Minimum Wages and the Elderly

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Abstract

I study the effects of minimum wages on the labor market outcomes of the elderly. In contrast to the groups that are more typically studied (e.g., teenagers), I find small, positive employment effects on those in their late sixties by using a variety of methods commonly used in the minimum wage literature. The point estimates of employment elasticities fall in the range of 0.1 to 0.3. The positive effects are not limited to the minimum wage workers; a broader class of workers including those who are paid wages well above the minimum wage are affected. To explain the results, I provide two pieces of evidence on labor-labor substitution. First, the industry-level employment elasticities of the young and elderly with respect to the minimum wage are negatively correlated. Second, I directly estimate the elasticity of substitution between young and older workers using the nested-CES production function framework. 2SLS estimates suggest that young and older workers are substitutes for each other. Although the estimated elasticity of substitution is small, it suggests that labor demand is shifted toward older workers when minimum wages are increased.

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1 Introduction

Older workers tend to earn lower wages (Mincer, 1974; Haider and Loughran, 2010; Maestas, 2010). Due to the aging population, older workers are increasingly important in the low-wage labor markets in developed countries. For example, in the United States, the fraction of workers aged 65 or above among low-wage workers whose hourly wages are below 120 percent of the effective minimum wage increased from 4% in 1990 to 6.2% in 2019. During the same time, the fraction of teenagers declined from 26.9% to 14.7%.[1] Given the aging population, the increasing trend of the fraction of older workers is likely to continue.

Among the policy tools affecting low-wage labor markets, the minimum wage is perhaps the most controversial and ubiquitous by both the public and academia. Despite the growing importance of older workers in the low-wage labor market and the vast economic literature examining either minimum wage or older populations, there exist very few papers that combine the two. This paper tries to fill that gap by analyzing the effects of minimum wage on the labor market outcomes of the elderly.

In this paper, I apply a variety of empirical strategies commonly used in the general minimum wage literature but focus on the elderly. I find small, positive employment effects of minimum wages on those in their late sixties instead of the negative effects on employment predicted by standard neoclassical economic theory. The point estimates of minimum wage-employment elasticities using commonly used methods fall in the range of 0.1 to 0.3. This agreement across methods is in sharp contrast to the results for teenagers, which tend to be negative or zero effects (Manning, 2021). These results suggest that the impacts on older workers are different. Further analysis regarding wage distribution confirms that older workers respond to minimum wages in a different manner. Unlike young and prime-age workers whose employment responses are limited to near minimum wages, some portion of the positive effects for older workers come from workers above the minimum wage.

These baseline employment effects raise two questions. First, why are employment effects on older workers positive? Second, why are workers whose hourly wage may not be directly raised by minimum wages also affected? To answer the first question, previous studies have tended to focus on labor supply decisions and interpret positive employment effects as a sign of delayed retirement (Borgschulte and Cho, 2020; Hampton and Totty, 2021). The logic behind this argument is as follows. By increasing workers' own wages, a higher minimum wage could provide more incentive for them to work longer. Although intuitive, this explanation has three limitations. First, the wage distribution analysis suggests that at least some portion of the positive responses come from a broader class of workers including those whose wages may not be increased by a minimum wage. Second, the same minimum wage increase will provide incentives to work more to teenagers

[1] My own calculation using Current Population Survey Outgoing Rotation Group.

and other younger low-wage workers as well as older workers, but older workers are the only population who actually do. Finally, in a competitive labor market with a binding minimum wage, labor demand primarily determines labor market outcomes; therefore, labor demand explanations should also be explored.

As an alternative explanation, I study labor-labor substitution between young and older workers. In response to a higher minimum wage, employers may shift their demand to workers with better human capital since the relative price of the least skilled workers has increased (e.g., Clemens et al., 2021; Butschek, 2022). Older workers may be more productive than their younger counterparts earning minimum wages and their turnover probability is much lower (Allen, 2019). If labor demand is shifted toward older workers with higher wages and better skills, the positive responses may extend to a broader class of workers.

I provide two pieces of evidence of labor-labor substitution. First, industry-level analysis suggests that the industry-specific minimum wage-employment elasticities of young and older workers are negatively correlated. This provides suggestive evidence of labor-labor substitution. More formally, I estimate the elasticity of substitution between younger and older workers using a nested constant elasticity of substitution (CES) production function framework and a simulated-wage instrumental variable exploiting minimum wage changes. The estimated elasticities of substitutions are approximately 0.5, implying a small degree of substitution.

This paper contributes to the active, growing literature on the minimum wage in several ways. First, using a variety of specifications, I study a group of workers (aged 65-70) who are understudied in the literature. Compared to existing papers that examine a broader age range of older workers and provide weaker positive or mixed evidence of employment effects (Borgschulte and Cho, 2020; Cengiz et al., 2022), I focus on a smaller group and show clearer, more robust positive effects. Second, this paper provides a new explanation based on labor-labor substitution between demographic groups. Both industry-level analysis and the nested-CES framework are consistent with labor demand shifts from younger minimum wage workers toward higher-wage, older workers.

This paper also addresses another strand of labor economic literature examining the elasticity of substitution between demographic groups. Two demographic groups of primary interest in this study, older (aged 65-70) and younger (aged 16-21) workers, are often excluded from the scope of other papers. This paper also harnesses a different source of identifying variation. Unlike studies using labor supply shifters for identification, I exploit policy variation affecting the relative wage. By applying a simulated instrument to local labor market outcomes, I provide evidence of labor-labor substitution between workers of different ages.

The remainder of the paper is organized as follows. In section 2, I discuss the related literature. My empirical strategies are discussed in section 3. Section 4 introduces and describes the data. Section 5 presents the empirical findings on the employment effects of minimum wages. Section 6 explores the role of labor-labor substitution to explain the results in section 5. Section 7 concludes the study.

2 Related Literature

Over decades of analyzing the employment effects of minimum wages, labor economists have often studied the effects on specific low-wage demographic groups such as teenagers.[2] Surprisingly little attention has been paid to the effects on older populations even though a larger portion of the older workers are affected by minimum wages, as recognized by Flinn (2010) and shown in Figure 1 below.

Recently, economists have started to examine the relationship between the minimum wage and the elderly in their sixties. By applying a canonical state-panel approach using the log of the minimum wage as a key regressor to CPS Basic Monthly files (1983-2016), Borgschulte and Cho (2020) report zero to small positive employment effects of minimum wages on older workers, with estimated minimum wage-employment elasticities ranging from 0 to 0.15. They further apply a border-county approach to the SSA's OASDI beneficiaries and provide evidence that a higher minimum wage makes Social Security beneficiaries delay the timing of claiming benefits, which is in line with positive employment effects. They provide two explanations for these effects. First, higher minimum wages provide more incentives to work for the elderly whose labor supply is fairly elastic. Second, demand may shift toward older workers. They find some suggestive evidence that labor demand has shifted from workers in their late fifties (ages 55-61) to those in their sixties (ages 62-70). In contrast to Borgschulte and Cho (2020), who use all observations, Cengiz et al. (2022) define relevant populations using machine learning techniques. Specifically, their machine learning technique predicts those who are more likely to earn minimum wages. Using an event-based approach, they report null employment effects on the elderly (ages 60-70) who are predicted to earn low wages.

Hampton and Totty (2021) examine the same question from a different angle, by focusing on those who earn near-minimum wage using longitudinal data. By using observations (aged 62-70) from SIPP (1978-2014) linked to IRS and OASDI data and the log of the minimum wage as primary regressors, they find that a higher minimum wage increases employment and reduces the permanent exit from the employment of low-wage workers whose wage are equal to or lower than the minimum wage plus two dollars. According to their preferred estimates, a 10-percent increase in the minimum wage is

[2]For a broader review of minimum wage effects on employment, see Brown (1999), Neumark and Wascher (2008), Belman and Wolfson (2014), and Belman et al. (2015). Focusing on teenagers, a recent review by Manning (2021, Figure 3) shows that teen employment elasticities with respect to minimum wages estimated by commonly used specifications lie in the range of -0.3 to 0.1.

associated with a 2 percent increase in employment (employment elasticity of approximately 0.2) and a 6.4 percent reduction in permanent employment exit evaluated at the sample mean. They provide evidence that a higher minimum wage delays Social Security benefit claiming, especially when the minimum wage is related to a binding earnings test. Unlike the effects on minimum wage workers, workers with slightly higher hourly wages are almost unaffected except for negative effects on part-time work. Hampton and Totty (2021) interpret these findings as a sign of delayed retirement. Compared to these existing studies, this paper finds larger, positive employment effects by focusing on workers aged 65-70. This paper also provides a new explanation of the positive effects based on labor-labor substitution.

Several additional papers examine older workers more broadly. By using the American Community Survey (2011-2016), Clemens et al. (2021) find that increases in the minimum wage increase the fraction of older workers (ages 50-64) employed in low-wage occupations, while the same increases reduce the fraction of younger workers (ages 16-21). This suggests labor-labor substitution toward older workers. By using observations from CPS (1980-2015), in contrast, Lordan and Neumark (2018) showed that higher minimum wages have an adverse effect on low-skilled older workers (ages 40+) in manufacturing and automatable jobs, suggesting labor-labor substitution from older workers. Borgschulte and Cho (2020) report that minimum wages reduce the number of hours worked and full-time work but not the overall employment of workers aged 55-61. Finally, by using Canadian data (1993-1999), Fang and Gunderson (2009) show the positive effects of large minimum wage increases on the employment of older workers (age 50 or above) who earned near-minimum wages prior to the increases.

There is a small but burgeoning literature on broader channels of adjustments responding to higher minimum wages, as recently reviewed by Clemens (2021). One line of adjustment to which this paper is more closely related is labor-labor substitution. When the wages of the least-skilled workers increase, firms may shift their demand toward higher-skilled workers, since the relative price of that labor falls. Although the argument that minimum wage stimulates employing more productive workers has a long history dating back to at least Webb (1912), empirical evidence on whether firms respond to a higher minimum wage in this way is mixed. Some papers have shown that labor demand is shifted toward higher skilled workers proxied by observable characteristics such as age, gender or education (Clemens et al., 2021; Fairris and Bujanda, 2008; Hirsch et al., 2015; Neumark and Wascher, 2011), while other papers do not find a detectable shift along the observable characteristics (e.g., Fairris and Bujanda, 2008; Giuliano, 2013; Butschek, 2022). By using the introduction of statutory minimum wage in Germany, Butschek (2022) reports evidence of labor-labor substitution toward higher productivity workers identified by the framework in Card et al. (2013) and he finds no evidence of labor-labor substitution using observable characteristics as a proxy for productivity. However, among these papers, only Clemens et al. (2021) consider older workers (under age 65). This paper adds to the literature by providing evidence of labor-labor substitution for a demographic group that has not been examined in the literature.

