Minimum Wages and the Uptake of Supplemental Security Income

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Abstract

This study investigates whether the minimum wage affects the uptake of Supplemental Security Income (SSI). To disentangle the effect of the minimum wage from underlying macroeconomic conditions, I use a triple differences model that exploits cross-state and temporal differences in the minimum wage and its differential effects on those individuals with and without a high school diploma. The results show that a one percent increase in the minimum wage leads to a 0.33 percent decline in SSI uptake. To substantiate the findings, this study employs an alternative approach, leveraging the discontinuity in minimum wage legislation at state borders by comparing SSI uptake within the contiguous state-border counties. Using this approach yields qualitatively similar findings, corroborating the baseline estimates.

Keywords: Minimum wage, Supplemental Security Income, border discontinuity, means-tested programs

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1 Introduction

Many states and localities are raising the minimum wage to $15 per hour, while contentious policy debates over the possible adoption of a $15 federal minimum wage continue. These unfolding events and debates have reignited interest in the effects of the minimum wage on a broad range of potential outcomes, including employment and participation in public assistance programs. Meanwhile, total expenditures on Supplemental Security Income (SSI), a leading means-tested U.S. program to provide income support to individuals with disabilities, have accelerated over time. Nominal spending on SSI reached approximately $54 billion in 2015, compared to $27 billion in 1995. Nearly 9.2 million people (approximately 2.9 percent of the total population) received SSI benefits in 2015. Researchers have extensively studied both the minimum wage and SSI, producing the voluminous literature on how these programs affect individuals' labor market choices and outcomes.[1] However, the evidence on how and whether the minimum wage affects the uptake of SSI is limited.

The impetus for individuals to enter and exit the SSI program, one of the two federally run disability insurance (DI) programs, could stem from how the minimum wage alters their labor market prospects and outcomes. The previous literature shows that increasing DI benefits incentivizes workers to exit the labor force and deteriorating labor market conditions motivate individuals to enroll in DI programs (Charles, Li, and Stephens 2018 and Black, Daniel, and Sanders 2002). Similarly, high potential earnings in the labor market dissuade individuals from collecting DI benefits (Milligan and Schirle 2019). Thus, an increase in the minimum wage provides higher income for individuals, which should increase the opportunity cost of collecting SSI benefits, reducing its attractiveness. In addition to proving that disability prevents them

[1] To name a few, Meer and West (2016), Neumark, Salas, and Wascher (2014a), Cengiz et al. (2019), Liu, Hyclak, and Regmi (2016), and Dube, Lester, and Reich (2010) provide evidence on employment. Likewise, there is an emerging literature on participation in various means-tested programs (Sabia and Nguyen 2017, Reich and West 2015, and Page, Spetz, and Millar 2005). Related to it, Dube (2019) investigates its effects on poverty. Another body of the literature documents the rising trend in SSI uptake, exploring possible explanations behind it (e.g.,Charles, Li, and Stephens 2018, Black, Daniel, and Sanders 2002, French and Song 2014 and Autor and Duggan 2003).

from engaging in meaningful work, individuals should have limited income and assets to meet SSI eligibility requirements. Moreover, a higher income accompanying a rise in the minimum wage may push individuals beyond the eligibility threshold. Despite the minimum wage literature providing mixed effects on employment, overwhelming evidence demonstrates positive effects on low-skilled workers' earnings. As a result, one would expect lower participation in SSI. Similarly, as documented in several studies, a minimum wage increase could leave some workers with fewer skills unemployed, potentially encouraging them to claim SSI benefits. Given the mix of potentially relevant channels, the effect of changes in the minimum wage on SSI uptake is *a priori* theoretically ambiguous.

In this paper, I provide one of the first investigations of whether changes in the minimum wage affect the SSI disability insurance program.[2] Uncovering the link between minimum wage changes and SSI receipt is crucial to enhancing the collective understanding of the potential disincentive effects of disability insurance programs and of the way minimum wage changes affect government spending on public assistance programs. One argument that proponents of the minimum wage have put forth is that a minimum-wage-induced reduction in participation in welfare programs lowers the need for higher taxes and helps firms offset the overall financial burden stemming from higher labor costs.

The main challenge confronted in decoupling the effect of the minimum wage on SSI uptake in the U.S. context is that minimum wage increases could be correlated with state-level macroeconomic conditions which are also related to changes in SSI participation. To overcome this challenge, I use cross-state variation in the minimum wage over time and individuals less likely to be affected by the minimum wage as a basis for comparison. Specifically, using individual-level

[2]While Social Security Disability Benefits Insurance (SSDI) is the other extensive disability insurance program, I choose to focus on SSI for a few reasons. First, I want to confine my analysis to the domain of the relationship of the minimum wage with means-tested programs. Second, SSI tends to attract low-income individuals or those with fewer skills, essentially affecting the type of individuals who are more likely to respond to or be affected by minimum wage changes. Given the lower-benefit amount for SSI and its relatively high suspension or termination rate, minimum wage changes, in theory, have a greater scope to influence SSI recipients. Third, in contrast to SSI, the information on SSDI receipts in the Current Population Survey (CPS) data seems to be more susceptible to measurement errors, as it also combines disability payments from other sources. Nevertheless, for completeness, I conduct my baseline models for SSDI and include the results in the Appendix.

data from the Current Population Survey (CPS) from 1992 to 2015, I define those individuals without a high school degree as the treatment group, and other individuals with a high school degree or beyond as the comparison group. This classification of the treatment group is based on the fact that minimum wage laws are considered to be more applicable to less-educated workers.[3]

To preview the results, I find that minimum wage increases significantly decrease SSI rolls. A one percent increase in the minimum wage leads to a 0.33 percent decline in an individual's likelihood of receiving SSI benefits. The results are robust to several checks, including the inclusion of state-by-year fixed effects and other alternative controls for unobserved confounders that are specific to states and vary over time. I show evidence that the minimum wage is negatively associated with SSI uptake among the group of high school dropouts, but no such association exists among those with a high school degree or beyond. This evidence corroborates that minimum wage laws are not systematically correlated with SSI uptake, further bolstering the baseline estimates.

To further substantiate micro evidence and connect my empirical approach to emerging literature, I leverage the discontinuity in minimum wage legislation at state borders and compare outcomes in counties within cross-state pairs. Counties adjacent to state borders are more likely to experience similar evolutions in labor markets and economic environments. Hence, this approach can serve as an alternative way to address identification threats stemming from underlying macroeconomic conditions or other unobservables across states. Consistent with the previous influential work (Charles, Li, and Stephens 2018, and Black, Daniel, and Sanders 2002), I use the per capita county-level benefit payment as a measure of SSI uptake. My baseline estimate shows that the elasticity of SSI benefit payment with respect to the minimum wage is around -0.17. Additionally, I assemble information on the number of SSI recipients from reports titled "SSI Recipients by State and County" from the Social Security Administration, which

[3]My calculation based on the CPS data reveals that approximately 27 percent of high school dropouts earn wages around the minimum wage (up to 120 percent of the effective minimum wage). In contrast, the proportion of minimum wage earners decreases among those with a high school degree, some college, and a college degree, reaching 13 percent, 10 percent, and 4 percent, respectively.

are publicly available only since 1998. The reports break down the recipients by age (under 18 years of age, ages 18 to 64, and 65 and older). Analyzing the effect on recipients by age yields two important messages. First, a rise in the minimum wage significantly reduces the number of recipients in the 18-64 age group. Second, estimates for those under 18 years and 65 or older are not statistically different from zero. Those individuals under 18 years of age or 65 and older have a lower attachment (or no attachment at all depending on the exact age profile) to the labor market and are not consequently expected to be responsive to minimum wage changes. Finding no evidence of the connection between the minimum wage and receipts of SSI by these two latter groups serves as a falsification test and helps to provide further validity to the research design of this study.

The paper proceeds as follows. Section 2 reviews related literature and illustrates potential channels through which the minimum wage operates to affect SSI uptake. Section 3 provides the institutional background on SSI, while Section 4 describes the sources of data and the summary statistics. I present the estimation procedure and the results based on individual-level data in Section 5, and I present the results based on aggregate data in Section 6. Section 7 offers concluding remarks.

2 Literature and Framework

2.1 Literature Review

By examining how the minimum wage affects participation in Supplemental Security Income (SSI), a prominent welfare program and a crucial component of disability insurance, this paper contributes to three strands of the literature.

First, this study broadens our understanding of the link between the minimum wage and welfare programs by providing timely evidence on SSI uptake. Despite the prevalence of the voluminous literature on the employment effects of the minimum wage, evidence on social safety nets is limited. Furthermore, the available evidence is as mixed and contentious as the evidence on employment. In a working paper written concurrently with this analysis, Duggan and Goda (2020) examine the association between the minimum wage and applications for disability insurance programs, including SSI. Their study uses a different time period (2000 to 2015), a different outcome variable, and a different identification strategy. Using county-level panel data, they provide evidence of a small positive effect of minimum wage hikes on the influx of applications for the disability insurance program. In contrast, this paper takes a more policy-centric approach, directly examining the question of whether the actual uptake of SSI changes in response to minimum wage increases. This analysis covers a longer time period, thus utilizing a wider range of variations.

Using the state-level panel data and controlling for the state- and year-fixed effects, Page, Spetz, and Millar (2005) analyze the association between the AFDC caseload and the minimum wage. In terms of magnitude, they find an elasticity ranging from 1 to 2 between the minimum wage and the AFDC caseload. However, as they note, their study's suggestion of the minimum wage leading to increased welfare dependency does not hold across different samples and does not withstand the inclusion of state-specific trends. In contrarily suggestive findings, Reich and West (2015) show that the minimum wage leads to a substantial decline in the participation in the Supplemental Nutrition Assistance Program (SNAP), previously known as food stamps, with the elasticity of up to -0.32. Revisiting the scope of the minimum wage in reducing public assistance programs, Sabia and Nguyen (2017) evaluate whether the minimum wage decreases participation in major welfare programs–the Supplemental Nutrition Assistance Program (SNAP), Medicaid, Housing Assistance programs, Temporary Assistance for Needy Families (TANF/AFDC), and the Special Supplemental Nutrition Program for Women, Infants and Children (WIC). They conclude that the minimum wage does not affect the participation in means-tested programs. One common thread or point of contention that these previous studies bring to light is the need to tackle unobserved state-level confounders. Not only does this study contribute to our understanding of the role of the minimum wage in public assistance programs, but it does so by adopting identification strategies that allow me to control for confounders more comprehensively and convincingly.

Second, this study relates directly to the literature examining the disincentive effects of labor market conditions on receiving federal disability insurance programs. The rise in disability insurance programs has coincided with deteriorating job opportunities for low-skilled workers, leading economists to seek proximate explanations in the labor market. Black, Daniel, and Sanders (2002) examine how earnings prospects, driven by exogenous changes in the price of coal in coal-producing states, including Kentucky, Ohio, Pennsylvania, and West Virginia, affect individuals' propensity to enroll in disability insurance programs. Charles, Li, and Stephens (2018) extend Black, Daniel, and Sanders (2002) by examining the connection between predicted employment growth and the uptakes of SSI and Social Security Disability Insurance (SSDI). Several other studies seek explanations for rising enrollment into the rolls of disability insurance (DI) and examine labor supply responses to DI, including SSI.[4]

Third, this analysis is connected with an emerging body of literature that examines the effect of the minimum wage beyond labor market outcomes (see Neumark 2024 for a recent review). Dube (2019) notes that the minimum wage can effectively lift people out of poverty. Aaronson, Agarwal, and French (2012a) find that a rise in the minimum wage leads to an increase in consumption. Dettling and Hsu (2020) show how the minimum wage improves the financial well-being of individuals, leading to a decrease in delinquency, an increase in credit scores, and greater access to credit card loans. Similarly, Regmi (2020) studies the effects of the minimum wage on children's cognitive achievement, and Renkin, Montialoux, and Siegenthaler (2020) and Leung (2021) examine how the minimum wage affects retail prices.

[4] For example, Autor and Duggan (2003), Goodman-Bacon and Schmidt (2020), Bound (1989), and Milligan and Schirle (2019).

2.2 Conceptual Framework

Before proceeding to empirical estimation, I present a conceptual framework to explain how a minimum wage increase operates to influence the prime-age working population's participation in Supplemental Security Insurance (SSI), guiding the empirical procedure. Indeed, there are several competing potential channels affecting an individual's decision to enter and exit the SSI program.

