNAP Elig.	(4) SNAP Partic.
9 before	-0.00390	-0.00527	-0.00709*	-0.00286
	(0.00390)	(0.00459)	(0.00396)	(0.00209)
8 before	-0.00297	-0.00711	-0.00647	-0.00117
	(0.00685)	(0.00718)	(0.00660)	(0.00257)
7 before	-0.00289	-0.00882	-0.00875	0.000958
	(0.00734)	(0.00762)	(0.00702)	(0.00256)
6 before	-0.00478	-0.0116	-0.0153*	-0.00224
	(0.00727)	(0.00947)	(0.00903)	(0.00326)
5 before	0.00519	0.000743	-0.00114	-0.00292
	(0.00473)	(0.00565)	(0.00522)	(0.00376)
4 before	0.00601	0.00281	0.00175	-4.05e-05
	(0.00550)	(0.00792)	(0.00781)	(0.00261)
3 before	-0.00444	-0.00808	-0.00647	-0.00444
	(0.00574)	(0.00807)	(0.00754)	(0.00441)
2 before	-0.00429	-0.00177	-0.00191	-0.000216
	(0.00604)	(0.00825)	(0.00823)	(0.00318)
1 before	-0.0111	-0.00187	-0.00115	0.00125
	(0.00821)	(0.00587)	(0.00567)	(0.00234)
Event time	-0.0126	-0.0133	-0.0131	-0.000273
	(0.00769)	(0.0118)	(0.00903)	(0.00225)
1 after	-0.00652	0.00302	-0.000644	0.00550
	(0.0149)	(0.0203)	(0.0196)	(0.00599)
2 after	-0.0331	0.0102	0.00282	0.00185
	(0.0289)	(0.0283)	(0.0303)	(0.00734)
3 after	-0.0398*	0.000664	-0.0111	0.000929
	(0.0209)	(0.0343)	(0.0387)	(0.00502)
4 after	-0.0399***	-0.0248**	-0.0199*	-0.00916***
	(0.00797)	(0.00982)	(0.0100)	(0.00305)
5 after	0.0105	0.0119	0.0140	-0.00421
	(0.0110)	(0.0118)	(0.0106)	(0.00628)
6 after	0.000743	0.00413	0.00583	0.00284
	(0.00905)	(0.0119)	(0.0104)	(0.00726)
7 after	0.00189	-0.00209	0.000522	-0.00195
	(0.0102)	(0.0120)	(0.00985)	(0.00686)
8 after	0.00759	-0.0322***	-0.0167**	0.0174***
	(0.00689)	(0.00818)	(0.00752)	(0.00557)
9 after	-0.0102	-0.0125	-0.0141**	0.000632
	(0.00767)	(0.00796)	(0.00672)	(0.00617)
Observations	543	543	543	543
R-squared	0.331	0.253	0.282	0.727
Number of statefips	49	49	49	49

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4b: Results of event-study regressions of the fractions of families that fall below 150% and 200% of the poverty line, as well as simulated SNAP eligibility rate and SNAP participation rate. Events are defined as minimum-wage increases of at least 7.5%. Significant negative effects in the 4th quarter ($p < 0.05$) for all dependent variables; and in the 3rd quarter for 150% of poverty.

VARIABLES	(1) 75% of Poverty	(2) 100% of Poverty	(3) 125% of Poverty
9 before	-0.00398	-0.00561*	-0.00530
	(0.00254)	(0.00287)	(0.00365)
8 before	0.000730	-0.00312	-0.00324
	(0.00436)	(0.00481)	(0.00485)
7 before	0.000162	-0.00284	-0.000123
	(0.00277)	(0.00384)	(0.00576)
6 before	0.000259	-0.000313	-3.97e-05
	(0.00315)	(0.00470)	(0.00727)
5 before	0.00423	0.00703**	0.00809**
	(0.00268)	(0.00284)	(0.00394)
4 before	0.00380	0.00471	0.00690
	(0.00350)	(0.00307)	(0.00531)
3 before	-0.00197	-0.00174	0.000583
	(0.00302)	(0.00296)	(0.00507)
2 before	-0.00723**	-0.00702*	-0.00468
	(0.00348)	(0.00371)	(0.00577)
1 before	-0.00656	-0.00877***	-0.00470
	(0.00443)	(0.00327)	(0.00399)
Event time	-0.00283	-0.00455	-0.00187
	(0.00438)	(0.00506)	(0.00366)
1 after	-0.00260	-0.00545	-0.000424
	(0.00292)	(0.00460)	(0.00247)
7 after	0.0318***	0.0202***	0.0204***
	(0.00577)	(0.00544)	(0.00578)
8 after	0.00407	-0.0102**	0.00767
	(0.00519)	(0.00489)	(0.00526)
9 after	0.00428	0.000851	-0.00288
	(0.00524)	(0.00623)	(0.00682)
Observations	543	543	543
R-squared	0.245	0.280	0.295
Number of statefips	49	49	49