This paper is also related to another active stream of literature studying complementarities or substitutability between younger and older workers. Due to the aging population, many developed countries are implementing labor market policies aiming to make older workers stay in the labor force longer (e.g. pension reform). One immediate question is whether this entails costs for the younger generation. The answer hinges on the substitutability between younger and older workers. If older and younger workers are substitutes for each other, making older workers work longer would hurt younger workers' labor market outcomes. The evidence is mixed. Studies using macroeconomic, country-level data tend to find null effects of delayed retirement on youth labor market outcomes (e.g. Gruber and Wise, 2010), while some recent studies using firm-level data provide evidence of the negative effects of delayed retirement on the labor market outcomes of younger workers (e.g., Bovini and Paradisi, 2019; Eckrote-Nordland, 2021). These studies, however, tend to focus on older workers below age 65 or younger workers completing their education. There is little evidence of substitution of teenagers or workers above age 65.

One exception is Mohnen (2021) using U.S. commuting zone-level data. Using Bartik-type instruments, Mohnen (2021) finds that delayed retirement of older workers (aged 55+) reduces the employment and outcome of younger adults (aged 22-30). Mohnen (2021) also finds that the negative effects become larger for teenagers (aged 16-21) and smaller for prime-age workers (aged 31-44), suggesting that the youngest workers are closer substitutes for the oldest workers. In this paper, I propose using a new instrument for identification to examine how labor demand responds to changes in relative wages.

Finally, this paper is also related to the literature examining substitutions between different demographic groups using the nested-CES production function framework. Labor economists have often estimated the elasticity of substitution using the effects of supply-side variations on wages (Welch, 1979; Katz and Murphy, 1992; Card and Lemieux, 2001; Borjas, 2003; Ottaviano and Peri, 2012). There are several differences between this paper and others. Existing papers tend to exclude the youngest or oldest workers from their analysis. These groups, however, are the primary focus of this paper. Building on the observation that the hourly wages of younger workers are more affected by local minimum wage changes, this paper focuses on the regional labor market instead of the national labor market approach used by much of the literature. I use a new instrumental variable as a shifter for the relative wage between demographic groups and estimate the degree of substitutability between age groups that have typically been ignored in other papers.

3 Empirical Strategy

Much of the minimum wage literature can be characterized as attempts to estimate the following model:

$$y = \beta f(MW) + X'\gamma + \Pi + \varepsilon$$

where y is the outcomes of interest, β is the parameter of interest capturing treatment effects, $f(MW)$ is a function measuring the intensity or change of the minimum wage, X is a vector of controls, Π is a set of fixed effects, and u is the idiosyncratic error term.

There is an ongoing debate over the identification strategy for minimum wage effects.[3] Important questions in this debate include the following: How can we define the treatment? What is the best way to define the treatment and control groups, and what is the best way to control different trends between states? The former is often related to the choice of $f(\cdot)$ while the latter is often related to the choice of Π. Answering these questions is hard, especially when researchers rely on different levels of geographic variation over different time frames. Researchers have proposed various ways to estimate β. Each method has advantages and disadvantages, and their powers vary depending on the research questions. Instead of adhering to one strategy, this study exploits a variety of specifications in the literature.

I begin with the canonical two-way fixed effects (TWFE) model in the spirit of Neumark and Wascher (1992). The regression specification follows Borgschulte and Cho (2020) for the context of older workers. In the rest of the paper, I call this the NW-type specification.

$$y_{ista} = \beta \ln MW_{st} + X'_{ista}\gamma + \phi_{sa} + \phi_{ta} + \varepsilon_{ista} \tag{1}$$

In equation (1), y_{ista} is the labor market outcomes of an individual i whose age is a and who resides in state s at time t. A key regressor is the log of the minimum wage, $\ln MW$. To account for age-specific differences across time and state, I use state-by-age specific fixed effects and time-by-age specific fixed effects. X_{ista} contains demographic controls including indicators for education level (five categories), race (four categories), gender, and marital status. This specification is closely related to one used by Borgschulte and Cho (2020) except that I employ individual-level observations and control for demographic characteristics instead of using state-time-age level aggregates. Using individual-level data allows us to exploit individual controls and is more convenient for subgroup analysis.

Although equation (1) is simple, intuitive, and easily interpretable, several studies argued that this specification is susceptible to different time trends across states (e.g.,

[3] For recent discussions, see Dube et al. (2010); Allegretto et al. (2011, 2017); Neumark et al. (2014); Meer and West (2016); Neumark and Wascher (2017); Cengiz et al. (2019)

Allegretto et al., 2011; Cengiz et al., 2019). Violation of the parallel-trend assumption can threaten causal interpretation. As a remedy, Allegretto et al. (2011) propose a way to use geographic proximity for better counterfactuals and more aggressively control state-specific time trends by including state-specific time linear (or sometimes higher-degree polynomial) trends and division-time-specific fixed effects. I call this the ADR-type specification. Specifically, I estimate the following:

$$y_{ista} = \beta \ln MW_{st} + X'_{ista}\gamma + \phi_{sa} + \phi_{sa} \cdot t + \phi_{ad(s)t} + \varepsilon_{ista} \tag{2}$$

which includes the state-age specific linear time trend ($\phi_{sa} \cdot t$) and division-time-age specific fixed effects ($\phi_{ad(s)t}$), following Borgschulte and Cho (2020). However, as pointed out by Meer and West (2016), with the dynamic effects, the inclusion of state-specific trends could wash out the treatment effects; hence the estimated parameters might be attenuated. Given the evidence that minimum wage effects may gradually affect employment through the hiring channel (e.g., Gopalan et al., 2021) rather than through instantaneous changes in the employment level, this concern is important. Equations 1 and 2 closely follow Borgschulte and Cho (2020)'s specifications.

Adjustments in employment often take time (Hamermesh, 1993), creating a potential for dynamic effects. Because of this concern, researchers have often added lags and/or leads of minimum wages (e.g., Neumark and Wascher, 1992; Meer and West, 2016; Dube, 2019) to their models. Dube (2019) argues that lagged minimum wage variables can mitigate the problem of state-specific time trends, and the coefficient of leading minimum wage terms can be used to determine the potential threat to the parallel trend assumptions. I estimate the distributed-lag models as a complementary specification for baseline employment analysis. Specifically, I include three years of leading and four years of lagged terms for minimum wages in equations (1) and (2), as shown in equations (1-D) and (2-D).

$$y_{ista} = \sum_{\tau=-3}^{4} \beta_\tau \ln MW_{s,t-\tau} + X'_{ista}\gamma + \phi_{sa} + \phi_{ta} + \varepsilon_{ista} \tag{1-D}$$

$$y_{ista} = \sum_{\tau=-3}^{4} \beta_\tau \ln MW_{s,t-\tau} + X'_{ista}\gamma + \phi_{sa} + \phi_{sa} \cdot t + \phi_{ad(s)t} + \varepsilon_{ista} \tag{2-D}$$

The next specification is based on the event-based approach used by Cengiz et al. (2022). I call it the CDLZ-type specification.

$$y_{ista} = \sum_{\tau=-3}^{4} \beta_\tau I^\tau_{st} + X'_{ista}\gamma + \phi_{sa} + \phi_{ta} + \Omega_{st} + \varepsilon_{ista} \tag{3}$$

Here, I_{st}^{τ} is a binary indicator variable equal to 1 when the large-scale state-level minimum wage increases occur τ years relative to time t in the state s. Given the different trends in outcomes across states, it provides a more transparent way to understand the effects. Since minimum wage effects could vary depending on the size of the increases (Clemens and Strain, 2021), focusing only on large-scale increases may provide a clearer picture. However, since increases with different sizes (larger than a certain threshold) are all treated as the same, it may not be possible to use important variation for identification. Furthermore, minimum wage increases often consist of a series of increases, which complicate the estimation and interpretation.

A key issue in equation (3) is how to define the treatments. I define treatment as a state-level minimum wage increase of 50 cents or larger in 2019 USD, excluding minimum wage increases enacted by the federal legislature. This definition of the treatments is close to that used by Cengiz et al. (2019, 2022). This gives me 172 treatments during a 40-year data period. The average increase is approximately 10% of the previous minimum wages. I control for large federal increases and small increases by including indicator variables for small changes and large federal changes with the same time window in Ω. Federal minimum wage increases are excluded for several reasons. Since federal minimum wage increases affect many states at the same time, it is difficult to find a relevant control, especially for earlier periods.[4] As a result, focusing only on the state-level increases may provide a more transparent source of variation. Furthermore, recent econometric literature on TWFE suggests that negative weights are likely to be assigned when larger portions of units are treated (e.g., de Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). Therefore, federal minimum wage increases are more likely to create a negative weight problem.

β in equations (1) and (2) and β_τ in equation (3) are not comparable. To compare estimates from different specifications, for the main analysis, I convert them into elasticities (or semi-elasticities in some cases). In the case of the CDLZ-type specification, I mainly report 3-year average elasticities.[5] For the main analysis, I also present the

[4]For instance, in the case of the 1979 federal minimum wage increase, 48 states and the District of Columbia experienced large-scale minimum wage increases due to action by the federal legislature. The remaining two states, Alaska and Connecticut, increased their own minimum wages at the same time.

[5]For equations (1) and (2), when y is measured by level (such as employment), the estimated $\hat{\beta}$ can be easily converted to elasticity by calculating $\hat{\beta}/\overline{y}$, where $\overline{y}$ is the average of y. In the case of equation (3), when y is measured by level, I calculate the 3-year average elasticity as follows. First, $\Delta\%y$ can be calculated by $\frac{\Delta y_{post} - \Delta y_{pre}}{\overline{y_{-1}}} = \frac{\left(\frac{1}{t+1}\sum_{\tau=0}^{t=2}\hat{\beta}_\tau - \frac{1}{3}\sum_{\tau=-1}^{-3}\hat{\beta}_\tau\right)}{\overline{y_{-1}}}$, in other words, the difference in the three-year average of pretreatment versus the three-year average of posttreatment outcomes relative to the control group normalized by the average of y_{ista} at period -1. Then this can be translated into elasticity by $\Delta\%y/\Delta\%MW$, where $\Delta\%MW$ is the percent change in the minimum wage for the treated. If y is measured in a log scale, I perform the same process without dividing by $\overline{y_{-1}}$. Instead of the average of $\hat{\beta}_\tau - \hat{\beta}_{-1}$ used by Cengiz et al. (2022), I compare the posttreatment coefficients against the 3-year average of the pretreatment to reduce the weight imposed on year -1. I additionally present the event-study figure for the primary outcome which shows $\hat{\beta}_\tau - \hat{\beta}_{-1}$, as a complementary analysis.

event-study figure together with the distributed-lag models including leads and lags of the minimum wages to examine the dynamic effects.