When the government raises the minimum wage, it affects (i) the employment prospects arising from firms' labor demand and (ii) the opportunity cost of being unemployed or a non-participant in the labor market for less-skilled workers. If individuals become jobless from an increase in the minimum wage, they may turn to SSI for income support. The neoclassical model posits that a higher minimum wage leads to a decline in employment. Contrarily, the monopsony model predicts that a higher minimum wage leads to higher employment and earnings levels. The voluminous minimum wage literature is mixed and contentious in line with the predictions of these theoretical models.

In a classical model, the impact of the minimum wage on participation in SSI is ambiguous. It depends on (i) the extent to which firms reduce their employment through reduced hiring or increased layoffs and (ii) the extent to which a higher minimum wage increases search efforts or attachment to the labor market for the unemployed. When firms do not lay off individuals because of minimum wage increases, one potential channel involving the transition of individuals from employment to SSI may be absent. In providing the evidence of adverse effects on employment, Gopalan et al. (2021) note that a decline in low-skilled workers in firms because of a minimum wage rise primary results from the decline in hiring. Likewise, when the unemployed or non-employed individuals sense that minimum wage rises increase the potential earnings, they may be attached to the labor market, reducing their interest in SSI. Adams, Meer, and Sloan (2018) provide evidence of the unemployed increasing job search time immediately after a rise in the minimum wage. Conversely, monopsony model predictions—higher employment and higher wages—suggest that the minimum wage should lead to a decline in SSI enrollments.

Notwithstanding the contentiousness of empirical findings on employment, the minimum wage literature points to a rise in wages of low-skilled workers. When a higher minimum wage increases earnings and subsequently assets of those low-skilled workers, they may be pushed out of the eligibility threshold for SSI benefit based on income and assets. Further, as the previous literature attributes the rise in the potential replacement rate (SSI benefits divided by (previous) earnings in the labor market) to the rise in disability rolls (Autor and Duggan 2003), an enhanced minimum wage can lead to a decline in the relative benefits of SSI payments and an increase in attachment to the labor market. The relative benefits could be especially important when separation from a job is endogenous or voluntary.

In summary, how changes in minimum wages affect enrollment in SSI encompass two channels: income and incentives. The resulting changes in income can affect individuals' eligibility for SSI and the potential replacement rate, which alters the intensity of their labor market attachment, thus inducing or dissuading their participation in SSI.

3 SSI Background

In this section, I provide a brief overview of Supplemental Security Income (SSI).[5] SSI, a nationwide means-tested program, came into operation in 1974 with an objective of helping people meet their immediate basic needs such as food, shelter, and clothing. Particularly, it provides cash assistance to aged, blind, and disabled people with limited or no income and fewer resources. The program comprises three types of recipients: (i) blind or disabled children, (ii) blind or disabled adults, and (iii) 65 or older. Administered by the federal government, (more precisely, the Social Security Administration) SSI operates with funding from general tax revenues. The program's parameters such as income, assets and medical eligibility and the level of benefits are uniform across states. Some states provide a supplemental payment in addition

[5]Interested readers may want to refer to Duggan, Kearney, and Rennane (2015) for an expansive review.

to the federal benefit amount. However, the share of states' payment is extremely low, just six percent of total SSI benefits (Duggan, Kearney, and Rennane 2015). Another important feature of this program is that it does not require its applicants or their family members to have prior work history, contrary to the Social Security Disability Insurance (SSDI) program. Therefore, it can be only source of income for "disabled" individuals lacking sufficient work history to quality for SSDI. SSI is also distinct from other means-tested programs like Temporary Assistance for Needy Families (TANF), the Supplemental Assistance Program (SNAP), and the Earned Income Tax Credit. Two distinctions between SSI and other means-tested programs worthy of note are: (i) it is more generous and (ii) it provides benefits for a long period of time, contrary to a temporary feature of the other programs.

To qualify for benefits, individuals, except those 65 and older, must meet the disability definition of the Social Security Administration. Furthermore, they must have little or no income, along with limited resources ($2,000 for an individual or a child, and $3,000 for a married couple.) Approximately 9.21 million people received SSI benefits in 2015. The average monthly payment was $733. Total spending in 2015 stood at approximately $55 billion. The amount has steadily been rising over the years (Figure A1).

4 Data and Summary Statistics

4.1 Data

I assemble data from a variety of sources. Below, I explain such sources and how I construct and restrict the sample.

Current Population Survey. I use individual-level data from the Annual Social and Economic Supplement (ASES) of the Current Population Survey (CPS), which is conducted every March and includes detailed information on socioeconomic and demographic characteristics. The data are extracted from the Integrated Public Use Microdata Series (Sarah Flood and Warren 2020).

Given the richness of the information it contains, it has been widely used in the literature to analyze various policy effects and create official statistics, including the annual estimate of poverty.

The sample covers the period from 1992 to 2015. Before 1992, the educational attainment variable was defined differently, creating measurement errors in classifying high school dropouts.[6] As noted below, to isolate the causal effects of SSI, this paper relies on a comparison between individuals without a high school degree and those with at least a high school degree.

I limit the sample to individuals in the prime-age working group (ages 25 to 54), a standard practice in the literature. I also drop those individuals who are in the armed forces.

One of the many advantages of the CPS data is that the survey explicitly asks individuals to report the amount of Supplemental Security Income (SSI) they received during the previous calendar year. This makes it possible to observe the sample of SSI recipients more precisely. Nonetheless, while the CPS has a few attractive features, like any other household survey, it has one disadvantage that is worthy of note. Particularly, respondents in the survey tend to underreport their participation in welfare programs (see Meyer, Mok, and Sullivan 2009 for detail review).

Aggregate SSI. To complement the micro-level analysis based on the CPS data, I use the aggregate data. I use SSI benefit payment at the county level from the Bureau of Economic Analysis's (BEA) Regional Economic Information System (REIS),[7] covering 1992-2015. The REIS provides annual estimates of personal income by source created at the county level. The measure of SSI uptake in this study is similar to that of Charles, Li, and Stephens (2018). One advantage of the BEA data over household surveys such as the CPS is that the BEA data are available at a more granular level, particularly at the county level.

[6]For example, the proportions of individuals in the sample who report their educational attainment as "12th grade, no diploma" and "high school diploma or equivalent" were 1.25 and 23.76 percent, respectively, in the period between 1992 and 2015, while the corresponding proportions were 26.02 and 2.74 percent in the years 1990 and 1991.

[7]The link is https://www.bea.gov/data/economic-accounts/regional.

Other Data. I collect the state-level minimum wage data from David Neumark.[8] I use the minimum wage available in the first month every year. Panel A of Figure A2 displays the variation in the minimum wage across states in 2015 and Panel B the growths of the minimum wage between 1992 and 2015. Both the level of the minimum wage and the growth rates reflect different underlying economic, demographic, and political characteristics. Generous minimum-wage states tend to be located in the northeast, west, and mid-west. Further, I collect the county-level unemployment rate data from the Bureau of Labor Statistics.[9] I retrieve county population estimates from the Surveillance, Epidemiology, and End Results (SEER) Program.[10]

4.2 Summary Statistics

Analytical CPS Sample. Table 1 provides the summary statistics for the analytical CPS sample. Columns 1-2 present the results for the sample of high school dropouts, and the last two present for those with a high school degree or beyond. I apply the ASES survey weight to calculate those statistics. The uptake of SSI appears to be much higher for high school dropouts. Demographically, the high school dropout sample has a disproportionately higher representation of Hispanics and an underrepresentation of the white population

Who are SSI recipients? To provide general demographic and educational information on SSI recipients, Table A1 presents their characteristics. About 12 percent of them report having been employed. Regarding racial composition, 55 percent are white, 27 percent black, 14 percent Hispanic, and 5 percent are other races. The mean age is about 41 years. Females are slightly over-represented, accounting for about 57 percent of the total recipients. Likewise, the recipients are overwhelmingly unmarried (67 percent). In terms of educational attainment, 36 percent of them do not have a high school degree, and 40 percent of them have a high school degree.

Analytical Aggregate Sample. Next, I present summary statistics for the alternative analyt-

[8] I extract the data from https://www.socsci.uci.edu/d̃neumark/datasets.html.
[9] The link is www.bls.gov/lau.
[10] The link is https://seer.cancer.gov/popdata/.

ical sample based on the aggregate-level data in Table A6. Panel A presents summary statistics for all counties and Panel B for border-pair counties. As noted below, counties in the border-pair sample appear as many times as the number of counties they border. The variable $ln(SSI)$ represents the natural log of the county-level benefit payment.

5 Micro Evidence from the CPS Data

I base the micro-level analysis on the Current Population Survey (CPS) data. The main advantage of using individual-level data is that it allows the use of a comparison group, providing an additional source of variation.

5.1 Main Empirical Estimation

A critical challenge in identifying the effects of minimum wage changes on the uptake of Supplemental Security Income (SSI) benefits is that legislation governing such changes should correlate with underlying macroeconomic conditions and the generosity of other welfare programs. Allegretto et al. (2017) document the non-random nature of minimum wage policies, with high- and low-minimum-wage states differing across several dimensions such as labor market conditions and political leaning—Democrat versus Republican.

In order to isolate the causal effects of the minimum wage on participating in SSI, I use a triple differences approach, which exploits cross-state and temporal differences in minimum wages and comparisons in the outcome of the potential treatment group (those without a high school degree) to that of the potential control group (those with a high school degree or beyond). The rationale behind constructing the treatment group is rooted in the expectation that minimum wage policy disproportionately affects less-educated individuals compared to more-educated individuals. This empirical strategy is, in spirit, similar to Dettling and Hsu (2020). I estimate, in particular, the following model:

$$SSI_{i,s,t-1} = \beta_1 ln(MW_{s,t-2}) + \beta_2 * \mathbf{1}[LHS_{i,t}] + \beta_3 \mathbf{1}[LHS_{i,t}] * ln(MW_{s,t-2}) + \delta X_{i,t} + \gamma_t + \varsigma_s + \epsilon_{it}, \quad (1)$$

where i represents individual, s state, and t survey year. In this model, $SSI_{i,s,t-1}$ is an indicator variable that takes the value of one if the individual received any amount of SSI benefit in the previous calendar year. Note that the CPS reports income from the previous calendar year, while it reports demographic information from the survey year. $ln(MW_{s,t-2})$ is the log of state-level minimum wage in year $t-2$. Given that the SSI application process is lengthy, running into several months, there should be a lag between a minimum wage rise and the receipt of, or exits from, SSI benefits, including suspensions or terminations. $\mathbf{1}[LHS_{i,t}]$ is a dummy variable that equals one if the individual has less than a high school degree, i.e., high school dropouts. The interaction between $ln(MW_{s,t-2})$ and $\mathbf{1}[LHS_{i,t}]$ is the variable of interest, and the parameter β_3 measures the effect of the minimum wage on the treatment group relative to the control group. γ_t is a vector of year fixed effects intended to capture the secular trend in SSI uptake. ς_s contains state fixed effects that capture state-level unobserved, time-invariant heterogeneities. $X_{i,t}$ includes individual demographics such as the race (dummies for non-Hispanic white, non-Hispanic black, Hispanic, and non-Hispanic other races), a dummy variable for marital status, age, and age squared. The objective behind the inclusion of these individual-level variables is to improve the precision of estimates.

I use the survey weight in all my analyses to make the sample representative of the population. Additionally, I cluster standard errors at the state level to account for the fact that unobserved factors within a state–the unit of policy–are probably correlated. The unit of analysis is an individual.

The maintained assumption necessary for identifying the parameter of interest in this econometric procedure is that any remaining confounders affect both high school dropouts and those with a high school degree or beyond similarly. For example, even if economic conditions or the business cycle influence the choices of state lawmakers to revise the minimum wage and individuals to collect SSI, this model can purge unobserved confounders under the maintained assumption.

Before presenting my baseline results, I show how the state-level minimum wage is associated with SSI participation by high school dropouts (the treatment group) versus high school or higher degree holders (the comparison group). I calculate the average minimum wage and participation in SSI by state over the period 1992-2015. As graphically visualized in Figure 1, a clear and steady association emerges between a higher minimum wage and a decline in participation among high school dropouts. However, for those with a high school degree or beyond, there is no association between the minimum wage and participation. Despite displaying a revealing correlation, it is important to note that such a correlation does not guarantee the causal relationship between SSI uptake and the minimum wage.