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5a: Results of event-study regressions of the fractions of families that fall below 75%, 100%, and 125% of the poverty line. Events are defined as minimum-wage increases of at least 10%. Significant negative effects in the 7th quarter ($p < 0.05$) for all dependent variables. Some significant pre-event coefficients, casting doubt on results.

VARIABLES	(1) 150% of Poverty	(2) 200% of Poverty	(3) SNAP Elig.	(4) SNAP Partic.
9 before	-0.00394	-0.00572	-0.00774**	-0.00220
	(0.00380)	(0.00460)	(0.00383)	(0.00195)
8 before	-0.00141	-0.00836	-0.00783	-0.00131
	(0.00727)	(0.00756)	(0.00694)	(0.00265)
7 before	-0.00151	-0.00964	-0.00969	0.000169
	(0.00770)	(0.00848)	(0.00786)	(0.00261)
6 before	-0.00244	-0.0107	-0.0145	-0.00274
	(0.00770)	(0.0107)	(0.0101)	(0.00344)
5 before	0.00620	0.00189	0.000199	-0.00278
	(0.00478)	(0.00608)	(0.00577)	(0.00391)
4 before	0.00624	0.00162	0.000623	0.000768
	(0.00607)	(0.00756)	(0.00777)	(0.00273)
3 before	0.00136	-0.000602	0.000117	0.000750
	(0.00473)	(0.00674)	(0.00624)	(0.00248)
2 before	-0.00345	-0.00229	-0.00353	0.00253
	(0.00605)	(0.00857)	(0.00848)	(0.00181)
1 before	-0.00342	-0.00219	-0.00431	0.00139
	(0.00413)	(0.00629)	(0.00601)	(0.00204)
Event time	-0.00442	-0.00252	-0.00511	-0.00141
	(0.00388)	(0.00555)	(0.00381)	(0.00162)
1 after	-0.00484*	-0.000486	-0.00390	-0.00412
	(0.00288)	(0.00562)	(0.00435)	(0.00307)
7 after	0.0121**	-0.00855	-0.000930	-0.000890
	(0.00498)	(0.00653)	(0.00577)	(0.00395)
8 after	0.00922**	-0.0333***	-0.0178***	0.0177***
	(0.00415)	(0.00536)	(0.00455)	(0.00399)
9 after	-0.00401	-0.00600	-0.00655	-0.00273
	(0.00705)	(0.00826)	(0.00711)	(0.00600)
Observations	543	543	543	543
R-squared	0.315	0.249	0.278	0.725
Number of statefips	49	49	49	49

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5b: Results of event-study regressions of the fractions of families that fall below 150% and 200% of the poverty line, as well as simulated SNAP eligibility rate and SNAP participation rate. Events are defined as minimum-wage increases of at least 10%. Significant negative effects in the 7th and 8th quarters ($p < 0.05$) for all dependent variables. Some variables were omitted by Stata.