All the aforementioned specifications are built on the TWFE framework. Recently, econometric literature on TWFE raises concerns about the interpretation of TWFE when treatment effects and timing are heterogeneous.[6] This concern could be more acute for the CDLZ-type specification since I aggregate minimum wage increases with different magnitudes by one treatment indicator. I complement the CDLZ-type specification by using a 'stacked-event approach' used by several recent papers on minimum wage (Cengiz et al., 2019, 2022; Clemens and Strain, 2021). The idea of this approach is simple. Suppose we are studying just one large-scale state-level minimum wage increase (or, one 'event') with a set of clean control states that do not experience large-scale state-level increases (but we can allow control states to experience federal or small increases). Analyzing this one event is not associated with any of the pitfalls addressed by recent econometric literature, since those pitfalls are caused by the combination of heterogeneous effects and heterogeneous timing of the events. Expanding this idea, I first construct an event-by-event data set containing treatment state and clean controls with an 8-year, 32-quarter window. I restrict the treatment to state-level increases that do not experience any other nominal minimum wage changes during 3 years before the treatments. This gives me 52 'clean' treatments. After creating this event-by-event data set, one can append (or 'stack') the data set and estimate the coefficient on the treatment indicators with the full set of event-specific state and time fixed effects. Baker et al. (2022) argue that this stacked-event approach is free from negative weighting problems. Specifically, I estimate the following:

$$y_{iksta} = \sum_{\tau=-3}^{4} \beta_\tau I_{st}^{\tau} + X'_{ista}\gamma + \phi_{ska} + \phi_{tka} + \Omega_{stk} + \varepsilon_{iksta} \tag{3-S}$$

where k is an index for events. The fixed effects are all event-specific, while the treatment indicators aggregate event-specific effects by a single parameter. I use this stacked-event approach as a complementary method for the baseline employment analysis.

4 Data and Descriptive Findings

The main source of information for this paper is the NBER extract of the Current Population Survey Outgoing Rotation Group (CPS-ORG) for the years 1979-2019.[7] The CPS-ORG has been the primary workhorse for minimum wage researchers during the last three decades due to its relatively larger size and precise information on hourly wages,

[6] For details, see de Chaisemartin and d'Haultfoeuille (2020); Goodman-Bacon (2021); Baker et al. (2022) among others.

[7] Available from `https://www.nber.org/research/data/current-population-survey-cps-data-nber`

which are essential for studying minimum wage.

The key variables for this paper include information on employment, hourly wages, working hours, and state minimum wages. I define employment as a binary variable that equals 1 if individuals work for pay, excluding self-employed workers, and 0 for individuals in all other categories including unemployed, self-employed, and those who are out of the labor force. Henceforth, whenever I use the terms 'employed' and 'employment', they exclude the self-employed and workers without pay unless explicitly noted. Information on hourly wages to the penny is available only for hourly paid workers. For salaried workers, I impute the hourly wages by dividing the weekly earnings by the usual weekly hours of work. If top-coded, I multiply the their hourly wages by 1.4. Hourly wages are adjusted by R-CPI-U-RS obtained from the U.S. Bureau of Labor Statistics.[8] Of the two measures of weekly working hours in the CPS-ORG (usual hours of work and hours worked in the last week), I use usual hours of work for the analysis. The minimum wage information is downloaded from Vaghul and Zipperer (2021).[9]

Although this study's main research question is the effect on the elderly (ages 65-70), I also present results for young (ages 16-21) and prime-aged (ages 30-54) workers for comparison; the rationale for these exact ages is discussed below. Young workers are the group that has been most extensively scrutinized by researchers, possibly because the majority of them work in minimum wage jobs. On the other hand, since most prime-age workers are not minimum wage workers, they are less likely to be affected by minimum wages. Including these two groups in the scope of the analysis facilitates understanding the effects on older workers and examining the validity of each specification.

Table 1 presents the key variables of interest for the three age groups. The labor market outcomes of older workers are often closer to those of younger workers, rather than to those of prime-age workers. As is well known, the employment-to-population ratio is high for prime-age adults, while it is much lower for younger and older groups. Few young workers are self-employed while older workers are more likely to be self-employed. Both part-time and minimum wage workers' proportions are calculated conditional on working. Approximately half of the young workers and more than a third of older workers work in part-time jobs, while the ratio is approximately 10 percent for the prime-age group. Furthermore, approximately half of the young workers and slightly less than one-fifth of older workers earn less than 1.2 times the effective minimum wage, while that ratio drops to 8.5 percent for prime-age workers.

To demonstrate the relative importance of the minimum wage for workers of different ages, I show the fraction of minimum wage workers among workers, defined as those whose hourly earnings are 120 percent of the minimum wage or lower, by age in Figure 1. This result is largely close to Figure 2.3 of Flinn (2010) and Figure 1 of Borgschulte

[8] Available from https://www.bls.gov/cpi/research-series/r-cpi-u-rs-home.htm

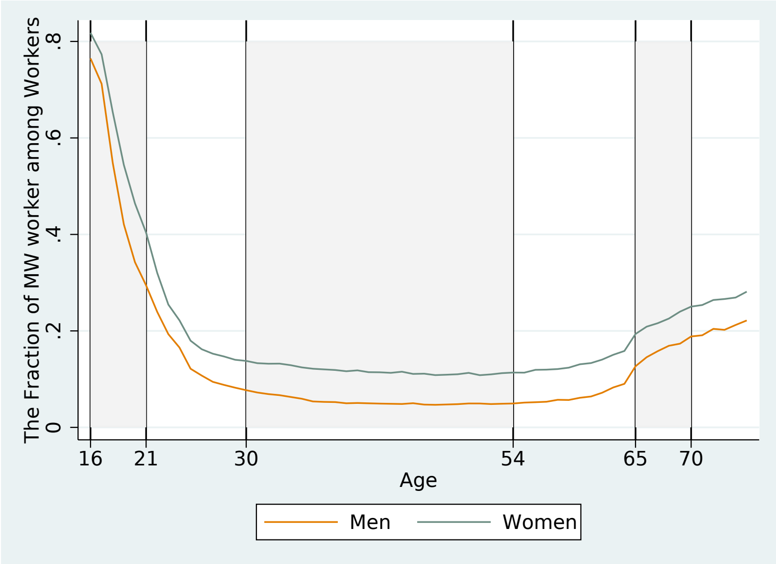
[9] Aavailable from https://github.com/benzipperer/historicalminwage/releases

Table 1: Descriptive Statistics

CPS-ORG, 1979-2019			
	Age 16-21	Age 30-54	Age 65-70
Panel A. Employment Variables			
Employed (Excluding Self-Employed)	0.451	0.691	0.180
Employed (Including Self-Employed)	0.460	0.784	0.240
Log Hourly Wage[b]	2.307	3.045	2.865
	(0.384)	(0.607)	(0.721)
Minimum Wage Workers[a,b]	0.511	0.085	0.185
Usual Hours of Work[b]	28.687	40.253	32.744
	(12.736)	(9.210)	(13.349)
Part-time[b]	0.513	0.108	0.372
Panel B. Demographic Variables			
Age	18.478	41.440	67.377
	(1.718)	(7.148)	(1.712)
Less than High School	0.490	0.130	0.251
High School Graduate	0.229	0.321	0.338
Some College	0.275	0.256	0.198
College Graduates	0.005	0.183	0.122
Advanced Degree	0.000	0.082	0.078
African-American	0.149	0.120	0.093
Hispanic	0.145	0.116	0.060
Observations	1428573	5770663	854730

[a] Minimum wage workers are defined as those whose hourly wages are lower than 1.2 times the effective minimum wage. Hence it includes subminimum wage workers. [b] is conditional on employment. All the results are weighted by the CPS earnings weight. Standard deviations are in parentheses. Standard deviations of dummy variables are not included in the table.

Figure 1: Minimum Wage Workers among Workers by Age



Source: CPS-ORG, 1979-2019. All the results are weighted by the CPS earnings weight. Minimum wage workers are defined as those whose hourly wage is 1.2 times the effective minimum wage or lower.

and Cho (2020). As is widely known, a large portion of teenagers is paid the minimum wage. However, the importance of minimum wages measured by the fraction of minimum wage workers among the workforce drops quickly. The ratio becomes low and stable from approximately ages 30 to 60, but from the early sixties, the proportion of minimum wage workers starts to rise, and it ultimately exceeds 20 percent for workers in their seventies.

Table 1 and Figure 1 aggregate all the observations during the last four decades. The labor market outcomes of the elderly have seen large changes during the last four decades. Appendix Figure A.2 shows the trends in the employment-to-population ratio, hourly wage, and fraction of minimum wage workers among workers for the three key age groups. In recent years, the elderly have been more likely to work, and if they work, they are more likely to earn higher wages. The median hourly wage (2019 USD) of older workers has increased dramatically from 1979 (approximately $12) to 2019 (approximately $19.8). It was closer to that of young workers in earlier periods, but it has caught up with the wages of prime-age workers in recent periods.

The fraction of minimum wage workers among all workers fluctuates with the real minimum wage, as is also captured by trends in the fraction of minimum wage workers among young workers. The same trend among older workers fluctuated together with that among younger workers until the mid-2000s but stabilized during the 2010s. Furthermore, although the fraction of minimum wage workers is still higher than that of prime-age workers, the gap in hourly wages almost disappears.

5 Effects of Minimum Wages on Employment

5.1 Baseline Employment Effects: Comparison across Ages and Methods

I begin with a set of age-by-age employment elasticities with respect to minimum wages using three specifications. Specifically, I estimate equations (1), (2), and (3) with the full set of age indicators interacting with the log of the minimum wage for equations (1) and (2) and treatment indicators for equation (3). Then, I convert age-specific coefficients to elasticities.

Figure 2 shows age-specific employment elasticities with respect to minimum wages from ages 16 to 74. As shown in Panel A, the employment effects of minimum wages are surprisingly different across ages. It shows negative employment elasticities significantly different from zero for teenagers, consistent with the literature using the log of minimum wage as a key regressor. However, as workers age, employment elasticity moves close to zero and then becomes relatively stable. The graph thus far is largely a mirror image of Figure 1. In contrast, from approximately age 60, employment elasticities become positive. For workers in their sixties, and especially their late sixties, the point estimates become positive, large, and generally significant, although the estimates are noisier.