5.2 Main Results

After providing visual evidence on the effects of the minimum wage, I then present baseline estimates based on Equation (1). I begin estimating my model without any individual controls. Column 1 of Table 2 contains the results. Next, I control for individual level characteristics, such as dummies for the race, age, age squared, and marital status. Column 2 contains the results, which are both qualitatively and quantitatively similar. In terms of magnitude, the coefficient on the interaction term $ln(MW_{s,t-2}) * \mathbf{1}[LHS_{i,t}]$ is -0.0196.[11] That means a one-percent increase in the minimum wage leads to approximately a 0.0196 percentage points decline in the likelihood that a high school dropout would collect SSI benefits as compared to an average individual in the control group. Given the mean value of SSI uptake of 6 percent among the treatment group, this represents approximately $\frac{0.0196}{6} = 0.33$ percent (an elasticity of 0.33).

Other coefficients provide an essential and meaningful context to interpret the main coef-

[11] As some high school graduates should work in minimum-wage jobs, I exclude this group from my analysis as a robustness check. Doing that provides an estimate and a standard error of 0.0122 and 0.0071, respectively.

ficient of interest. The variable $\mathbf{1}[LHS_{i,t}]$ is positive and precise, illustrating the differences in the uptake of SSI between high school dropouts and those with a high school degree or beyond. The coefficient on the minimum wage variable is of a very small magnitude. This precisely estimated null effect indicates that the minimum wage is not correlated with underlying unobservable confounders determining participation in SSI. This coefficient would measure the effect of the minimum wage if all individuals received at least a high school degree, that is, $\mathbf{1}[LHS_{i,t}] = 0$.

The coefficient on the interaction term provides the relative effect of the minimum wage among high school dropouts compared to those with a high school degree or beyond. Given that the effect on those with a high school degree or beyond is close to zero, it is likely that the effect estimated from the interaction term represents the total effect of a decrease in SSI uptake for high-school dropouts.

Although the magnitude seems to be large, the effect appears to be plausible upon closer investigation of the substantial suspensions to SSI payments, where persistent suspensions (lasting longer than 12 months) are technically terminations. In 2015, the ratio of suspended recipients to the total recipients aged 18-64 years was about 13 percent, according to the Annual Statistical Report by the Social Security Administration (SSA).[12] Out of the total suspensions, 49 percent were due to excess income. In my analytical sample, nearly six percent of treated individuals are collecting SSI benefits, which translates into 60 per 1000 individuals receiving benefits. To contextualize the magnitude, if the minimum wage were to rise by 10 percent, then the number of the SSI receipts would decrease by 2, which reduces the figure to 58 per 1000 individuals. This represents a decline of 3.3 percent, a magnitude equivalent to one-third of the suspensions due to excess income. It is important to emphasize that as SSI enrollees have fewer qualified assets and a relatively lower benefit level, most could be low-income people, the type whose labor market outcomes are likely affected by the minimum wage. Moreover, the minimum wage might discourage individuals from joining SSI by diminishing its relative value, and potentially

[12]The link for the report is https://www.ssa.gov/policy/docs/statcomps/ssi_asr/2015/ssi_asr15.pdf.

disqualifying them from applying for it in the first place due to excess income, consequently leading to a potential reduction in enrollments. This is especially true given that in 2015, approximately 16 percent of applications for SSI benefits for individuals aged 18 to 64 were denied due to non-medical reasons, one of which is excess resources.

In a related paper, Duggan and Goda (2020) find that minimum wage increases lead to a slight uptick in applications for the disability program, including SSI. However, in some of their specifications, the effect is no longer statistically different from zero or the direction of the effect becomes negative, especially when using the lagged minimum wage. While these findings in Duggan and Goda (2020) speak to the potential "push" factor of the minimum wage on the SSI program, they do not directly speak to the actual enrollment or the uptake of the SSI program. It is possible that the rise in applications may be driven by those who are most likely to be rejected, considering that a considerable percentage of applications is rejected. For example, in 2015, only 31.7 percent of SSI benefit applicants aged 16-64 years were awarded. Minimum wage changes can affect SSI receipts by influencing enrollments, exits (including suspensions and terminations), or a combination of both. Overall, the results of Duggan and Goda (2020) do not contradict the findings in this paper. As noted before, a reduction in SSI receipts in my paper may largely be attributed to suspensions or terminations resulting from higher earnings due to minimum wage hikes. Additionally, an increase in SSI applications does not necessarily rule out the possibility of a decline in actual awards and enrollments.

Potential Threats. The major contentiousness in the minimum wage literature about identifying its effects revolves around sufficiently capturing unobserved factors, including the business cycle. The inability to control for those factors, which can drive changes in the minimum wage and participation in social welfare programs, may bias estimates.

To analyze the sensitivity of the results, I first control for the seasonally adjusted state-level unemployment rates. The results are nearly identical (Column 1 of Table 3).[13] A more

[13]To further investigate whether the uptake of other social welfare programs confounds the observed relationship between the minimum wage and SSI uptake, I control for participation in major welfare programs.

credible, comprehensive approach that I take to safeguard the estimates from potential biases is to non-parametrically control for time-varying state-level confounders by including state-by-year fixed effects. This approach makes it possible to control for year-over-year state-level changes in unobserved confounders, such as the underlying macroeconomic environment. Note that in this specification, the effect of the minimum wage is not separately identified as state-by-year fixed effects subsume it. Column 2 of Table 3 contains the results.

Additional Analysis. After providing robust, credible evidence against other state-level unobserved factors explaining these findings, I further explore alternative approaches used in the literature for completeness, connecting the current approach to those described in the literature. First, I use state-specific linear trends to capture the secular trends in SSI uptake or other economic conditions that evolve linearly over time across states. Additionally, I include Census division-by-year fixed effects to address spatial heterogeneities. It is worth noting that there is a total of 9 Census divisions, representing different regions of the country. Table A2 contains the results. Expectedly and reassuringly, the results are similar. Additionally, to examine the sensitivity of the results, I use the minimum wage in real terms. In the absence of official cost-of-living measures across states during the sample period, I use the widely used national measure of cost-of-living, the Consumer Price Index for All Urban Consumers published by the Bureau of Labor Statistics. Column 1 of Table A3 contains the results. Likewise, I also use minimum wages in levels and present the results in Column 2 of Table A3. The results are both qualitatively and quantitatively similar.

Overall, the results withstand various types of specifications and controls for unobserved confounders. The slew of checks validates the claim that the minimum wage causes a decline in SSI participation.

Pre-Great Recession Period. My sample period includes the Great Recession and its after-

Specifically, I include per capita Temporary Assistance for Needy Families (TANF) receipts, food stamps receipts, unemployment insurance (UI) initial claims, Earned Income Tax Credit (EITC) spending, and Medicaid spending in the previous calendar year at the state level. The coefficient and standard error on the interaction term are -0.0195 and 0.0065, respectively.

math, leading to some concern over my main results being biased by its heterogeneous impacts across states. To the extent that minimum wage laws were correlated with the severity of the recession and associated expansions in social safety nets, especially unemployment insurance,[14] it is possible that confounding factors may drive the results. Severe economic downturns can accelerate the destruction of low-skilled jobs, which are typically minimum wage jobs. Studying the role of minimum wage changes in the recent Great Recession in the U.S., Addison, Blackburn, and Cotti (2013) provide some support that states facing the deepest recessions are more likely to bear negative employment effects. Clemens and Wither's (2019) findings of larger and deeper effects of the minimum wage during the period surrounding the Great Recession provide an additional piece of corroborating evidence on this topic. Therefore, I exclude the years after 2007 and re-estimate my preferred specification. Table A4 presents the results, with Column 1 showing the results based on Equation 1 and Column 2 showing the results estimated by adding state-by-year fixed effects.

5.3 Heterogeneous Analysis

By Gender. It is well-documented that men and women face different labor market experiences and tradeoffs between home and market production. Therefore, I estimate the effect of the minimum wage on SSI uptake separately. Table 4 presents the results by gender: Column 1 for women and column 2 for men. The response of both groups to SSI is similar.

By Marital Status. There are contrasting channels through which the minimum wage can generate heterogeneous effects for the married and unmarried. With one spouse participating in the labor market, the other can find SSI benefits effectively complement family earnings and focus on home production, becoming more responsive to it. Conversely, given the income and asset thresholds for SSI eligibility, it is reasonable that the married are more likely to cross the thresholds, becoming ineligible. Table 5 reports the results by marital status. The effects are

[14] During and aftermath of the Great Recession, unemployment insurance was extended up to as many as 99 weeks, up from the regular 26 weeks.

concentrated in unmarried individuals.

5.4 Alternative Classification

In an alternative classification, I group individuals based on their hourly wage during the previous calendar year. Since the CPS-ASEC does not provide information on hourly wages, I estimate it by dividing their earned income during the previous year by the total number of hours worked. This calculation is based on information on "usual hours worked per week last year" and "weeks worked last year."

For the first estimation, I create three groups: (i) individuals earning 60 percent below the minimum wage, including zero income, (ii) individuals earning between 60 percent and 120 percent of the minimum wage, (iii) individuals earning 120 percent above the minimum wage.[15] This strategy is similar in spirit to that of Aaronson, Agarwal, and French (2012b). I estimate the model parallel to Equation 1.[16] Individuals earning 120 percent above the minimum wage serve as the reference group. Column 1 of Table A5 reports the results. The minimum wage significantly reduces the uptake of SSI among those earnings between 60 and 120 percent of the minimum wage. However, such a relationship does not exist for those who have zero earnings or less than 60 percent of the minimum wage.

To provide more nuanced estimates, I expand the classification into 5 groups by dividing individuals who earn 120 percent above the minimum wage into two three groups: (i) individuals earning between 120 percent and 180 percent of the minimum wage, (ii) individuals earning

[15] For this classification, I use the minimum wage observed in the same year as their hourly wages.

[16] I employ the following econometric specification: $SSI_{i,s,t-1} = \beta_1 ln(MW_{s,t-2}) + \beta_2 \mathbb{1}[0 \leq wage \leq 0.6 * MW] \times ln(MW_{s,t-2}) + \beta_3 \mathbb{1}[0.6 * MW < wage \leq 1.2 * MW] \times ln(MW_{s,t-2}) + \beta_4 \mathbb{1}[0 \leq wage \leq 0.6 * MW] + \beta_5 \mathbb{1}[0.6 * MW < wage \leq 1.2 * MW] + \delta X_{i,t} + \gamma_t + \varsigma_s + \epsilon_{it}$. In this model, $\mathbb{1}[0 \leq wage \leq 0.6 * MW]$ and $\mathbb{1}[0.6 * MW < wage \leq 1.2 * MW]$ are indicators of whether the individual's hourly wages were between 0 and 60 percent of the minimum wage, and between 60 and 120 percent of the minimum wage, respectively. The other variables are defined as before. It is not uncommon to have wages reported below the minimum wage, which could be related to measurement errors in self-reported income in the household survey data such as the CPS (e.g., Autor, Manning, and Smith 2016) or the prevalence of "avoidance and evasion of minimum wage regulation" as explored in two papers by Clemens and Strain (2022b) and Clemens and Strain (2022a). Furthermore, one reason for including individuals with zero income is that some of them were unemployed due to firms potentially cutting back or refraining from hiring due to a higher minimum wage.

between 180 percent and 240 percent of the minimum wage, and (iii) individuals earning above 240 percent of the minimum wage. Individuals earning 240 percent above the minimum wage serve as the reference group. As reported in Column 2 of Table A5, the effect for individuals earning zero or way below the minimum wage is not statistically different from zero. However, the effect is significant for those earnings around the minimum wage. The effect tends to persist for those earnings slightly above the minimum wage (around 120-180 percent of the minimum wage), albeit in a smaller magnitude. This could be due to measurement errors in calculating hourly wages, or it may reflect the spillover effect of the minimum wage, which is consistent with the previous literature (Gopalan et al. 2021, Autor, Manning, and Smith 2016, Gregory and Zierahn-Weilage 2022 Clemens and Strain 2022b and Clemens and Strain 2022a). The effect disappears for those earning 180 to 240 percent of the minimum wage.[17]

6 Macro Evidence

I have provided robust estimates on how the minimum wage affects SSI participation using the individual-level data. To complement the micro findings, I use aggregate data, which presents two advantages. First, aggregate participation in SSI is not susceptible to measurement error stemming from respondents' under-reporting. Second, the availability of data at a more refined geographical level (county), enables me to leverage alternative identification strategies to control for local economic conditions. The aggregate analysis aims to further complement and enrich the findings based on individual-level data.