VARIABLES	(1) 75% of Poverty	(2) 100% of Poverty	(3) 125% of Poverty
9 before	-0.000322**	-0.000450**	-0.000392*
	(0.000148)	(0.000178)	(0.000225)
8 before	-0.000130	-0.000282	-0.000266
	(0.000217)	(0.000256)	(0.000254)
7 before	-0.000170	-0.000310	-0.000176
	(0.000143)	(0.000203)	(0.000284)
6 before	-0.000208	-0.000293	-0.000356
	(0.000235)	(0.000309)	(0.000447)
5 before	2.18e-06	0.000197	0.000198
	(0.000389)	(0.000358)	(0.000349)
4 before	-0.000352	-0.000111	-4.38e-05
	(0.000555)	(0.000442)	(0.000424)
3 before	-0.000560	-0.000574	-0.000552
	(0.000447)	(0.000419)	(0.000551)
2 before	-0.000501*	-0.000336	-0.000258
	(0.000277)	(0.000352)	(0.000464)
1 before	-0.000940*	-0.000731*	-0.000468
	(0.000552)	(0.000391)	(0.000482)
Event time	-0.000328	-0.000399	-0.000257
	(0.000330)	(0.000358)	(0.000427)
1 after	-0.00118*	-0.000647	-0.000481
	(0.000660)	(0.000616)	(0.000450)
2 after	-0.00266***	-0.00285***	-0.00336***
	(0.000583)	(0.000709)	(0.000944)
3 after	-0.00297***	-0.00345***	-0.00425***
	(0.000766)	(0.000600)	(0.00103)
4 after	-0.00208***	-0.00141**	-0.00231**
	(0.000497)	(0.000676)	(0.000883)
5 after	-0.000116	4.76e-05	-0.000214
	(0.000617)	(0.000755)	(0.000866)
6 after	-0.000710	-0.000591	-0.00111
	(0.00102)	(0.000815)	(0.000788)
7 after	-0.000399	-0.000435	-0.000598
	(0.000783)	(0.000810)	(0.000916)
8 after	-0.00113	-0.00115	-0.000611
	(0.00114)	(0.00101)	(0.00119)
9 after	-0.000323	-0.000548	-0.000722
	(0.000608)	(0.000644)	(0.000748)
Observations	543	543	543
R-squared	0.265	0.300	0.316
Number of statefips	49	49	49

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6a: Results of event-study regressions of the fractions of families that fall below 75%, 100%, and 125% of the poverty line. All wage-increase events are included and are weighted according to the percentage size of the increase. Significant negative effects for the 2nd through 4th quarters ($p < 0.05$) for all dependent variables.

VARIABLES	(1) 150% of Poverty	(2) 200% of Poverty	(3) SNAP Elig.	(4) SNAP Partic.
9 before	-0.000335	-0.000460	-0.000496*	-0.000157
	(0.000235)	(0.000299)	(0.000263)	(0.000126)
8 before	-0.000232	-0.000539	-0.000500	-0.000106
	(0.000357)	(0.000373)	(0.000328)	(0.000138)
7 before	-0.000318	-0.000655	-0.000629*	-2.42e-05
	(0.000369)	(0.000411)	(0.000367)	(0.000136)
6 before	-0.000494	-0.000782	-0.00104*	-0.000192
	(0.000464)	(0.000590)	(0.000567)	(0.000196)
5 before	5.76e-06	1.92e-05	-0.000205	-0.000143
	(0.000372)	(0.000457)	(0.000449)	(0.000296)
4 before	-0.000235	-0.000392	-0.000429	-0.000112
	(0.000511)	(0.000596)	(0.000606)	(0.000230)
3 before	-0.000502	-0.000735	-0.000541	-0.000354
	(0.000549)	(0.000656)	(0.000625)	(0.000368)
2 before	-0.000166	-0.000354	-0.000317	-2.92e-05
	(0.000436)	(0.000546)	(0.000529)	(0.000183)
1 before	-0.000412	-0.000214	-0.000110	-4.16e-05
	(0.000451)	(0.000473)	(0.000464)	(0.000173)
Event time	-0.000289	-0.000216	-0.000273	2.09e-05
	(0.000478)	(0.000655)	(0.000590)	(0.000190)
1 after	-0.000853	8.18e-05	-0.000157	5.56e-05
	(0.000862)	(0.00107)	(0.00107)	(0.000457)
2 after	-0.00376*	-0.000308	-0.000891	-4.89e-07
	(0.00197)	(0.00202)	(0.00213)	(0.000446)
3 after	-0.00450***	-0.00170	-0.00275	-0.000563
	(0.00143)	(0.00260)	(0.00287)	(0.000717)
4 after	-0.00283**	-0.000882	-0.00106	-0.00138*
	(0.00112)	(0.00137)	(0.00117)	(0.000787)
5 after	0.000606	0.000669	0.000773	-0.000180
	(0.000828)	(0.000964)	(0.000877)	(0.000775)
6 after	-0.000650	-4.85e-06	6.84e-05	0.000294
	(0.000858)	(0.00121)	(0.00104)	(0.000903)
7 after	-0.000797	-0.00130	-0.000996	-0.000667
	(0.000974)	(0.00120)	(0.000992)	(0.000706)
8 after	-0.00103	-0.00236*	-0.00190	-0.000237
	(0.00126)	(0.00131)	(0.00123)	(0.000943)
9 after	-0.00145*	-0.00160	-0.00161*	-0.000683
	(0.000803)	(0.000974)	(0.000906)	(0.000689)
Observations	543	543	543	543
R-squared	0.339	0.260	0.290	0.729
Number of statefips	49	49	49	49