Although the estimates in Panels B and C are different from those in Panel A regarding young workers, the results are similar for everyone else. Until approximately age 60, the point estimates in Panels B and C look like a horizontal line at zero with little fluctuations. However, from approximately the mid-sixties, employment elasticities deviate from zero and turn positive. This is clearer for estimates with the ADR-type specification, and less so for the estimates with the CDLZ-type specification.[10]

Based on these results, most of my analysis focuses on three age groups: young workers (aged 16-21), prime-age workers (aged 30-54), and older workers (aged 65-70). My age criteria are slightly different from those in previous studies, but they are driven by similarities within each group.[11] Each focal age range is shaded in Figures 1 and 2.

Table 2 presents the baseline employment effects of minimum wages for these three focal age groups. In Panel C, I report 3-year average elasticities from the baseline CDLZ-type specification and stacked-event approach. Appendix B contains expanded tables

[10]Using CPS Basic Monthly (1983-2016), Borgschulte and Cho (2020, Figure 3) provide similar age-specific employment and labor force participation elasticities (from age 50 to 70) using an empirical specification closer to the ADR-type specification. Their results do not show clear positive employment elasticities for people in their late sixties. The definition of employment in Borgschulte and Cho (2020) includes self-employed workers, while this paper does not. Later in Table 3, I show that the effects of the minimum wage on the self-employed and unemployed estimated by the ADR-type specification are negative (although not large). This offsets some of the positive effects on these ages.

[11]Both Borgschulte and Cho (2020) and Hampton and Totty (2021) focus on ages 62-70, and Cengiz et al. (2022) study ages 60-70.

Figure 2: Employment Elasticities by Age and Method

Source: CPS-ORG, 1979-2019. All the results are weighted by the CPS-ORG earnings weight. The dependent variable is a binary variable of employment (excluding self-employment). The estimated coefficients are converted to elasticities as described in section 3 Each dot shows point estimates of elasticity and each bar shows the 95% confidence interval. Robust standard errors are in parentheses and clustered at the state level. (Panels A and B are obtained from pooled regression of ages 16-74, while Panel C is obtained from separate age-by-age specific regression due to the lack of computing power.) See text for details.

Table 2: Employment Effects of Minimum Wages

	Dep var: Employed		
	Age 16-21 (N: 1,428,573) (1)	Age 30-54 (N: 5,770,663) (2)	Age 65-70 (N: 854,730) (3)
Panel A. Estimation using the *NW-type* Specification			
Elasticity w.r.t. Minimum Wage	-0.183***	0.027	0.166+
	(0.051)	(0.016)	(0.086)
Panel B. Estimation using the *ADR-type* Specification			
Elasticity w.r.t. Minimum Wage	0.026	0.031**	0.232**
	(0.037)	(0.011)	(0.069)
Panel C. Estimation using the *CDLZ-type* Specification			
3Y Average Effects			
Baseline			
Elasticity w.r.t. Minimum Wage	0.023	0.020	0.118*
	(0.067)	(0.019)	(0.058)
Stacked-Event Approach			
Elasticity w.r.t. Minimum Wage	-0.105	0.022	0.287
	(0.154)	(0.029)	(0.250)

All the results are weighted by the earnings weights (*earnwt*) in the CPS-ORG. Robust standard errors are in parentheses and clustered at the state-level. All the results include state-age specific fixed effects, time-age specific fixed effects, categorical variables of education, and race, and indicators for female and married observations. Panels A and B use the log of minimum wage for identification. Panel B includes state-age specific linear trends and division-time-age specific fixed effects from Panel A. Panel C uses an 8-year window of state-level large minimum wage increases and includes the indicator for small and federal minimum wage effects for the same window. In the stacked-event approach, some observations in clean control states are used multiple times. The total number of observations used in the stacked-event approach is 6,704,412 for column (1), 28,387,532 for column (2), and 4,196,649 for column (3). The unit of time is the quarter. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively.

including longer run effects and other complementary results. Columns (1), (2), and (3) show the effects on the young, prime-age, and the elderly, respectively.

As widely found elsewhere and shown in Figure 2, in column (1), the point estimates of employment effects on young workers fall roughly within the range [-0.2, 0], and the NW-type specification tends to produce more negative estimates.[12] As expected, the employment elasticities of prime-age workers are very close to zero, and all the estimates fall within a very narrow range [-0.05, 0.05]. Although some estimates are statistically significant, they are small and very close in magnitude to estimates from other specifications. Positive elasticity in this range is hardly economically meaningful. The results thus far successfully replicate stylized results in the literature.

Next, I turn to the results in column (3) for the minimum wage effects on employment for the elderly. Unlike young and prime-age workers, all the specifications in column (3) report positive employment elasticities with respect to minimum wage. The point estimates are small and fall roughly within the interval [0.1, 0.3], and the majority are statistically significantly different from zero at the conventional level. This implies that if the minimum wage increases by 10 percent, the employment-to-population ratio increases by approximately 1 to 3 percent, or 0.2 to 0.5 percentage points. The effects are larger in Panel B, where estimates are more likely to be attenuated due to the inclusion of state-specific linear trends (Meer and West, 2016). The results using the stacked-event approach are aligned with estimates using other specifications, suggesting that positive estimates are not driven by negative weights or other pitfalls of TWFE.

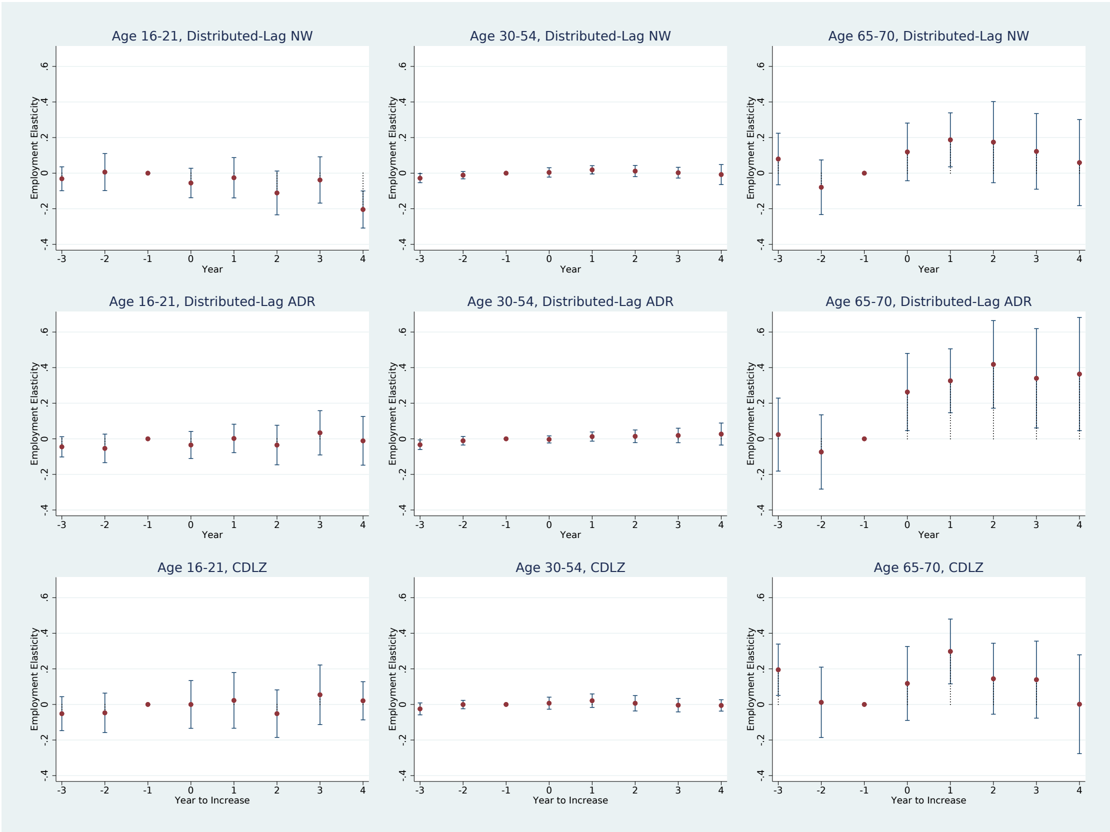
Although the magnitudes of employment elasticities are not large, these estimates are larger than those in the literature. By combining specifications similar to those in Panels A and B and the CPS Basic Monthly (1983-2016), Borgschulte and Cho (2020, Table 3) report employment elasticities on the elderly (age 62-70) in the range [0, 0.15], depending on the specification and definition of employment.[13] With the same age range, 62-70, Hampton and Totty (2021) report employment elasticity of approximately 0.2 using workers earning near-minimum wages. Since minimum wage workers constitute a small portion of the older workforce, the implied overall employment elasticities are much smaller than 0.2. By focusing on the older ages, I can more clearly demonstrate the positive employment effects on the elderly. Furthermore, by adding new results using the event-based and stacked-event approaches, I can address that these results are not driven by negative weights or other pitfalls of the TWFE specification.

Figure 3 explores the dynamic effects and pretrend by using distributed-lag models and event-based approaches. In the distributed-lag models, I present the cumulative elas-

[12] Wolfson and Belman (2019) and Manning (2021) provide a more detailed discussion of the elasticities in the literature and their sensitivities to specifications.

[13] Note that their 'employment' includes the self-employed, and their 'wage and salary employed' is identical to my 'employment' variable.

Figure 3: Dynamic Effects on Employment



The first row shows the results using the distributed-lag NW-type specification, and the second row shows estimates from the distributed-lag ADR-type specification. Each dot shows employment elasticities calculated by the joint sum of the coefficients up to that term divided by the sample average, normalized to make the -1 year term to zero. The third row shows the estimates from the standard event-based approach calculated by $\left((\beta_\tau - \beta_{-1})/\overline{y_{-1}}\right) \cdot (1/\Delta MW)$. All the estimates include the same set of covariates as in Table 2.

ticities calculated by the joint sum of the coefficients from the three-year leading terms up to that year divided by the sample average, following Dube (2019). The elasticities are further normalized to make the -1 year term to zero.[14]

Regarding the elderly, the three methods produce similar results. Positive effects on employment grow in the short run (approximately 2 years) but disappear in the medium run. The two-year cumulative employment elasticities in the first two rows and employment elasticities to large-scale increases a year after the events are in the range of 0.2 to 0.4, compared to the year -1, and they are statistically significant at the conventional level. After that, the positive effects gradually disappear, although they persist longer in the ADR-type specifications. Figure 3 also does not show any noticeable pretrends, except for the estimate on the 3 years prior to the increase from the CDLZ-type specification.[15]

I present additional complementary analysis in Appendices C and D. Appendix C shows the effects on other important labor market outcomes: weekly working hours and hourly wages. Conditional on working, I do not find any detectable effects on the working hours and hourly wages of the elderly. Appendix D examines various issues including event-by-event estimates, heterogeneity by employment status in the previous year, and heterogeneity by education. Although the effects are often noisy due to the smaller sample size, in general, I do not find evidence of negative employment effects on the elderly.