6.1 Cross-border Minimum Wage Variation at State Borders

I first employ an empirical approach that exploits policy discontinuity in minimum wage legislation at state borders. Dube, Lester, and Reich (2010) introduced this empirical strategy to study the disemployment effects of the minimum wage, aiming to address the identification

[17] While excluding those with no income, the patterns of the results remain qualitatively similar. Nevertheless, the effect, though of a smaller magnitude, seems to persist for individuals in the higher wage distribution as well.

challenges faced in a traditional approach based on state-level panel data. Various studies in the minimum wage literature has used this approach (e.g., Aaronson et al. 2018, Coviello, Deserranno, and Persico 2022, and Gopalan et al. 2021). Despite its appeal and use, the debate surrounding the validity of identification in this approach persists (Neumark, Salas, and Wascher 2014b). Nevertheless, this estimation can also serve as an alternative method to disentangle the effect of minimum wages on SSI payments, connecting this study to the body of the minimum wage literature based on this approach. In this research design, I compare the per capita SSI benefit payments within contiguous counties at state borders, which happen to be in different states and subsequently subject to different minimum wage laws.[18] I use the following empirical specification:

$$ln(SSI_{cpt}) = \beta_1 ln(MW_{c,t-1}) + \gamma_c + \varphi_{pt} + ln(Pop_{ct}) + \epsilon_{cpt}. \tag{2}$$

In this model, $log(SSI_{cpt})$ is total SSI payment in county c and year t, $ln(MW_{c,t-1})$ the natural logarithm of the effective minimum wage which is the higher of the federal and state minimum wages in county c and year $t-1$, and γ_c a vector of county fixed effects. Likewise, φ_{pt} denotes a vector of county-pair-by-year fixed effects which nonparametrically control for time-varying, common confounding factors in a cross-border pair. The parameter of interest β_1 measures the elasticity of SSI payment with respect to the minimum wage. I use the log of the population as a control variable so that the outcome variable can be interpreted as the log of per capita SSI payment. Since identifying the parameter of interest in this model relies on comparing the outcome in a cross-border counties pair, creating a border-pair for each county is necessary. Therefore, a county appears in the data as many times as the number of other counties it borders. My analytical sample consists of 61,856 observations spanning the period 1992-2015, including 601 contiguous county pairs. I cluster standard errors at the state-level.

Establishing the causal effects of the minimum wage on SSI uptake requires an identifying

[18]Figure A3 displays the average minimum wage across cross-state counties for the period 1992-2015.

assumption that counties experiencing a minimum wage hike would have exhibited a trend in SSI uptake similar to that in counties across state borders. This is after controlling for county fixed effects, which eliminate static differences across counties, as well as the time-varying county-level observables, particularly the unemployment rate. However, the identifying assumption of this model is still subject to debates and critiques (Neumark, Salas, and Wascher 2014b). Below, I examine a concern related to the identifying assumption: the potential movement of workers across state borders in response to minimum wage hikes.

6.1.1 The Movement of Workers Across State Borders

If individuals in the bordering counties commute to work in another state in response to a rise in the minimum wage, this poses a potential threat to the identifying assumption in this model. To assess the likelihood of workers in bordering counties working in neighboring states, I turn to the Census 2000 and American Community Survey (ACS) data from 2005 to 2015, which report the primary workplace of respondents.[19] I restrict the sample to the prime working-age employed. In my analytical sample of neighboring counties across state borders, nearly 90 percent of them work within the state of their residence. To directly examine the role of the relative minimum wage on cross-state movement of workers, I use an empirical specification parallel to Equation 2. I regress an outcome variable indicating whether a resident works in a neighboring state on the relative minimum wage between it and the state of residence. Table A7 reports the results by educational attainment, consistent with the scope of the minimum wage's potential to affect

[19] In the ACS and Census data, the county of residence is not identifiable for all respondents. The most granular level of geographical identification available is the Public Use Microdata Area (PUMA), which may contains one or multiple counties. The information on PUMA, without which not all counties can be identified, is available only in the 2000 Census and in the ACS from 2005 during my analytical sample. Therefore, I need to restrict my sample to the 2000 Census and the ACS 2005 to 2015. The boundary of PUMA changes every 10 years. In my analytical sample period, the PUMAs' boundaries change after 2012, so I use two crosswalks (one for the period 2000 and 2005 to 2011 and another for the period 2012 to 2015) to allocate PUMAs to counties. (I use the Geocorr applications from the Missouri Census Data Center to create these crosswalks. The link is https://mcdc.missouri.edu/applications/geocorr.html.) Since PUMAs can span across multiple counties, they may be stratified into multiple counties. I allocate these PUMAs to all possible counties. Individuals from those PUMAs may appear multiple times in my sample. To account for these multiple reappearances, I weight each individual by the proportional probability of belonging to a given county from each PUMA. Additionally, I apply the sample weight from the ACS.

individuals differently. The effects are not statistically different from zero, providing evidence of the labor marker segregation across the border lines. This offers some reassurance about the validity of this research design.

6.1.2 Results

This section presents the results derived from the approach based on discontinuities in minimum wage policies at state borders, as specified in Equation (2). Table 6 presents the results. The results show that higher minimum wages significantly reduce the uptake of SSI benefits. The elasticity of SSI benefit payment with respect to the minimum wage is around -0.17 (Column 1). Putting this estimate in the context of the literature regarding SSI, Charles, Li, and Stephens (2018), using similar data to this study, has estimated the elasticity with respect to earnings as -0.16.

Regarding magnitude, the macro estimate (elasticity of -0.17) in absolute terms is smaller than the estimate from the individual-level data. The discrepancy between micro and macro elasticities arises because the micro estimate is based on prime-age working individuals, the type of individuals that the minimum wage policy is expected to affect, while the macro effect is based on all recipients, including children and the elderly, for whom the policy is largely inapplicable. To reconcile these micro and macro effects, I extrapolate the elasticity from 25- to 54-year-olds to estimate the elasticity for the entire population of SSI recipients. To do so, I calculate the share of SSI recipients aged 25-54 years in the analytical CPS sample, which is approximately 46 percent. Thus, a back-of-the-envelope calculation suggests that the elasticity for the entire SSI recipient population is -0.15, which is obtained by multiplying the elasticity estimate for individuals aged 25-54 years by their share in the sample. While this assumes no minimum wage effect outside the age-range of 25-54, there might be some effect on those outside this range, potentially altering the extrapolated estimate. Still, this composition difference has scope to largely explain the discrepancy. Additionally, it cannot be ruled out that some of the discrepancy may also stem from sampling variation and measurement errors in the data.

Robustness Check. The previous literature shows the role of business cycle fluctuations in participation in means-tested and disability insurance programs. To examine whether the business cycle is driving the results, I re-estimate the model controlling for the county-level, seasonally adjusted unemployment rate. As expected and reassuringly, the results are almost identical (Column 2 of Table 6).[20] These results bolster the validity of the research design. Note that the model identifies the causal effect of the minimum wage under the assumption that the underlying business cycles are not different in a cross-border pair. Having virtually no impact on the main estimate when controlling for the unemployment rate provides strong evidence that the business cycles evolve smoothly across borders without being correlated with changes in the minimum wage.

Further, as noted above, a county can appear multiple times. To account for these multiple appearances, I re-estimate the model by weighting it by the inverse of the number of times it is observed in county pairs. The results are almost identical (Table B1).

Estimation of Dynamic Effects. To further support the plausibility of my identifying assumption, I estimate a distributed lead-lag model, including three years of leads and three years of lags. I specify the model that follows the strategy of Dube, Lester, and Reich (2010).

$$ln(SSI_{cpt}) = \sum_{j=-3}^{3} \beta_j \Delta ln(MW_{c,t+j}) + \beta_{-4} ln(MW_{c,t-4}) + \gamma_c + \varphi_{pt} + ln(Pop_{ct}) + \epsilon_{cpt}. \quad (3)$$

Each Δ represents the first difference in the minimum wage between two consecutive years in county c. Each coefficient on $\Delta ln(MW_{c,t+j})$ identifies the cumulative effect of minimum wage changes, representing the summation of all effects from three years prior to the minimum wage increase up to a particular year of interest. For instance, β_{+3} measures the effect of the minimum wage 3 years before the change, while β_{+2} measures the cumulative effects 3 years and 2 years before the change, and so on. Likewise, β_{-4} estimates the long-run cumulative effect of

[20] For completeness, I estimate my model using the minimum wage in levels. As presented in Table A8, the results are similar.

the minimum wage up to the period four years after the change. As presented in Table 7, this coefficient is statistically significant. All the coefficients on the leads are not statistically different from zero. If the baseline results reveal pre-existing differences between counties, not the actual effect of the minimum wage, we expect to find statistically significant effects of minimum wage changes in the future.

Alternative Measure. Thus far, I use the well-regarded works in the literature to define the uptake of SSI benefits. While the calculated per capita SSI benefit payment sheds light on the overall trend in SSI expenditure and its uptake, it does not allow me to provide nuanced estimates about the characteristics of recipients. I next go on to construct data on SSI recipients' characteristics. I assemble information on the number of SSI recipients from 1998 to 2015 using publicly available "SSI Recipients by State and County" reports from the Social Security Administration.[21] Note that such reports are publicly available only since 1998. These reports divide recipients into three groups: under 18 years of age, ages 18 to 64, and 65 and older. I re-estimate the main results using the specification based on minimum wage legislation discontinuity at state borders. Table 8 provides the results; Panel A for the period 1998 to 2015 and Panel B for the period 1998 to 2007. Two main messages stand out. First, I find statistically significant effects for the age group of 18-64. Second, estimates for under 18 years and 65 or older are not statistically different from zero. Those individuals under 18 years of age or 65 and older have a lower attachment (or no attachment at all depending on the exact age profile) to the labor market and are not consequently responsive to minimum wage changes. Statistically insignificant effects for those age groups help to provide further validity to the research design of this study.

Pre-Great Recession Period. As noted above, it is possible that the Great Recession could bias the results. Therefore, I exclude the years after 2007 and re-estimate my preferred specification. Table A9 presents the results. Column 1 provides the estimate derived without any control variable and Column 2 controls for the unemployment rate. The effects are slightly stronger as compared to baseline estimates, mirroring the pattern observed in the individual-

[21] https://www.ssa.gov/policy/docs/statcomps/ssi_sc/1998/index.html

level data above. The findings could also be viewed in the context of Charles, Li, and Stephens's (2018) "puzzling" discovery of SSI being non-responsive to labor market conditions in recent years, implying a weaker effect of the minimum wage.

6.2 Low- and High-Income Counties Comparison

Although the above-presented identification strategy, which focuses on counties in a cross-border pair, is plausibly appealing, it has certain disadvantages. Particularly, one argument against the above-illustrated border discontinuity approach is that limiting the analysis to contiguous state-bordering counties may throw away important variation needed to identify the effect of minimum wages (Neumark, Salas, and Wascher 2014c). To further enhance the credibility of the findings, I examine the extent to which the level of the minimum wage differently affects the uptake of SSI disability insurance in low-income counties compared to high-income counties. Given that the minimum wage is considered to be more binding in low-income counties, we expect it to have a disproportionately larger effect on those areas. Using county-level per capita income data from the Bureau of Economic Analysis's (BEA) Regional Economic Information System (REIS),[22] I classify counties as high- and low-income. I adopt the following empirical strategy.

$$ln(SSI_{ct}) = \beta_1 \mathbf{1}[LowIncome_{ct}] + \beta_2 ln(MW_{c,t-1}) + \beta_3 ln(MW_{c,t-1}) * \mathbf{1}[LowIncome_{ct}] + \gamma_c + \tau_t + ln(Pop_{ct}) + \epsilon_{ct}, \tag{4}$$

where $\mathbf{1}[LowIncome_{ct}]$ is an indicator variable for county c in year t for having per capita income below the median. Other variables are defined as above. β_3, the parameter of interest, measures the differential effects of the minimum wage between low-income and high-income counties, while purging common confounding factors. Under the assumption that changes in the minimum wage are not correlated with other confounders affecting both types of counties differently, β_3 identifies the causal effect.