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6b: Results of event-study regressions of the fractions of families that fall below 150% and 200% of the poverty line, as well as simulated SNAP eligibility rate and SNAP participation rate. All wage-increase events are included and are weighted according to the percentage size of the increase. Significant negative effects for the 2nd through 4th quarters ($p < 0.05$) for 150% of poverty.

VARIABLES	(1)	(2)	(3)	(4)
Log minimum wage	-0.0238***	-0.0238***	-0.0301**	-0.0301**
	(0.00661)	(0.00661)	(0.0130)	(0.0130)
Constant	0.203**	0.203**	0.231	0.231
	(0.0944)	(0.0944)	(0.165)	(0.165)
Observations	3,240	3,240	880	880
R-squared	0.697	0.697	0.747	0.747
Number of statefips	48	48	48	48
Year Controls	FE	Linear	FE	Linear
Level	Quarterly	Quarterly	Yearly	Yearly

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Results of replication of Reich and West's (2015) state panel study of the effect of the minimum wage on SNAP participation. Columns (1) and (2) are results of quarterly state panels, and columns (3) and (4) are resuls of yearly state panels. Each version is run with both linear and fixed-effect versions of Census-division-specific year controls. Results compare closely to those of Reich and West (2015), who obtain a coefficient of -0.031.

Figures

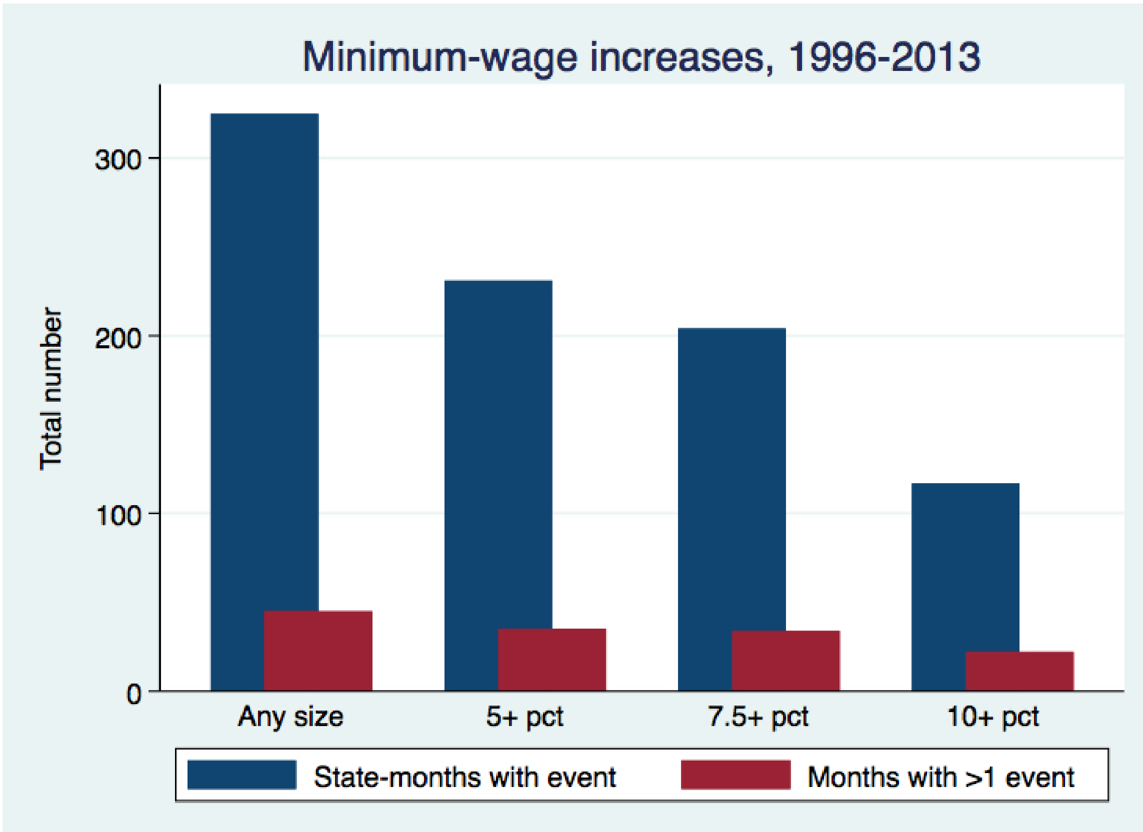

Figure 1: Number of minimum-wage increases of each size throughout the entire dataset (both in terms of state-quarter observations containing increases, and quarters in which at least one state saw an increase).

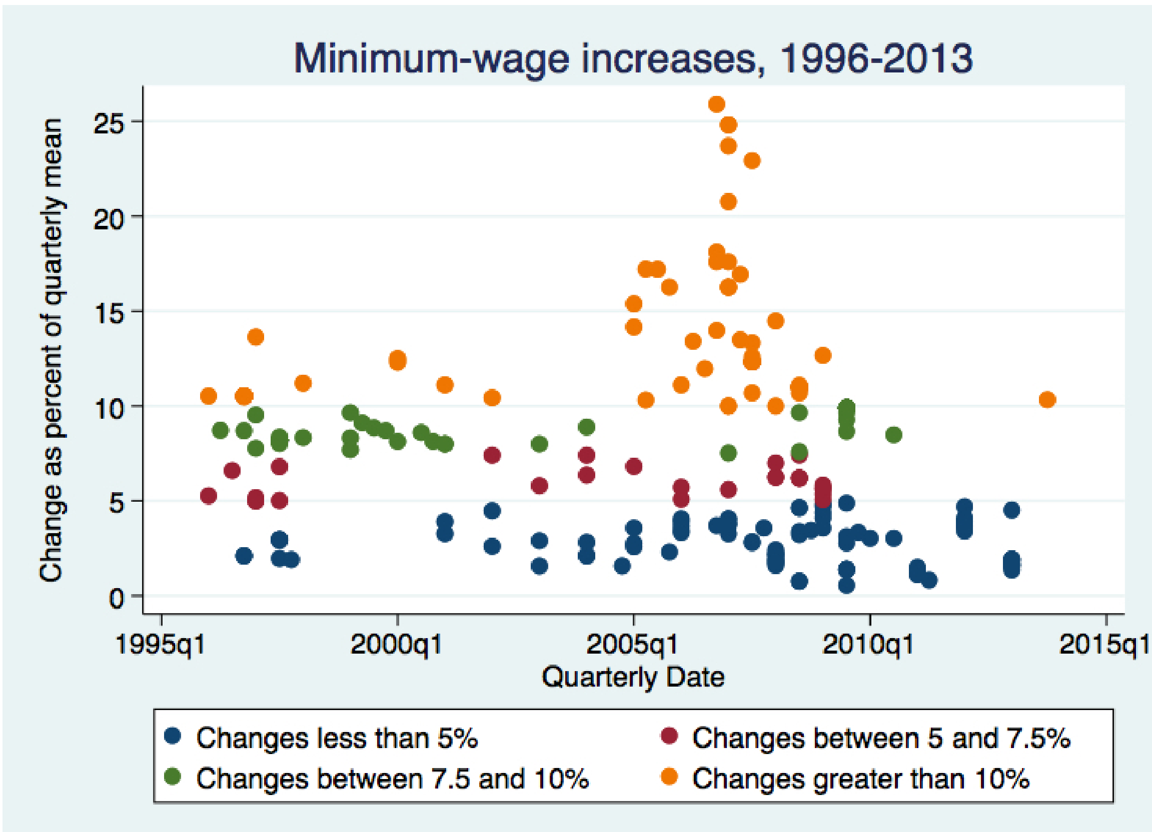

Figure 2: Scatter plot of minimum-wage increases of each size over time.