In summary, although a larger fraction of the elderly, especially less-educated workers, earn the minimum wage, there is no evidence of disemployment effects as suggested by standard neoclassical theory, consistent with previous studies (Borgschulte and Cho, 2020; Hampton and Totty, 2021; Cengiz et al., 2022). Instead, this subsection provides evidence of small, positive effects of the minimum wage on elderly employment for those in their late sixties. These positive effects are robust to a variety of specifications. Given the standard labor demand theory, which implies negative labor demand elasticities with respect to wages, these results require further investigation.

5.2 Employment Effects across the Wage Distribution

Another approach to examining the employment effects of the minimum wage is to examine the effects on wage distribution. This has become a useful tool for the anatomy of employment effects in recent minimum wage studies (e.g., Cengiz et al., 2019; Derenoncourt and Montialoux, 2021; Forsythe, 2022). I begin by applying the bunching approach

[14]For instance, the elasticities in the year 2 are calculated by $(\sum_{t=-3}^{2}\hat{\beta}_t - \sum_{t=-3}^{-1}\hat{\beta}_t)/\overline{y} = (\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2)/\overline{y}$.

[15]Note that the employment elasticities in Table 2 are calculated by the difference between the 3-year average pre-period and post-period, instead of using a year before the treatment as a base. The event-study figure shows that it is a conservative estimate.

proposed by Cengiz et al. (2019). This method is based on the analysis using wage bin-by-bin aggregate and estimates the effects of minimum wage increases on the number of workers in the wage bins relative to the new minimum. A detailed discussion of this method and regression specification is provided in Appendix E.

Although this method provides a powerful tool to characterize the effects along the wage distribution, it is highly data-demanding. The basic unit of the bunching approach is the state-quarter-bin level aggregate. Subgroups such as the elderly often lack sufficient numbers of observations. To overcome this problem and compare the results across specifications, I complement the analysis by using a simpler alternative approach to estimating the effects on the cumulative distribution. Specifically, I use a set of binary indicator variables, $I(\text{Employed and hourly wage } \leq c)$ with a different set of criteria. For c, I specify 10 to 150 percent of the median wage with a 10 percent interval for c. The average of minimum-to-median ratio is 0.45, ranging from 0.287 to 0.795. For 90 percent of the population, the minimum-to-median ratio falls in the range of 0.363 to 0.559. (See Appendix Figure A.3 for the distribution of the ratio.) The average median hourly wage is approximately \$18. It is calculated from all workers including part-time or part-year workers and non-prime-wage workers.

The primary focus of the analysis in this subsection is to examine who in the wage distribution responds to minimum wage changes. For that purpose, instead of rescaling the coefficients by different values across c to convert them into elasticities, I normalize the coefficients with the same ratio.[16] These normalized semi-elasticities show the change in the probability of working with wages lower than c relative to employment.[17]

Panel A in Figure 4 shows the results using the bunching approach. Here, the wage bins are numbered relative to the new minimum.[18] The gray lines show the cumulative effects up to that wage bin. The definition of the treatment is identical to that in equation (3). Following the original method in Cengiz et al. (2019), this shows the effects relative to the previous employment level, not elasticities. Given the average sizes of minimum wage increases, multiplying by 10 approximates the employment elasticities. Appendix B presents larger graphs for each panel. Panel B in Figure 4 shows the effects on the number of workers below a certain wage using three baseline specifications. Intuitively, these lines are analogous to the gray lines in Panel A.

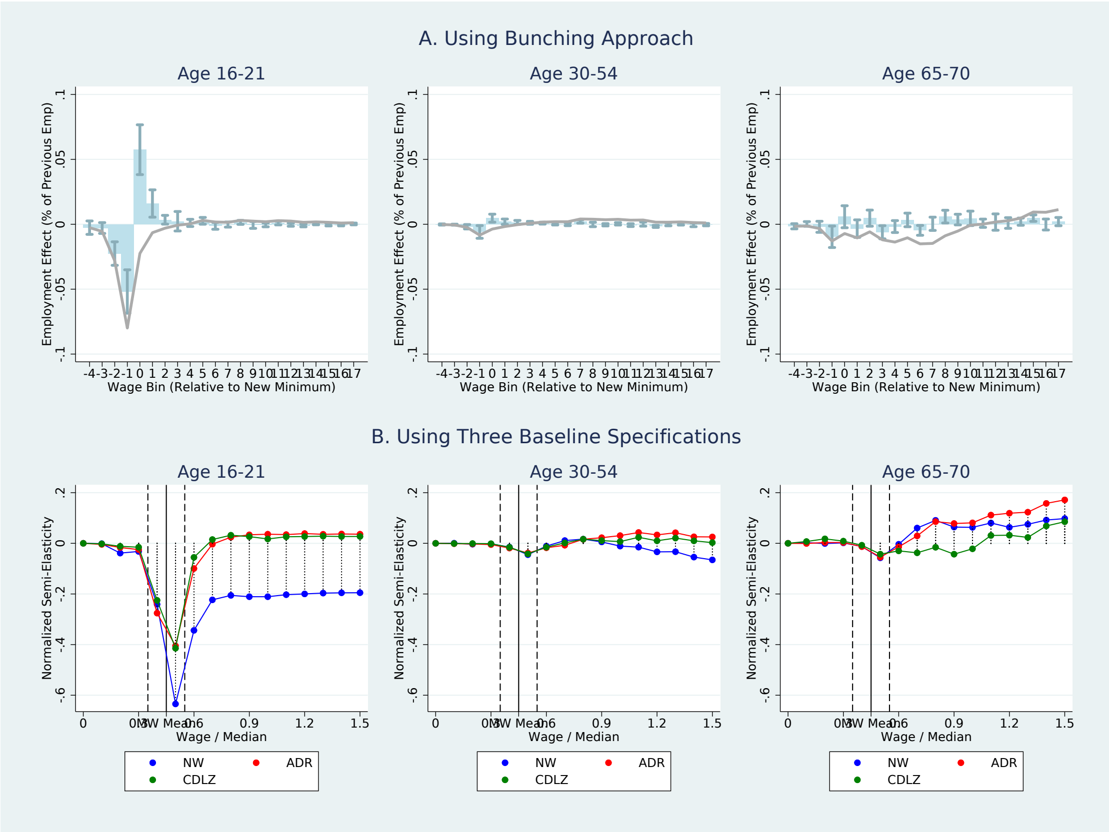
The left panels show the large negative effects on the lower part of the wage dis-

[16]This is the baseline average employment-to-population ratio of the age group for the NW- and ADR-type specifications and the average employment-to-population ratio of the treated state before the treatment for the CDLZ-type specification.

[17]For example, the normalized effect at a certain c is 0.1, which means that a 10 percent increase in minimum wage increases the number of workers below c by 1 percent of the total employment.

[18]Specifically, 0 indicates the 25-cent wage bin containing the new minimum wage and the three bins above it (or, 'just-above-minimum' in the example), and the wage bin -1 implies four 25-cent wage bins below the new minimum.

Figure 4: Effect of Minimum Wage along the Wage Distribution



In Panel A, each bar shows the employment effects on the wage bin normalized by the employment-to-population ratio of each age group before the treatment. The gray lines in Panel A show the cumulative effects up to that wage bin. In Panel B, the blue, green, and red dots show the estimates for the young (16-21), prime-age (30-54), and elderly (65-70), respectively. See text for details. The black solid line shows the average minimum wage-median wage ratio (approximately 45 percent of the median wage), and the black dotted lines show the 5th and 95th percentiles of the minimum to median ratio, respectively.

tribution of the young workers for all the specifications. The magnitude of the missing jobs (negative effects below the new minimum) is smaller in Panel B, since 50 percent of the median wage is higher than the minimum wage in some cases. Within Panel B, the negative effects are larger in the NW-type specification. These large negative effects are offset by positive effects on the workers above the minimum (Panel A) or 50 percent of the median (Panel B). In Panel B, the size of the positive effects on the number of workers above 50 percent of the median is similar across the specifications. Therefore, the long-lasting debates over teenager employment effects boil down to measuring the effects on employment below the new minima. In the case of prime-age workers, the magnitude of the missing jobs is much smaller than that for young workers, and it is offset by the positive effects above the minimum wage. For all three specifications, the effects on the number of workers below 70 percent of the median are virtually zero, which implies the workers are just shifted. However, in the case of the NW-type specification, the negative effects grow for higher values of c, which raises some concerns regarding the validity of the specification.[19] Except for that, for both young and prime-age workers, I do not find any detectable effects on the region above 70 percent of the median wage. Seventy percent of the median is approximately 4 dollars above the average minimum wage; hence, workers below 70 percent of the median can be characterized as near-minimum wage workers.

Once again, the results differ for the elderly. All the specifications show negative effects on the lower part of the distribution that are larger than those on prime-age workers. Focusing on near-minimum wages (70 percent of the median or up to 5 dollars above the new minimum), the cumulative effects are much smaller than the total positive employment effects. In the NW- and ADR-type specifications of Panel B, the minimum wage has positive effects on the number of workers below 70 percent of the median, but these are only approximately half of the total employment effects in section 5.1. In Panel A and the CDLZ-type specification of Panel B, the effects on near-minimum wage workers are even negative, and the positive effects come instead from workers above this region. For all the specifications, however, the effects up to 17 dollars above the new minimum (roughly \$25) or 130 percent of the median hourly wage (roughly \$23.5) become closer to the total employment effects in section 5.1. This shows that the responses of near-minimum wage workers cannot explain all the positive effects identified in section 5.1 and that the positive effects extend to workers who are paid well above the minimum wage.

Overall, this subsection shows that positive employment effects on older populations are not limited to near-minimum wage workers but extend more broadly to low- or even medium-wage workers. The effects on near-minimum wage workers are not sufficient to explain the overall positive employment effects on the elderly, and this may explain the difference between my estimates and those in Hampton and Totty (2021) or Cengiz et al. (2022). Hampton and Totty (2021) analyze near-minimum wage workers, and Cengiz et al. (2022) examines the effects on individuals who are more likely to work in minimum

[19]Note that the overall effects on the prime-age workers are zero. This means that these negative effects are offset by positive effects on high-wage workers.

wage jobs.[20] This feature raises a question. These wage ranges (70 to 130 percent of the median-wage) seem to be too high to be affected by spillover effects.