I begin by presenting the results estimated using the specification identical to Equation

[22] The link is https://www.bea.gov/data/economic-accounts/regional.

(4). Column 1 of Panel A of Table A10 contains the results, comparing the differential effect of the minimum wage between low-income and high-income counties. Next, I control for time-varying non-linear, unobserved regional economic shocks across the nine Census divisions via the inclusion of Census division×year fixed effects (Column 2). I also control for unobserved factors that affect both the minimum wage and the SSI benefit uptake linearly via state-specific linear trends (Column 3) and for the business cycle via county-level unemployment rates (Column 4).

In terms of magnitude, the effect in a preferred specification that richly controls for various state-specific unobservable is that a one percent increase in the minimum wage reduces the uptake of SSI participation by around 0.10 percent in low-income counties as compared to high-income ones (Column 4). The magnitude is weaker than the effect observed in the model based on cross-border counties, likely because this estimate represents the relative effect between counties more likely to face a higher impact of the minimum wage versus a lower impact.

Finally, I divide counties into quartiles based on their per-capita income and compare the outcome in counties in the first-, second-, and third-income quartiles relative to those in the top-income quartile.[23] Panel B of Table A10 presents the results. I run four specifications parallel to those above. I find that the effects are concentrated in the counties in the lowest-income quartile. In addition, the specifications that add Census division×year fixed effects, state-specific linear trends, or the unemployment rate yield statistically significant effects in the counties in the second-lowest income quartile as well (Columns 3-4).[24] In my preferred specification, the effect is around -0.15 percent (Column 4), slightly stronger in magnitude than the one observed for counties with per capita income below the median. This is reasonable, given that the minimum wage could have a higher scope to influence SSI uptake in such low-income counties.

In a more parsimonious model reported in Column 1, the main effect of the minimum

[23] I use the regression model of the form $ln(SSI_{ct}) = \beta_1 ln(MW_{c,t-1}) + \sum_{q=2}^{4} \phi_q \mathbf{1}[Income_q] + \sum_{q=2}^{4} \alpha_q \mathbf{1}[Income_q] * ln(MW_{c,t-1}) + \gamma_c + \tau_t + ln(Pop_{ct}) + \epsilon_{ct}$.

[24] As part of a robustness check, I create interactions between past characteristics of a country, particularly the unemployment rate and high school dropout rate and year dummies and control for these interaction terms. As reported in Table B3, the results are qualitatively similar.

wage is positive, suggesting the possible correlation between minimum wage changes and other state-level factors that contribute to SSI receipts. The coefficient on the main term represents the effect, if all counties were of the high-income type, and it could pick up other confounders that jointly determine the minimum wage and the uptake of SSI. As noted in Allegretto et al. (2017), this could be picking up the fact that high-minimum wage states tend to be Democratic and be geographically concentrated. However, under the maintained identifying assumption, the coefficient on the interaction term (the coefficient of interest) is not susceptible to these confounders. Additionally, the main effect is no longer statistically significant when state- or region-specific controls are used (Columns 2-4).

For the reasons explained above, I drop the sample after 2007, and re-run all these specifications. Table A11 in Appendix contains the results, which are qualitatively similar.

Alternative Classification: As an additional robustness check, I use the county-level high-school dropout rate to categorize counties into above-median and below-median.[25] I apply the same specification used in Equation 4. Panel A of Table B2 reports the results. Further, I divide counties into four quartiles based on their high school dropout rate. The results show that the effect of the minimum wage on SSI uptake is greater in counties with a higher proportion of high-school dropouts. Overall, these results are consistent with the baseline estimates based on the CPS data, showing that the minimum wage is more likely to influence the uptake of SSI among high-school dropouts.

7 Conclusion

To the extent that the minimum wage influences individuals' income, incentive to enter and exit the labor market, and employment opportunities, it can alter their participation in Supplemental

[25] I collect the county-level high school dropout rates from the Department of Agriculture. The link is https://www.ers.usda.gov/data-products/countylevel-data-sets/county-level-data-sets-download-data/. The data are available for 1990, 2000, and for the combined years of 2007 to 2011. For the missing years, I use the data from the preceding year.

Security Income (SSI), a leading means-tested program in the U.S. This paper empirically examines how the minimum wage affects the uptake of SSI. Using different datasets and empirical approaches, I show that minimum wage changes significantly affect individuals' participation in SSI. My analysis based on the individual-level data finds an elasticity of -0.33 between the minimum wage and SSI uptake. Alternatively, I use the per capita county-level SSI benefits payment as a measure of SSI uptake, consistent with the previous works, and estimate the macro effect of the minimum wage.

To provide a rough estimate of cost-saving in SSI benefits payments resulting from a rise in the minimum wage, I consider the following estimates. First, in my analytical CPS sample, I extrapolate the elasticity based on 25- to 54-year-olds to estimate the elasticity for the entire population of SSI recipients. Notably, the share of SSI recipients aged 25-54 years in the analytical CPS sample is about 46 percent. Thus, a back-of-the-envelope calculation suggests that the elasticity for the entire population of SSI recipients is -0.15, which is obtained by multiplying the elasticity estimate for individuals aged 25-54 years by their share in the sample. In my analytical CPS sample, a one percent increase in the minimum wage represents around \$0.058 from its average value of \$5.8. If the minimum wage were to increase by one dollar (nearly 17.2 percent), this would result in a decline of around 2.58 percent ($=-0.15\times17.2$) in SSI recipients. Given the number of SSI recipients totaling 9.2 million in 2015, a one-dollar increase in the minimum wage leads to a reduction in the number of SSI recipients by approximately 240,000. With each recipient collecting SSI benefits of \$8,796 per year ($=12\times$ \$773) in 2015, this translates into a total saving of \$1.97 billion per year.

By examining the link between the minimum wage and the uptake of SSI, this paper highlights the role of the minimum wage in participation in welfare programs, a topic that is inconclusive in the literature. This study carries a critical policy implication that a higher minimum wage can help reduce welfare dependency. When rich data are available, one possible extension for future research is to consider the combined effect of the minimum wage on participation in all welfare programs.

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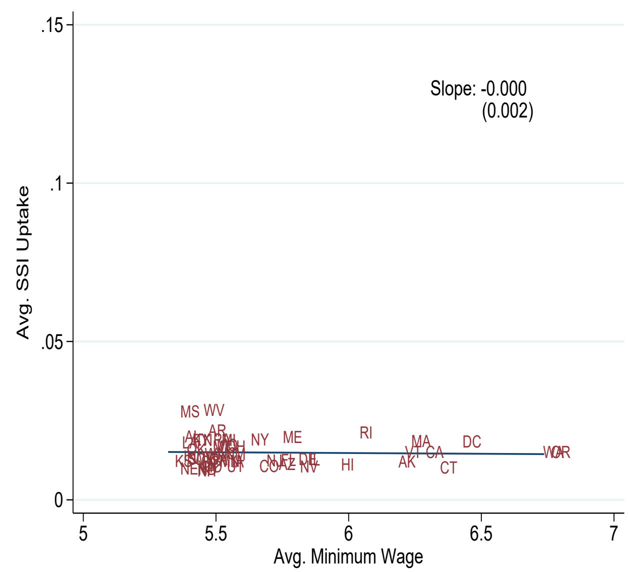
Figure 1: MW and SSI Take Up

(a) LHS

(b) HS or beyond



Notes: This figure plots the relationship between the average minimum wage and the average rate of SSI uptake by state between 1992 and 2015. The relationship is plotted separately for individuals with less than a high school (LHS) degree (Panel A) and for those with a high school (HS) degree or beyond (Panel B)

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Table 1: **Summary Statistics: CPS Sample**

	LHS		HS or Beyond	
	Mean	SD	Mean	SD
SSI Uptake	6.22%	24.16%	1.50%	12.15%
White	37.77%	48.48%	71.32%	45.23%
Black	13.60%	34.28%	11.68%	32.12%
Hispanic	43.60%	49.59%	10.46%	30.61%
Other	5.03%	21.86%	6.54%	24.73%
Age	39.18	8.57	39.36	8.49
Female	46.65%	49.89%	51.44%	49.98%
Married	55.96%	49.64%	62.83%	48.33%
MW	$5.94	$1.36	$6.02	$1.36
Unemp Rate	6.25%	1.92%	6.11%	1.93%
N	219,928		1,625,763	

Notes: This table presents summary statistics separately for individuals with less than a high school (LHS) diploma and those with at least a high school (HS) diploma (Panel B). The statistics are calculated using the Annual Social and Economic Supplement (ASES) of the Current Population Survey (CPS) for the period 1992-2015.

Table 2: **Effects of the Minimum Wage on the Uptake of SSI: CPS Sample**

	(1)	(2)
LHS×ln(MW)	-0.0238***	-0.0196***
	(0.0074)	(0.0064)
LHS	0.0885***	0.0923***
	(0.0107)	(0.0100)
ln(MW)	0.0024	0.0024
	(0.0031)	(0.0032)
N	1,845,691	1,845,691
Year FEs	Y	Y
State FEs	Y	Y
Indiv. Controls	N	Y

Notes: The table presents the results based on Equation (1). The interaction term between an indicator for individuals without a high school degree and the log of state-level minimum wage *LHS*×*ln(MW)* is the variable of interest. I begin by presenting the results without any individual controls (Column 1). Column 2 adds individual controls such as dummies for race (white, black, and Hispanic), a dummy for marital status, age, and age squared. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table 3: **Controlling for Time-Varying State-Level Unobservables: CPS Sample**

	(1)	(2)
LHS×ln(MW)	-0.0196***	-0.0194***
	(0.0064)	(0.0064)
LHS	0.0924***	0.0921***
	(0.0100)	(0.0100)
ln(MW)	0.0020	
	(0.0028)	
N	1,845,691	1,845,691
Year FEs	Y	Y
State FEs	Y	Y
State-by-year FEs	N	Y
Indiv. Controls	Y	Y

Notes: The table presents the results derived by adding time-varying state-specific confounders to the model based on Equation (1). In particular, Column 1 adds the state unemployment rate. Column 2 uses state-by-year fixed effects. The interaction term between an indicator for individuals without a high school degree and the log of state-level minimum wage *LHS×ln(MW)* is the variable of interest. Individual controls include dummies for race (white, black, and Hispanic), a dummy for marital status, age, and age squared. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table 4: **Heterogeneity by Gender: CPS Sample**

	Women	Men
LHS×ln(MW)	-0.0183**	-0.0198***
	(0.0089)	(0.0061)
LHS	0.1008***	0.0831***
	(0.0136)	(0.0103)
ln(MW)	0.0058	-0.0012
	(0.0048)	(0.0035)
N	966,037	879,654
Year FEs	Y	Y
State FEs	Y	Y
Controls	N	Y

Notes: The table presents the results by gender. Column 1 presents the results for men and Column 2 for women. The interaction term between an indicator for individuals without a high school degree and the log of state-level minimum wage *LHS×ln(MW)* is the variable of interest. Individual controls include dummies for race (white, black, and Hispanic), a dummy for marital status, age, and age squared. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table 5: **Effects by Marital Status: CPS Sample**

	Married	Unmarried
LHS×ln(MW)	-0.0075	-0.0461***
	(0.0045)	(0.0087)
LHS	0.0380***	0.1838***
	(0.0084)	(0.0138)
ln(MW)	0.0002	0.0102
	(0.0021)	(0.0080)
N	1,214,924	630,767
Year FEs	Y	Y
State FEs	Y	Y
Indiv. Controls	N	Y

Notes: The table presents the results by marital status. Column 1 presents the results for the married and Column 2 for the unmarried. The interaction term between an indicator for individuals without a high school degree and the log of state-level minimum wage *LHS×ln(MW)* is the variable of interest. Individual controls include dummies for race (white, black, and Hispanic), a dummy for marital status, age, and age squared. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table 6: **Effects on SSI Benefit Payment: Aggregate Sample**

	(1)	(2)
ln(MW)	-0.1660***	-0.1686***
	(0.0485)	(0.0484)
N	61,856	61,856
County FEs	Y	Y
Cross-border pair FEs	Y	Y
Unemp. rate	N	Y

Notes: The results are estimated using Equation (2). Both the minimum wage and the unemployment rate are measured in year $t-1$. Column 2 adds the county-level unemployment rate as a control variable. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table 7: **Estimation of Dynamic Effects: Aggregate Sample**

	(1)	(2)
$\Delta\ln(\mathrm{MW}_{t+3})$	-0.0013	-0.0006
	(0.0593)	(0.0590)
$\Delta\ln(\mathrm{MW}_{t+2})$	-0.0587	-0.0574
	(0.0599)	(0.0595)
$\Delta\ln(\mathrm{MW}_{t+1})$	-0.0318	-0.0311
	(0.0779)	(0.0777)
$\Delta\ln(\mathrm{MW}_{t})$	-0.1095	-0.1090
	(0.0981)	(0.0978)
$\Delta\ln(\mathrm{MW}_{t-1})$	-0.1697*	-0.1710*
	(0.0968)	(0.0968)
$\Delta\ln(\mathrm{MW}_{t-2})$	-0.2290**	-0.2281**
	(0.1074)	(0.1064)
$\Delta\ln(\mathrm{MW}_{t-3})$	-0.1918*	-0.1933*
	(0.1113)	(0.1116)
$\ln(\mathrm{MW}_{t-4})$	-0.3871***	-0.3918***
	(0.1200)	(0.1207)
N	61,856	61,856
County FEs	Y	Y
Cross-border pair FEs	Y	Y
Unemp. rate	N	Y

Notes: The results are estimated using Equation (3). The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

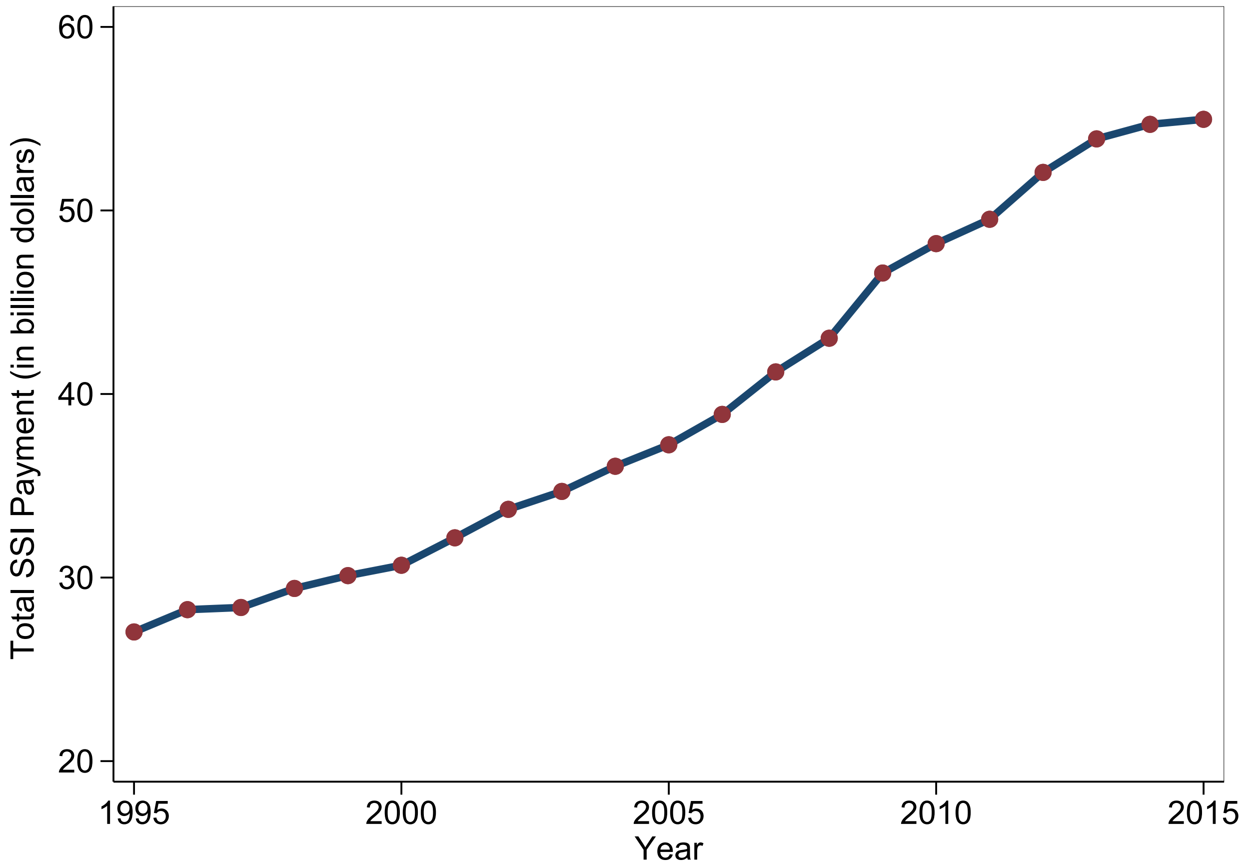
Table 8: **Effects on the Number of SSI Recipients**

	Ages 18-64	Under 18 years	65 years or older
Panel A: 1998-2015			
ln(MW)	-0.1206***	0.0418	0.0289
	(0.0363)	(0.0569)	(0.0554)
N	41,879	40,206	40,321
Panel B: 1998-2007			
ln(MW)	-0.1720***	0.0353	0.0052
	(0.0575)	(0.1209)	(0.0765)
N	24,693	24,466	24,543
County FEs	Y	Y	Y
Cross-border pair FEs	Y	Y	Y

Notes: The table presents the results estimated based on Equation (2). The minimum wage is measured in the year $t-1$. Panel A presents the results for the period 1998 to 2015 and Panel B for the period 1998 to 2007. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

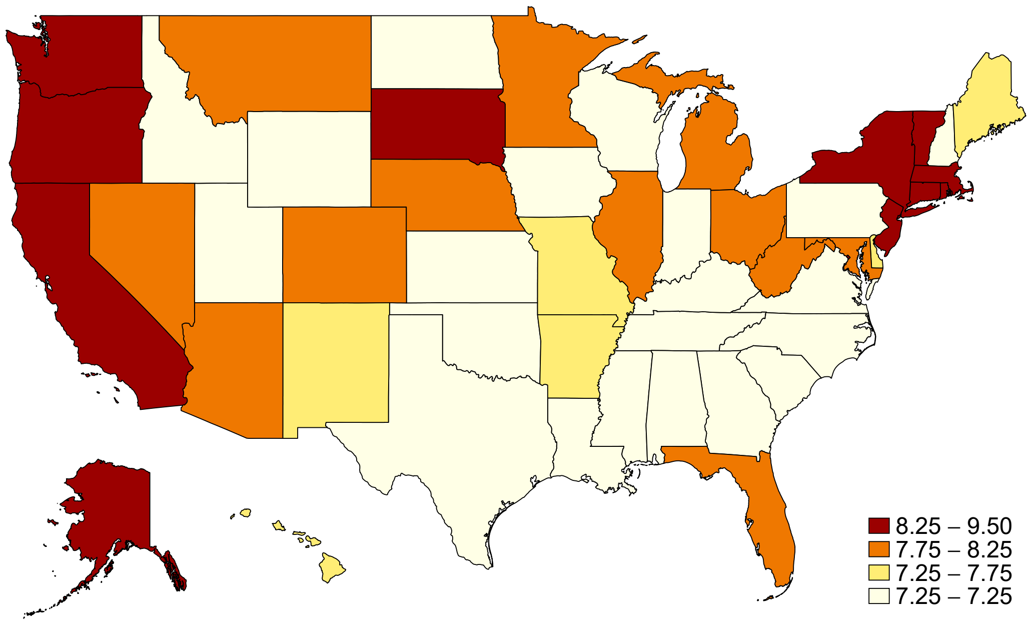
Appendix A

Figure A1: Growth in the Total SSI Payment

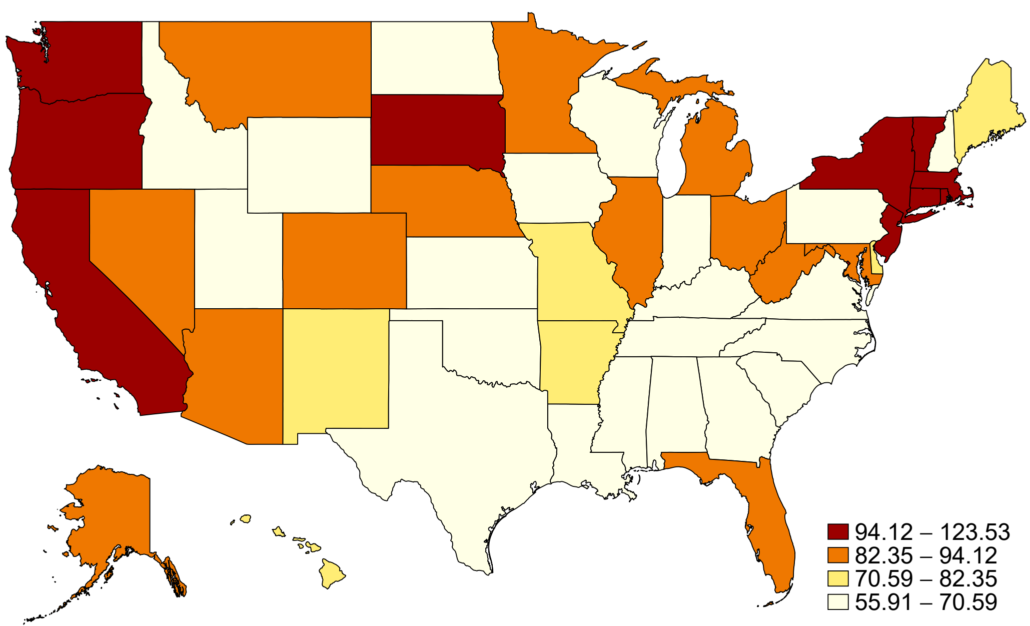


Notes: The figure displays the trend in the total Supplemental Security Income (SSI) payment from 1995 to 2015.
Source: SSI Annual Statistical Report, 2015, Social Security Administration.

Figure A2: Variation in Minimum Wages



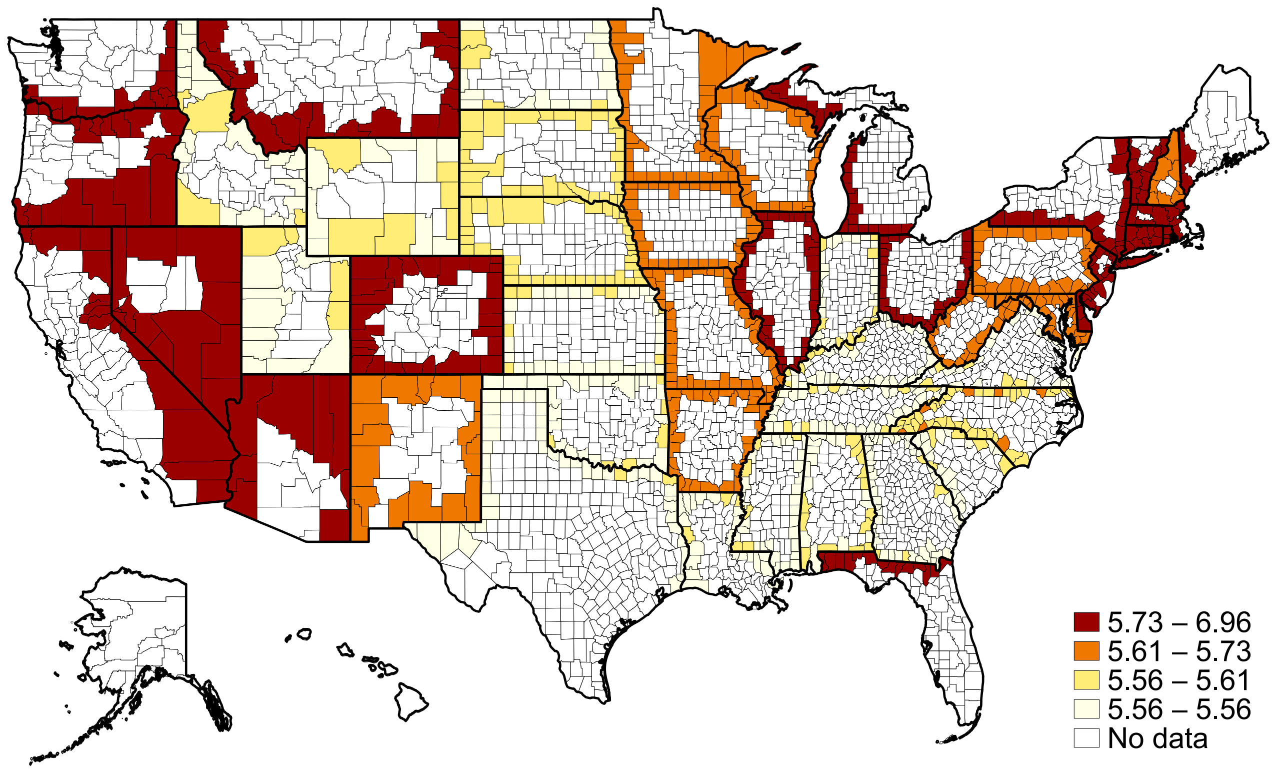
(a) Cross-State Variation in Minimum Wages in Dollars in 2015



(b) Minimum Wage Growth Rates from 1992 to 2015 by State

Notes: Panel A displays the variation in the minimum wage across states in 2015. Panel B presents the growth rates of the minimum wage by state between 1992 and 2015. The minimum wage represents the higher of the federal or state minimum wage.