5.3 Where Do the Additional Employees Come From? Effects on Various Labor Market Status

This subsection examines how the minimum wage affects labor market status: employment, unemployment, self-employment, and being out of the labor force. To compare the exact magnitudes, I present semi-elasticities. Since each category is mutually exclusive, the coefficients should sum up to zero. Appendix B contains a table with usual elasticities. Focusing on the older population, Table 3 reveals that an increase in employment is associated with a decrease in the fraction of the elderly who are out of the labor force, while the effects are not precisely estimated. The effects on unemployed or self-employed workers are not clear. This shows that a higher minimum wage attracts workers who are out of the labor force, suggesting that higher minimum wages increase the labor supply.

6 Why Positive?

This section provides an economic explanation for the empirical findings in the last section. I find small, positive employment effects of minimum wages on older workers in line with recent papers (Borgschulte and Cho, 2020; Hampton and Totty, 2021). Existing papers often interpret the results as a sign of delayed retirement and increased labor supply that come from wage effects. However, several important questions remain. First, the analysis of the wage distribution suggests that at least some portion of the positive effects come from workers whose hourly wage may not be directly determined by the minimum wage. This calls into question the explanatory power of the labor supply responses. Second, higher minimum wages create even larger incentives for young or other minimum wage workers, while they generally do not show positive responses. Third, under the binding minimum wage in standard neoclassical economics, employment outcomes are more likely to be determined by labor demand than by movement along the supply curve.

This section seeks an alternative, possibly complementary explanation for the positive employment effects. The key idea is as follows. The minimum wage is a wage rate for the least-skilled workers such as teenagers. A higher minimum wage increases the relative price of the least-skilled workers, and employers may shift their demand toward better-skilled workers. With this labor-labor substitution, effects are not necessarily limited to the least skilled population; rather, small effects can be found among a broader class of

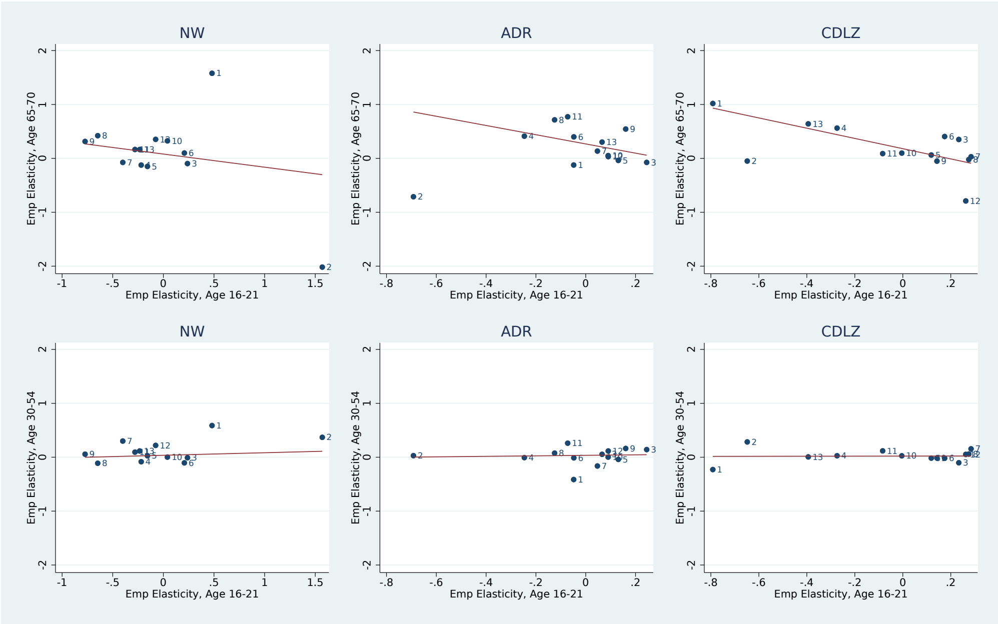
[20]Hampton and Totty (2021) also report null employment effects on workers who earned 5-10 dollars above the minimum wage before the increases. The slope of the effects in Panel B is relatively flatter, which may lead to insignificant estimates in this range.

Table 3: Effects of Minimum Wage on Various Labor Force Status

	Employed (E) (1)	Unemployed (U) (2)	Self-Employed (S) (3)	Out of the Labor Force (OLF) (4)
Panel A. Age 16-21 (N: 1,428,573)				
Estimation using the *NW-type* Specification				
Semi-Elasticity	-0.083***	-0.001	0.000	0.083**
	(0.023)	(0.011)	(0.002)	(0.029)
Estimation using the *ADR-type* Specification				
Semi-Elasticity	0.012	-0.010	-0.004	0.002
	(0.017)	(0.010)	(0.003)	(0.015)
Estimation using the *CDLZ-type* Specification				
3Y Average Effects				
Semi-Elasticity	0.010	0.002	0.006*	-0.018
	(0.027)	(0.012)	(0.003)	(0.021)
Panel B. Age 30-54 (N: 5,770,663)				
Estimation using the *NW-type* Specification				
Semi-Elasticity	0.019	-0.007	0.005	-0.017
	(0.011)	(0.006)	(0.006)	(0.010)
Estimation using the *ADR-type* Specification				
Semi-Elasticity	0.022**	-0.009	-0.000	-0.013*
	(0.008)	(0.006)	(0.004)	(0.005)
Estimation using the *CDLZ-type* Specification				
3Y Average Effects				
Semi-Elasticity	0.014	0.002	-0.016**	0.000
	(0.013)	(0.005)	(0.005)	(0.007)
Panel C. Age 65-70 (N: 854,730)				
Estimation using the *NW-type* Specification				
Semi-Elasticity	0.030+	-0.000	0.033***	-0.063**
	(0.016)	(0.003)	(0.009)	(0.022)
Estimation using the *ADR-type* Specification				
Semi-Elasticity	0.042**	-0.004	-0.015	-0.024
	(0.012)	(0.004)	(0.011)	(0.014)
Estimation using the *CDLZ-type* Specification				
3Y Average Effects				
Semi-Elasticity	0.025*	-0.004	0.000	-0.021
	(0.012)	(0.004)	(0.011)	(0.018)

Robust standard errors are in parentheses and clustered at the state level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. See notes to Table 2 for more details.

Figure 5: Industry-Level Analysis



Linear fitted lines are weighted by the fraction of workers employed in each industry among the total workforce.

workers. This section focuses on the substitution between young and older workers.

6.1 Industry-Level Analysis

I begin with a descriptive examination of the possibility of labor-labor substitution based on an industry-level approach. Specifically, I classify industries into 13 consistent categories based on the method proposed by Pollard (2019). Detailed information on this classification is provided in Appendix A.1. Using the consistent industry information at hand, I examine the industry-specific employment elasticities with respect to minimum wages for the three age groups. After estimating the industry-age-specific employment elasticities, I plot the prime-age and elderly industry-level employment elasticities against those of the young. If minimum wage causes labor-labor substitution between workers of different ages, the relationship will be negative. In contrast, if everyone in the same industry is affected in the same manner regardless of their ages, the relationships will be positive.

The results are shown in Figure 5. The first row shows the relationship between industry-level employment elasticities with respect to minimum wages of the young and elderly, and the bottom row shows the same relationship between the young and prime-age. The linear fitted lines are weighted by the fraction of workers employed in each industry among the total workforce. The top row shows a negative relationship between young and elderly employment elasticities, implying that the number of older workers increased in industries that reduced the number of young workers. This relationship is especially clear in the ADR- and CDLZ-type specification with a slope of approximately negative 1 and becomes weaker in the NW-type specification. In contrast, the employment effects on young and prime-age workers are not correlated, primarily due to the null effects on the prime-age workers.

However, this analysis has several limitations. First, industry-level estimates are highly imprecise and noisy. Furthermore, different methods often identify different industries as positively or negatively affected industries. This problem is especially severe for some industries that do not employ many younger or older workers (e.g., agriculture (industry 1) or mining (industry 2)). Despite these limitations, industry-level analysis can be taken as suggestive evidence of labor-labor substitution between young and older workers.

6.2 Estimating the Elasticity of Substitution Using Minimum Wage Changes

To more formally examine the possibility of labor-labor substitution, this subsection estimates the elasticity of substitution using a simple nested-CES production function framework. Labor economists have long been interested in estimating the elasticity of substitution between workers with different skills and demographics, and the nested-CES framework has been a powerful weapon in labor economists' arsenal (e.g., Welch, 1979; Katz and Murphy, 1992; Card and Lemieux, 2001; Borjas, 2003; Ottaviano and Peri, 2012). It greatly simplifies the nature of substitution without losing too much detail.

Due to the lack of observations especially for older workers, I impose the simplest possible structure to determine the elasticity of substitution between groups. Consider the following state or state-industry-level aggregate production function using capital and a variety of labor inputs aggregated into L:

$$Y = F(L_y, L_p, L_o, K) = AK^{\alpha}L^{1-\alpha}$$

L_y, L_p and L_o are the employment of the young, prime-age, and older workers, respectively. Aggregated labor input, L, is a CES aggregate of prime-age and non-prime-age workers. In other words:

$$L = \left[\theta_{np}L_{np}^{\frac{\sigma_p-1}{\sigma_p}} + (1-\theta_{np})L_p^{\frac{\sigma_p-1}{\sigma_p}}\right]^{\frac{\sigma_p}{\sigma_p-1}}$$

and the labor of non-prime-age workers, L_{np} is again a CES aggregate of young and older workers:

$$L_{np} = \left[\theta L_y^{\frac{\sigma-1}{\sigma}} + (1-\theta) L_o^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

The CES production function imposes the same rate of substitution between factors in the same layer. If I put young, prime-age, and older workers in the same layer, I impose the restriction of an identical rate of substitution between different age groups. Given the analysis in the previous subsection, this restriction may not be plausible. To avoid this problem, I impose an additional layer of non-prime and prime-age workers.

In a competitive market equilibrium, wage equals the value of the marginal productivity of labor. It can be derived that

$$\ln(L_y/L_o) = \sigma \ln(\theta/(1-\theta)) - \sigma \ln(w_y/w_o) \tag{4}$$

In other words, the relationship between relative wages and relative employment reveals the elasticity of substitution, holding relative productivity constant. (see Appendix F for details). For the estimation, I use the following specification:

$$\ln(L_y/L_o)_{st} = -\sigma \ln(w_y/w_o)_{st} + \phi_s + \phi_t + \varepsilon_{st} \tag{5}$$

ϕ_s and ϕ_t are state and time fixed effects, respectively.

An econometric challenge in consistently estimating σ from equation (5) is controlling for unobservable relative productivity. Researchers can observe relative wages and relative employment, which are equilibrium prices and quantities. Positive productivity shock for a certain group increases labor demand for that group, which increases both wages and employment. If the set of fixed effects in equation (5) can control for relative productivity, the OLS estimate can consistently estimate σ. Otherwise, equation (5) has an omitted variable bias problem which creates a positive bias in the estimates.