Figure A3: Average Minimum Wage Across Cross-State Border Counties



Notes: The figure displays the average minimum wage across the cross-state border counties for the period 1992-2015.

Table A1: **Characteristics of SSI Recipients: CPS Sample**

	Mean	SD
Employment	12.17%	32.70%
White	54.96%	49.75%
Black	26.59%	44.18%
Hispanic	13.77%	34.46%
Other	4.68%	21.12%
Female	57.01%	49.51%
Married	22.52%	41.77%
Less than High School	35.76%	47.93%
High School	39.57%	48.90%
Some College	19.27%	39.45%
College	5.39%	22.58%
Age	40.90	8.62

Notes: The table presents characteristics of SSI recipients using the Current Population Survey from 1992-2015.

Table A2: **Alternative Controls for State and Division Specific Confounders: CPS Sample**

	(1)	(2)	(3)
LHS×ln(MW)	-0.0194***	-0.0196***	-0.0194***
	(0.0064)	(0.0064)	(0.0064)
LHS	0.0920***	0.0923***	0.0920***
	(0.0100)	(0.0100)	(0.0100)
ln(MW)	0.0054*	0.0024	0.0054*
	(0.0031)	(0.0032)	(0.0031)
N	1,845,691	1,845,691	1,845,691
Year FEs	Y	Y	Y
State FEs	Y	Y	Y
State Trends	Y	N	Y
Division-by-year FEs	N	Y	Y
Indiv. Controls	Y	Y	Y

Notes: The table presents the results derived by adding time-varying state-specific confounders to the model based on Equation (1). In particular, Column 1 adds state-specific linear trends. Column 2 adds division-by-year fixed effects. Column 3 adds both the linear trends and division-by-year fixed effects simultaneously. The interaction term between an indicator for individuals without a high school degree and the log of state-level minimum wage *LHS×ln(MW)* is the variable of interest. Individual controls include dummies for race (white, black, and Hispanic), a dummy for marital status, age, and age squared. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table A3: **Using MW in Levels and Real Term: CPS Sample**

	(1)	(2)
LHS×MW	-0.0036***	
	(0.0012)	
LHS	0.0792***	0.0705***
	(0.0067)	(0.0048)
MW		
LHS×RealMW		-0.0013***
		(0.0003)
RealMW		-0.0000
		(0.0003)
N	1,845,691	1,845,691
Year FEs	Y	Y
State FEs	Y	Y
Indiv. Controls	Y	Y

Notes: Column 1 presents the results derived using the minimum wage in levels and Column 2 using the minimum wage in 1990 dollars. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table A4: **Dropping after 2007: CPS Sample**

	(1)	(2)
LHS×ln(MW)	-0.0256**	-0.0255**
	(0.0110)	(0.0114)
LHS	0.0988***	0.0988***
	(0.0162)	(0.0169)
ln(MW)	0.0084**	
	(0.0036)	
N	1,178,421	1,178,421
Year FEs	Y	Y
State FEs	Y	Y
State-by-year FEs	N	Y
Indiv. Controls	Y	Y

Notes: Column 1 of the table presents the results based on Equation (1). Column 2 further adds state-by-year fixed effects. The sample is restricted to the pre-Great Recession period, 1992-2007. The interaction term between an indicator for having less than high school degree and the log of state-level minimum wage *LHS×ln(MW)* is the variable of interest. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table A5: **Alternative Classification Based on Income: CPS data**

	(1)	(2)
$\mathbb{1}[0 \geq Income \leq 0.6 * MW]$ ×ln(MW)	0.0045	0.0030
	(0.0066)	(0.0066)
$\mathbb{1}[0.6 * MW < Income \leq 1.2 * MW]$ ×ln(MW)	-0.0094***	-0.0109***
	(0.0021)	(0.0023)
$\mathbb{1}[1.2 * MW < Income \leq 1.8 * MW]$ ×ln(MW)		-0.0043**
		(0.0016)
$\mathbb{1}[1.8 * MW < Income \leq 2.4 * MW]$ ×ln(MW)		-0.0004
		(0.0008)
$\mathbb{1}[0 \geq Income \leq 0.6 * MW]$	0.0603***	0.0606***
	(0.0105)	(0.0106)
$\mathbb{1}[0.6 * MW < Income \leq 1.2 * MW]$	0.0174***	0.0175***
	(0.0037)	(0.0040)
$\mathbb{1}[1.2 * MW < Income \leq 1.8 * MW]$		0.0021
		(0.0030)
$\mathbb{1}[1.8 * MW < Income \leq 2.4 * MW]$		-0.0047***
		(0.0016)
ln(MW)	-0.0018	0.0012
	(0.0035)	(0.0033)
N	1845691	1845691
Year FEs	Y	Y
State FEs	Y	Y
Indiv. Controls	Y	Y

Notes: Column 1 displays estimates obtained by categorizing individuals into three groups, while Column 2 shows estimates obtained by dividing individuals into five groups. See the text for details. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table A6: **Summary Statistics: Aggregate Sample**

	Mean	SD
Panel A: All Counties		
ln(SSI)	7.92	1.66
MW	5.72	1.24
Unemp. Rate	6.29	2.92
ln(Pop)	10.24	1.43
N	73,819	
Panel B: Border-Pair Counties		
ln(SSI)	8.02	1.68
MW	5.73	1.24
Unemp Rate	6.28	2.85
ln(Pop)	10.32	1.44
N	61,856	

Notes: The table presents summary statistics. Panel A includes all counties, while Panel B presents the summary statistics for the border-pair counties. Note that a county appears in the border-pair sample as many times as the number of other counties it borders.

Table A7: **Movement of Workers across State Borders**

	LHS (1)	(2) HS (2)	Some College (3)	College (4)
RelativeMW	-0.0054	0.0178	-0.0068	-0.0010
	(0.0151)	(0.0323)	(0.0129)	(0.0140)
N	2,366,427	4,009,436	9,327,206	8,203,576
County FEs	Y	Y	Y	Y
Cross-border pair FEs	Y	Y	Y	Y

Notes: The table presents the results concerning the likelihood of the employed working in a neighboring state in response to the relative minimum wage. Drawing on the Census 2000 and American Community Survey (ACS) data from 2005 to 2015, the sample is limited to employed individuals living in counties at state borders. The first column presents the results for those without a high school degree, the second column for those with a high school degree, and the third column for those with some college, and the fourth column for those with a college degree. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table A8: **Using MW in Levels: Aggregate Sample**

	(1)	(2)
MW	-0.0282***	-0.0288***
	(0.0090)	(0.0090)
N	61,856	61,856
County FEs	Y	Y
Cross-border pair FEs	Y	Y
Unemp. rate	N	Y

Notes: The results are estimated using Equation (2). Both the minimum wage and the unemployment rate are measured in year $t-1$. I use the minimum wage in levels. Column 2 adds the county-level unemployment rate as a control variable. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table A9: **Dropping after 2007: Aggregate Sample**

	(1)	(2)
ln(MW)	-0.2217**	-0.2208**
	(0.0954)	(0.0935)
N	41,164	41,164
County FEs	Y	Y
Cross-border pair FEs	Y	Y
Unemp. rate	N	Y

Notes: I use the sample period from 1992-2007. Both the minimum wage and the unemployment rate are measured in year $t-1$. The results are estimated using Equation (2). Column 2 adds the county-level unemployment rate as a control variable. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table A10: **Low versus High Income Countries: Aggregate Sample**

	(1)	(2)	(3)	(4)
Panel A				
$\mathbb{1}$[Low Income]*ln(MW)	-0.1322***	-0.0768***	-0.1075***	-0.1011***
	(0.0370)	(0.0257)	(0.0228)	(0.0225)
$\mathbb{1}$[Low Income]	0.2547***	0.1641***	0.2077***	0.1934***
	(0.0639)	(0.0454)	(0.0425)	(0.0417)
ln(MW)	0.2517***	-0.0862	-0.0245	-0.0260
	(0.0785)	(0.1090)	(0.0617)	(0.0626)
N	73,819	73,819	73,819	73,819
Panel B				
$\mathbb{1}[\text{Income}_{Q_1}]$*ln(MW)	-0.2097***	-0.1292***	-0.1789***	-0.1688***
	(0.0565)	(0.0408)	(0.0359)	(0.0362)
$\mathbb{1}[\text{Income}_{Q_2}]$*ln(MW)	-0.0369	-0.0065	-0.0621*	-0.0569*
	(0.0433)	(0.0379)	(0.0319)	(0.0310)
$\mathbb{1}[\text{Income}_{Q_3}]$*ln(MW)	0.0115	0.0210	-0.0175	-0.0145
	(0.0354)	(0.0324)	(0.0242)	(0.0241)
$\mathbb{1}[\text{Income}_{Q_1}]$	0.4256***	0.3003***	0.3679***	0.3429***
	(0.0980)	(0.0718)	(0.0687)	(0.0683)
$\mathbb{1}[\text{Income}_{Q_2}]$	0.1310*	0.0834	0.1630***	0.1491**
	(0.0739)	(0.0666)	(0.0599)	(0.0579)
$\mathbb{1}[\text{Income}_{Q_3}]$	0.0267	0.0100	0.0666	0.0588
	(0.0588)	(0.0543)	(0.0434)	(0.0430)
ln(MW)	0.2255***	-0.0990	-0.0168	-0.0197
	(0.0829)	(0.1136)	(0.0635)	(0.0639)
N	73,819	73,819	73,819	73,819
County FEs	Y	Y	Y	Y
Year FEs	Y	N	N	N
Division-by-year FEs	N	Y	Y	Y
State-specific linear trends	N	N	Y	Y
Unemp. rate	N	N	N	Y

Notes: Panel A presents the results derived using Equation (4). Both the minimum wage and the unemployment rate are measured in year $t-1$. Panel B presents the results that are estimated by dividing counties into quartiles based on their per-capita income and compares the outcome in counties in the first-, second-, and third-income quartiles relative to those in the top-income quartile. The first column uses county and year fixed effects, the second column adds division-by-year fixed effects, the third column further adds state-specific linear trends, and the fourth column adds county-level unemployment rates. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table A11: **Low versus High Income Countries: Dropping after 2007**

	(1)	(2)	(3)	(4)
Panel A				
𝟙[Low Income]*ln(MW)	-0.1735***	-0.1155***	-0.1119***	-0.0988***
	(0.0604)	(0.0427)	(0.0275)	(0.0281)
𝟙[Low Income]	0.2800***	0.1892***	0.1810***	0.1594***
	(0.0940)	(0.0670)	(0.0447)	(0.0452)
ln(MW)	0.3351***	-0.1573	-0.0836	-0.0843
	(0.0983)	(0.1898)	(0.1692)	(0.1690)
N	49,201	49,201	49,201	49,200
Panel B				
𝟙[Income_{Q_1}]*ln(MW)	-0.2512**	-0.1599**	-0.1697***	-0.1486***
	(0.1061)	(0.0786)	(0.0517)	(0.0521)
𝟙[Income_{Q_2}]*ln(MW)	-0.1247	-0.0800	-0.0884**	-0.0768*
	(0.0776)	(0.0671)	(0.0403)	(0.0422)
𝟙[Income_{Q_2}]*ln(MW)	-0.0230	0.0054	-0.0164	-0.0098
	(0.0718)	(0.0654)	(0.0408)	(0.0416)
𝟙[Income_{Q_1}]	0.4249**	0.2803**	0.2858***	0.2503***
	(0.1644)	(0.1218)	(0.0844)	(0.0843)
𝟙[Income_{Q_2}]	0.2198*	0.1490	0.1547**	0.1350*
	(0.1212)	(0.1053)	(0.0664)	(0.0691)
𝟙[Income_{Q_3}]	0.0548	0.0088	0.0370	0.0260
	(0.1111)	(0.1011)	(0.0648)	(0.0662)
ln(MW)	0.3317***	-0.1616	-0.0786	-0.0820
	(0.1083)	(0.1811)	(0.1666)	(0.1661)
N	49,201	49,201	49,201	49,201
County FEs	Y	Y	Y	Y
Year FEs	Y	N	N	N
Division-by-year FEs	N	Y	Y	Y
State-specific linear trends	N	N	Y	Y
Unemp. rate	N	N	N	Y

Notes: Panel A presents the results derived using Equation (4). Both the minimum wage and the unemployment rate are measured in year $t-1$. Panel B presents the results that are estimated by dividing counties into quartiles based on their per-capita income and compares the outcome in counties in the first-, second-, and third-income quartiles relative to those in the top-income quartile. I limit the sample to the pre-Great Recession Period, 1992-2007. The first column uses county and year fixed effects, the second column adds division-by-year fixed effects, the third column further adds state-specific linear trends, and the fourth column adds the county-level unemployment rate. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Appendix B: Additional Robustness Checks

Table B1: **Effects on SSI Benefit Payment: Aggregate Sample**

	(1)	(2)
ln(MW)	-0.1681***	-0.1714***
	(0.0460)	(0.0458)
County FEs	Y	Y
Cross-border pair FEs	Y	Y
Unemp. rate	N	Y

Notes: The table presents the results that are estimated based on Equation (2). Both the minimum wage and the unemployment rate are measured in year $t-1$. I apply the weight, calculated as the inverse of the number of times that a county appears in border-pairs. Column 2 adds the county-level unemployment rate as a control variable. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table B2: **Classifying Counties by High-School Dropout Rates**

	(1)	(2)	(3)	(4)
Panel A				
$\mathbb{1}$[High Dropout]*ln(MW)	-0.2493***	-0.2150***	-0.2120***	-0.2017***
	(0.0391)	(0.0413)	(0.0323)	(0.0329)
$\mathbb{1}$[High Dropout]	0.4797***	0.4136***	0.4022***	0.3835***
	(0.0706)	(0.0756)	(0.0609)	(0.0622)
ln(MW)	0.2597***	-0.0294	0.0104	0.0074
	(0.0742)	(0.1166)	(0.0617)	(0.0624)
Panel B				
$\mathbb{1}$[High Dropout$_{Q_4}$]*ln(MW)	-0.3987***	-0.3938***	-0.3936***	-0.3769***
	(0.0540)	(0.0584)	(0.0503)	(0.0516)
$\mathbb{1}$[High Dropout$_{Q_3}$]*ln(MW)	-0.1818***	-0.1904***	-0.2186***	-0.2105***
	(0.0432)	(0.0477)	(0.0396)	(0.0397)
$\mathbb{1}$[High Dropout$_{Q_2}$]*ln(MW)	-0.0912**	-0.0940**	-0.1188***	-0.1156***
	(0.0432)	(0.0392)	(0.0355)	(0.0355)
$\mathbb{1}$[High Dropout$_{Q_4}$]	0.8007***	0.7772***	0.7767***	0.7473***
	(0.1037)	(0.1095)	(0.0949)	(0.0972)
$\mathbb{1}$[High Dropout$_{Q_3}$]	0.4033***	0.4070***	0.4551***	0.4392***
	(0.0816)	(0.0851)	(0.0731)	(0.0735)
$\mathbb{1}$[High Dropout$_{Q_2}$]	0.1970**	0.1964***	0.2450***	0.2385***
	(0.0739)	(0.0641)	(0.0599)	(0.0598)
ln(Min.Wage)	0.2672***	0.0169	0.0717	0.0674
	(0.0823)	(0.1135)	(0.0655)	(0.0661)
County FEs	Y	Y	Y	Y
Year FEs	Y	N	N	N
Division-by-year FEs	N	Y	Y	Y
State-specific linear trends	N	N	Y	Y
Unemp. rate	N	N	N	Y

Notes: Panel A presents the results derived using Equation (4). Both the minimum wage and the unemployment rate are measured in year $t-1$. Panel B presents the results that are estimated by dividing counties into quartiles based on their high school dropout rates and compares the outcome in counties in the fourth, third, and second quartiles relative to those in the first quartile. The first column uses county and year fixed effects, the second column adds division-by-year fixed effects, the third column further adds state-specific linear trends, and the fourth column adds the county-level unemployment rate. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table B3: **Using Additional Controls**

Panel A	
$\mathbb{1}$[Low Income]*ln(MW)	-0.1030***
	(0.0354)
$\mathbb{1}$[Low Income]	0.1960***
	(0.0620)
ln(MW)	0.1716**
	(0.0709)
Panel B	
$\mathbb{1}[\text{Income}_{Q_1}]$*ln(MW)	-0.1841***
	(0.0632)
$\mathbb{1}[\text{Income}_{Q_2}]$*ln(MW)	-0.0473
	(0.0475)
$\mathbb{1}[\text{Income}_{Q_2}]$*ln(MW)	-0.0103
	(0.0361)
$\mathbb{1}[\text{Income}_{Q_1}]$	0.3610***
	(0.1090)
$\mathbb{1}[\text{Income}_{Q_2}]$	0.1344
	(0.0830)
$\mathbb{1}[\text{Income}_{Q_3}]$	0.0557
	(0.0614)
ln(MW)	0.1639**
	(0.0778)
County FEs	Y
Year FEs	Y

Notes: Panel A presents the results derived using Equation (4). Panel B presents the results that are estimated by dividing counties into quartiles based on their per-capita income and compares the outcome in counties in the first-, second-, and third-income quartiles relative to those in the top-income quartile. I include controls for the interactions between county-level characteristics from previous years, such as the unemployment rate and high school graduation rate, and year indicators. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Appendix C: SSDI

For completeness, I expand the analysis to examine the impact of the minimum wage on Social Security Disability Insurance (SSDI).

Micro evidence: For the individual level analysis, I use the variable "INCDISAB" from the Current Population Survey (CPS), which records "how much pre-tax income (if any) the respondent received from disability income during the previous calendar year." There is a possibility that the variable related to SSDI uptake in the CPS may capture some of the uptake of SSI, as respondents collecting SSI may report receiving disability insurance (DI) benefits. I estimate the model parallel to Equation (1) in the text. Table C1 reports the results, reflecting a similar pattern observed in SSI participation as described in Section 5.2 of the text.

Macro evidence: For the aggregate level analysis, I compile data from two sources. First, I use county-level SSDI payment data for the period 1992 to 2011 from Charles, Li, and Stephens (2018). Second, using Social Security's reports on Old-Age, Survivors, and Disability Insurance (OASDI) Beneficiaries by State and County, I expand their data to the year 2015.[26] Table C2, based on Equation 2, and Table C3, based on Equation 4, present the results. The effects are statistically significant and qualitatively similar to the ones observed for SSI when using the approach that leverages cross-border minimum wage variation at state borders (see Section 6.1 in the text for comparison). However, the effects are not statistically significant when employing an approach that compares the differential effect of the minimum wage between high- and low-income counties. (The corresponding estimates for SSI are reported in Section 6.2.) This could indicate weaker evidence regarding the effect of the minimum wage on the uptake of SSDI.

[26] https://www.ssa.gov/policy/docs/statcomps/

Table C1: **Effects of the Minimum Wage on the Uptake of SSDI: CPS Sample (Compare to Table 2)**

	(1)	(2)
LHS×ln(MW)	-0.0083***	-0.0075***
	(0.0017)	(0.0016)
LHS	0.0184***	0.0203***
	(0.0033)	(0.0030)
ln(MW)	-0.0011	-0.0011
	(0.0019)	(0.0020)
Year FEs	Y	Y
State FEs	Y	Y
Indiv. Controls	N	Y

Notes: The table presents the results based on Equation (1). The interaction term between an indicator for individuals without a high school degree and the log of state-level minimum wage *LHS×ln(MW)* is the variable of interest. I begin presenting the results without any individual controls (Column 1). Column 2 adds individual controls such as dummies for race (white, black, and Hispanic), a dummy for marital status, age, and age squared. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table C2: **Effects on SSDI Benefit Payment: Aggregate Sample (Compare to Table 6)**

	(1)	(2)
ln(MW)	-0.1683***	-0.1701***
	(0.0475)	(0.0465)
County FEs	Y	Y
Cross-border pair FEs	Y	Y
Unemp. rate	N	Y

Notes: The results are estimated using Equation (2). Both the minimum wage and the unemployment rate are measured in year $t-1$. Column 2 adds the county-level unemployment rate as a control variable. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.

Table C3: **Effects on SSDI Benefit Payment: Low versus High Income Countries (Compare to Table A10)**

	(1)	(2)	(3)	(4)
Panel A				
$\mathbb{1}$[Low Income]*ln(MW)	0.0266	0.0100	-0.0067	0.0089
	(0.0323)	(0.0240)	(0.0201)	(0.0198)
$\mathbb{1}$[Low Income]	-0.0364	-0.0095	0.0154	-0.0102
	(0.0499)	(0.0371)	(0.0309)	(0.0305)
ln(MW)	0.0281	-0.0312	-0.0035	-0.0048
	(0.0627)	(0.0869)	(0.0443)	(0.0425)
Panel B				
$\mathbb{1}[\text{Income}_{Q_1}]$*ln(MW)	-0.0023	0.0038	-0.0346	-0.0260
	(0.0329)	(0.0242)	(0.0244)	(0.0250)
$\mathbb{1}[\text{Income}_{Q_2}]$*ln(MW)	0.0565**	0.0541**	0.0071	0.0116
	(0.0255)	(0.0219)	(0.0193)	(0.0187)
$\mathbb{1}[\text{Income}_{Q_2}]$*ln(MW)	0.0645***	0.0682***	0.0419***	0.0446***
	(0.0184)	(0.0175)	(0.0153)	(0.0152)
$\mathbb{1}[\text{Income}_{Q_1}]$	0.0529	0.0373	0.0901**	0.0687
	(0.0534)	(0.0425)	(0.0441)	(0.0446)
$\mathbb{1}[\text{Income}_{Q_2}]$	-0.0519	-0.0547	0.0155	0.0034
	(0.0404)	(0.0374)	(0.0346)	(0.0334)
$\mathbb{1}[\text{Income}_{Q_3}]$	-0.0815**	-0.0926***	-0.0551**	-0.0621**
	(0.0310)	(0.0299)	(0.0263)	(0.0261)
ln(MW)	-0.0800	-0.1321**	-0.0099	-0.0111
	(0.0557)	(0.0581)	(0.0301)	(0.0306)
County FEs	Y	Y	Y	Y
Year FEs	Y	N	N	N
Division-by-year FEs	N	Y	Y	Y
State-specific linear trends	N	N	Y	Y
Unemp. rate	N	N	N	Y

Notes: Panel A presents the results derived using Equation (4). Both the minimum wage and the unemployment rate are measured in year $t-1$. Panel B presents the results that are estimated by dividing counties into quartiles based on their per-capita income and compares the outcome in counties in the first-, second-, and third-income quartiles relative to those in the top-income quartile. The first column uses county and year fixed effects, the second column adds division-by-year fixed effects, the third column further adds state-specific linear trends, and the fourth column adds county-level unemployment rates. The standard errors are clustered at the state level. *** denotes significance at the one percent level, ** denotes at the five percent level, and * denotes at the ten percent level.