The literature often relies on the assumption that relative productivity is time-invariant or follows a linear trend (e.g., Katz and Murphy, 1992; Ottaviano and Peri, 2012 for the elasticity of substitution between domestic workers and immigrants). Other studies use supply shifters such as immigration (e.g., Borjas, 2003; Ottaviano and Peri, 2012 for upper levels) as instrumental variables for relative supply, setting the relative wage as a dependent variable. The last method can be understood as estimating the labor demand curve using shifts in the labor supply.

In this paper, I take a different approach, utilizing an instrumental variable of the relative wage ratio in equation (5). I propose an instrumental variable exploiting the change in minimum wages in the spirit of simulated eligibility instruments (e.g, Currie and Gruber, 1996 for Medicaid expansion; Gruber and Saez, 2002 for the effects of taxes). I calculate the simulated wage by applying future minimum wages to the wage distribution of the base year (1979). To calculate the simulated average wage with future minimum wages, I use the wage distribution of the comparison year below the minimum wage.[21] Specifically, I calculate the simulated wage as follows. First, I calculate the conditional average above the threshold using the base year and below the threshold using the comparison year. Second, I calculate the weighted sum of these two conditional averages, using the fraction of workers above and below the threshold in the base year as weights. This method is in line with the "tail pasting" method of DiNardo et al. (1996) with simplification. A detailed discussion of this method is provided in Appendix G.

The key identifying assumption of this simulated wage instrument is that it is uncorrelated with future changes in relative productivity or other unobservable components. Since I only exploit minimum wage changes to simulate the average wage, future productivity shock is unlikely to affect the simulated wage instrument. Using this simulated wage instrumental variable, I estimate equation (5) using 2SLS.

One important issue in estimating equation (5) is the choice of the unit of the labor market. The literature tends to focus on the national-market approach (e.g., Card and Lemieux, 2001; Borjas, 2003; Ottaviano and Peri, 2012), with the idea that internal migration will equate the regional wages of workers with a certain set of skills. However, given the evidence showing that the wages of teenagers and other young workers are highly affected by minimum wages, young workers' wages are more likely to be determined locally than nationally. Furthermore, the elderly are the population with the lower internal migration rate (Benetsky et al., 2015). Therefore, for the analysis related to non-prime-age workers, a regional market approach may be appropriate. Based on this concern, I use the state as the unit of analysis.

Table 4 shows the estimated elasticity of substitution between young workers and workers in other age groups. Unlike analyses thus far, I use the year instead of the quarter for the unit of time to maximize the number of observations in each cell. The coefficients in columns (1) through (3) imply a negative of the elasticity of substitution between young and older workers. The larger (in absolute terms) this value is, the more substitutable these groups are. For comparison, I additionally use the coefficients estimated from the same equation using young and prime-age workers. Since I place the prime-age and non-prime-age workers in different layers, the interpretation of the coefficients can differ from the elasticity of substitution in the production function (see Appendix F for details). Note that if the estimated coefficients between the young and prime-age workers are similar or larger in absolute terms, the nesting structure is no longer plausible. Hence, it can be used to evaluate the structure.

[21] In practice I use 1.2 times the maximum minimum wage of the base and comparison years for the threshold.

Table 4: Elasticity of Substitution

	Dep: ln Rel Emp					
	Young and Elderly Coefficient = $-\sigma$			Young and Prime-Age		
	OLS	Simulated IV	Simulated IV	OLS	Simulated IV	Simulated IV
	(1)	(2)	(3)	(4)	(5)	(6)
ln Rel Wage	-0.030	-0.637*	-0.649*	0.167*	-0.025	0.010
	(0.033)	(0.249)	(0.294)	(0.071)	(0.199)	(0.138)
First-stage	-	1.275	1.058	-	1.801	1.899
First-stage F	-	24.61	21.15	-	209.10	198.72
Obs	2,091	2,091	2,091	2,091	2,091	2,091
State-FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
State-Linear Trend	N	N	Y	N	N	Y

Each cell is weighted by the total number of workers at the state-year level. Robust standard errors are clustered at the state level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively.

In columns (1) and (4), the OLS estimates are close to zero or even positive, suggesting that workers of different ages may not be substitutes in production. In contrast, the columns using instrumental variables show that OLS estimates are positively biased. The 2SLS estimate for young and prime-age workers is close to zero, while that for young and older workers shows a small degree of substitution. The results are robust to the inclusion of state-specific linear time trends. The first stage is very strong for the relationship between the young and prime-age workers, and weaker but still stronger than the conventional threshold in the weak-IV test in columns (2) and (3). This suggests that young and older workers are substitutes for each other, but that the degree of substitution is not high.

Table 4 uses state-year level aggregates. The role of the minimum wage, however, varies greatly across industries. In some industries, it may not affect both relative wages and employment, while in others, it may play a substantial role in determining both. To use this industry-level variation, in Table 5, I use state-year-industry level aggregates, instead of state-year level aggregates. One challenge in this analysis is the insufficient number of observations. Simulated instruments work well when there are enough observations both below and above the minimum wage in both the base and comparison year. To minimize the cells with too few observations, I focus on two industry groups: Leisure and Hospitality and the Wholesale and Retail Trade. These two industries have been studied extensively in the minimum wage literature. All other industries are classified into just one group. I further exclude some cells if they lack observations either above or below the minimum wages.

Table 5 shows the results. Panels A and C use state-year level aggregates, and Panels

Table 5: Elasticity of Substitution, Industry Level

	Dep: ln Rel Emp				
	OLS	Simulated IV	OLS	Simulated IV	Simulated IV
	(1)	(2)	(3)	(4)	(5)
	Panel A. The Young and Elderly				
ln Rel Wage	0.097**	-0.279	0.038	-0.299*	-0.366*
	(0.032)	(0.840)	(0.027)	(0.142)	(0.156)
First-stage	-	0.166	-	0.919	0.825
First-stage F	-	21.98	-	51.20	56.40
Obs	4,749	4,749	4,748	4,748	4,748
	Panel B. The Young and Elderly (5-Year Aggregate)				
ln Rel Wage	0.101	0.467	-0.077	-0.410*	-0.681*
	(0.075)	(0.532)	(0.054)	(0.182)	(0.271)
First-stage	-	0.264	-	1.383	1.116
First-stage F	-	33.05	-	32.57	19.28
Obs	1,189	1,189	1,189	1,189	1,189
	Panel C. The Young and Prime-Age				
ln Rel Wage	0.195**	1.356	0.147*	0.203	0.151
	(0.063)	(1.034)	(0.056)	(0.156)	(0.106)
First-stage	-	0.331	-	1.427	1.422
First-stage F	-	44.29	-	259.56	139.84
Obs	6,185	6,185	6,185	6,185	6,185
	Panel D. The Young and Prime-Age (5-Year Aggregate)				
ln Rel Wage	0.397**	0.645	0.333**	0.541+	0.118
	(0.117)	(0.437)	(0.115)	(0.304)	(0.194)
First-stage	-	0.691	-	1.456	1.598
First-stage F	-	108.49	-	93.99	88.07
Obs	1,224	1,224	1,224	1,224	1,224
State-FE	Y	Y	N	N	N
Time FE	Y	Y	N	N	N
Ind FE	Y	Y	N	N	N
State-Ind-FE	N	N	Y	Y	Y
Time-Ind-FE	N	N	Y	Y	Y
State-Ind Linear Trend	N	N	N	N	Y

Each cell is weighted by the total number of workers at the state-time-industry level. Robust standard errors are clustered at the state level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively.

B and D use 5-year aggregates. A 5-year aggregate has more observations in each cell, and it may be complicated by multiple minimum wage changes during the 5-year interval. Columns (1) and (3) show the OLS estimates.

Columns (1) and (2) use state, time, and industry fixed effects. In column (2), all the estimates are imprecisely estimated. In columns (3) through (5), I add state-industry-specific fixed effects and time-industry-specific fixed effects. Since I am using the state-industry level aggregates, state-industry-specific fixed effects may be a better choice of unit-specific fixed effects. Therefore, these are my preferred estimates. In column (4), the estimated coefficients are positive for the young and prime-age groups and negative for the young and elderly groups. Since the estimated coefficients in Panels A and B imply the negative of the elasticity of substitution, this suggests that young and older workers are substitutable. Adding state-industry-specific fixed effects in column (5) does not greatly change the results. In sum, the estimated elasticity of substitution is approximately 0.3 to 0.6, which is close to the estimates in Table 4.

Overall, using a nested-CES framework, I estimate the small degree of elasticity of substitution between young and older workers. However, the magnitude of the estimated coefficients is fairly small. As a comparison, in Katz and Murphy (1992), the elasticity of substitution between better- and less-educated prime-age workers is approximately 1.4. In Ottaviano and Peri (2012), the elasticity of substitution between younger (1-20 years of potential experience) and older (21-40 years of potential experience) prime-age workers with the same education level is approximately 3 to 4.

Several potential issues may affect these lower estimates. First, I use aggregates of workers with any education, while better-educated older workers may not be a substitute for the young workers. Second, using the local market may provide attenuated estimates if wages across local markets are equalized. Although the migration rate of the elderly is generally low, their wages might be affected by the migration of prime-age workers or the location choice of the employers. In Borjas (2003) in the immigration context, wage effects using the local labor market approach are approximately one-third of the estimated effects using the national market approach. Furthermore, workers may be able to move across industries. Industries employing young workers often require minimal training or formal education. This can also explain the lower elasticity of substitution in Table 5.

One important question remains. Both industry-level analysis in section 6.1 and direct estimation of elasticity of substitution in section 6.2 suggest that although older workers are substitutes for young workers, prime-age are not. Immediate question is to ask why. There are several possible reasons why. First, compared to prime-age workers, older workers tend to work in a relatively similar set of industries to young workers. In Appendix H, I measure the similarity of industry distribution between groups of workers using the index of congruence proposed by Welch (1999). This analysis shows that, compared to the prime-age workers, the industry distribution of older workers is relatively similar to that of young workers. This partially explains why older workers are a closer substitute. Second, the labor supply elasticities of older workers are higher than those of prime-age workers. When labor supply is more elastic, the same degree of increase in labor demand is translated into a larger increase in employment. Both reasons suggest that employers may want to hire prime-age workers, but they may end up finding older workers for their vacancies.

7 Discussion and Conclusion

This paper examines the effects of minimum wages on the labor market outcomes of older workers and explains the effects based on labor-labor substitution. I find positive effects on employment of the older population aged 65-70 and these positive effects are not limited to minimum wage workers but a broader class of workers are affected. Further analysis suggests that these positive effects may come from demand shifted from the young minimum wage workers, although the degree of substitution is not high. This pattern of labor-labor substitution is consistent with evidence from managers' surveys (Hirsch et al., 2015) which find that managers consider hiring older/more experienced workers when the minimum wage is higher.

These results have several policy implications. First, when analyzing the effects of minimum wages, just focusing on teenagers may overstate the possible welfare loss or detrimental effects on employment. If minimum wages stimulate firms to adjust their composition of the workforce, we may need to consider a broader class of workers for a more comprehensive analysis of the minimum wages.

Second, evidence of labor-labor substitution suggests that firms' responses could be larger than what can be measured by the change in the number of workers. As reviewed by Clemens (2021), recent and burgeoning literature examines various channels of adjustments to minimum wages. This paper provides evidence in line with Clemens (2021).

Third, my results have policy implications in an era of the aging population and frequent minimum wage increases. In the United States, many state legislatures are raising their own minimum wages to $15 or even higher. When the minimum wage becomes higher, employers may search for more reliable, experienced workers. The results in section 6 show that older workers are good candidates for those employers. In the era of the aging population, it may be even easier to adjust their workforce, since there are relatively more older workers in the labor market.

From a broader perspective, it has policy implications related to the elderly. Due to the aging population, many developed countries are considering and/or implementing labor market policies aiming to increase the labor force participation and labor supply of the older population. To achieve the goal of increasing employment of the older population and reducing the welfare burden, however, analysis of the labor demand for older workers is necessary as well. This paper sheds light on this issue by assessing how minimum wages affect the labor demand for older workers.

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A Data Appendix

A.1 Industry Classification

The industry classification of the CPS-ORG has experienced multiple changes throughout the sample period (1979-2019). Several changes were made to the 3-digit detailed industry codes, and the same detailed industry is often classified as different major industry classifications. Therefore, industry classification of the CPS-ORG is highly inconsistent across time. To overcome this problem, this paper relies on the consistent industry code proposed by Pollard (2019, Table C-5). This method aggregates detailed industries into 47 industries (excluding armed forces) and 13 large industries. To maximize the number of observations in each cell, I use 13 major industry codes. Table A.1 shows the list of industries

Table A.1: List of Industries

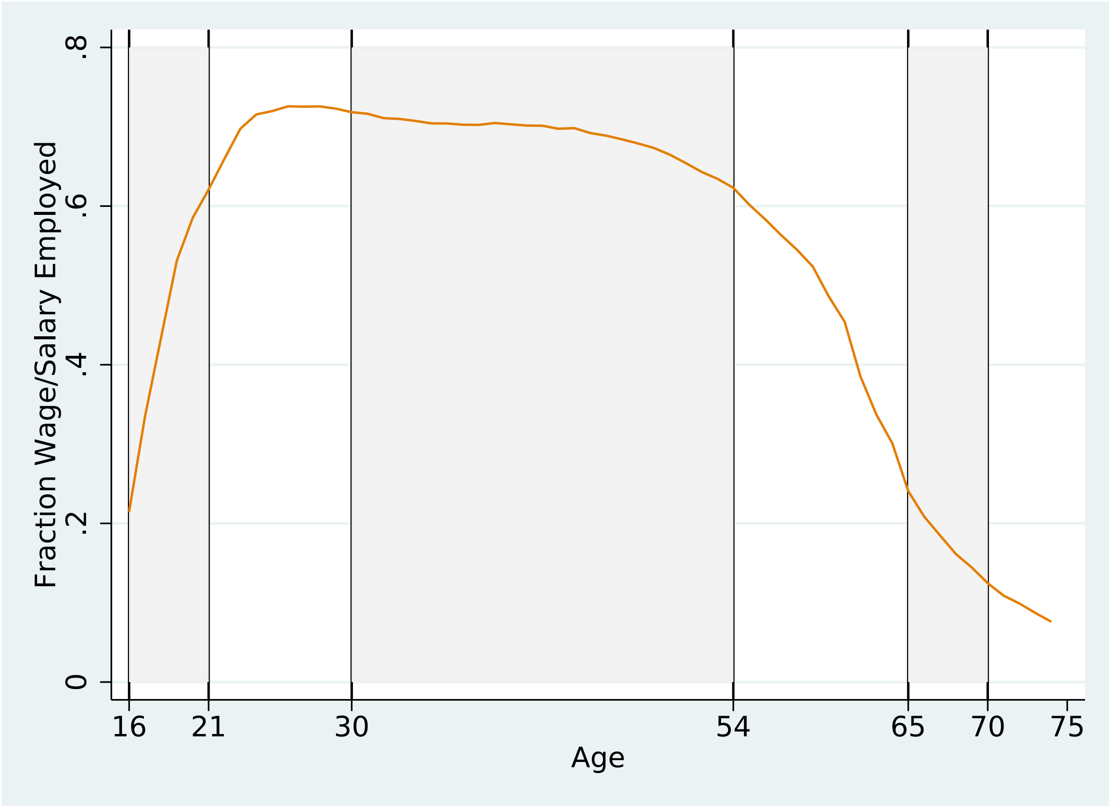
Number	Industries
1	Agriculture, Forestry, Fishing, and Hunting
2	Mining
3	Construction
4	Manufacturing
5	Wholesale and Retail Trade
6	Transportation and Utilities
7	Information
8	Financial Activities
9	Professional and Business services
10	Education and Health services
11	Leisure and Hospitality
12	Other Services
13	Public administration

Source: Pollard (2019)

A.2 Additional Descriptive Figures and Tables

This subsection presents complementary figures depicting the data. Figure A.1 first shows the evolution of the employment-to-population ratio by age. This ratio increases dramatically over age 16-21, which is the age range examined in this study. It is relatively flat from age 25 to early 50 but starts to decline at approximately age 50. It declines faster in the early 60s. Only fewer than 10 percent of the elderly older than 70 work.

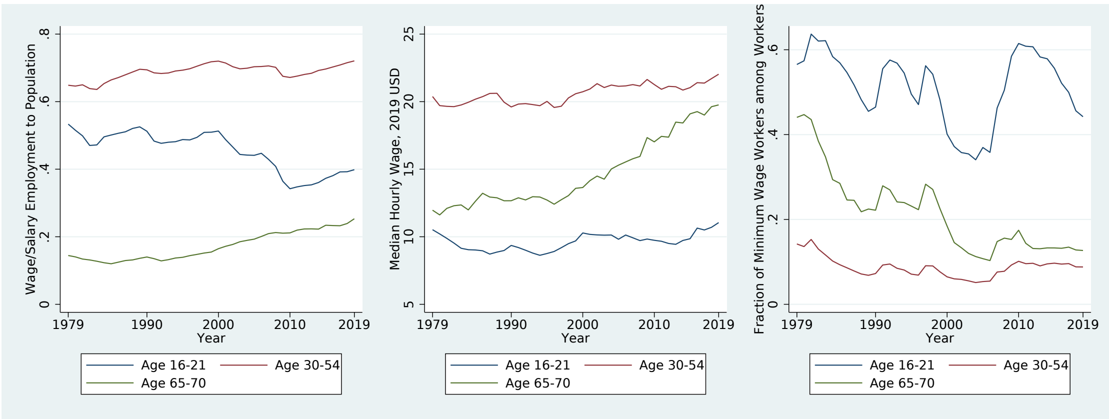
Figure A.1: Employment-to-Population Ratio by Age



Source: CPS-ORG, 1979-2019. All the results are weighted by the CPS earnings weight.

Figure A.1 is drawn using all observations from 1979 to 2019. However, it may mask a drastic change in labor market outcomes during the last four decades. Figure A.2 shows the trends in three labor market outcomes: the employment-to-population ratio, median hourly wage, and fraction of minimum wage workers among workers. In all three panels, red lines show the trends among prime-age workers, blue lines show those among the young and green lines show the trends among the elderly.

Figure A.2: Trends in Labor Market Outcomes by Age, 1979-2019

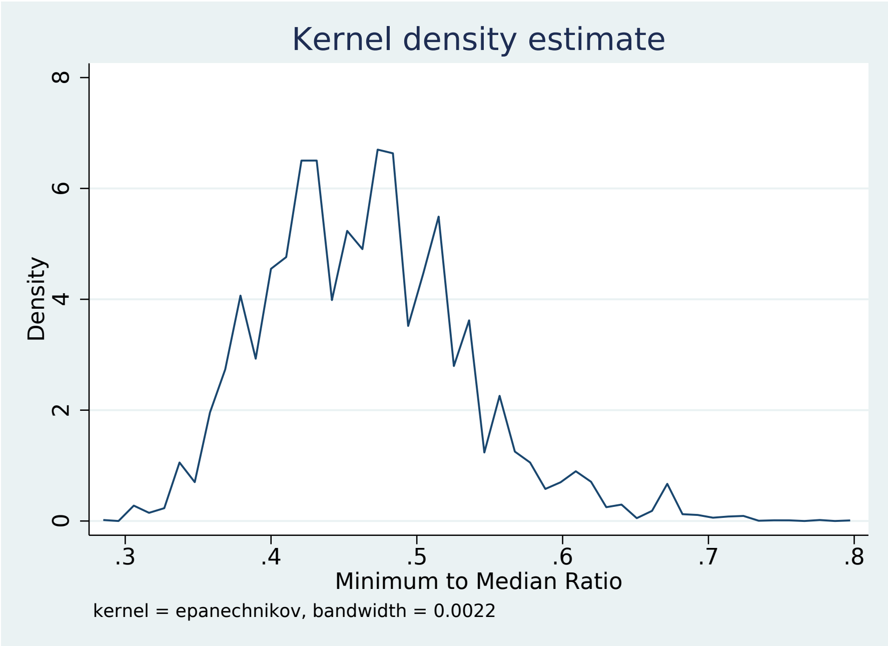


Source: CPS-ORG, 1979-2019. The left and right panels are weighted by the CPS earnings weight, and the middle panel is unweighted. Minimum wage workers are defined as those whose hourly wage is the effective minimum wage * 1.2 or lower.

As shown in the left panel, the employment-to-population ratio of the young workers has decreased from approximately the early 2000s. It was approximately half during the 1980s and 1990s, but it has dropped to approximately 40 percent in recent years. In contrast, this ratio starts to increase for the elderly at more or less the same time.

The middle panel, showing the trend in median hourly wage, may be the most striking. The median hourly wage of older workers saw drastic increases, unlike those of prime-age or young workers. The median hourly wage of older workers was very close to that of young workers in earlier periods. It started to increase from the late 1990s and recently has become closer to the median hourly wage of prime-age workers. As a result, the fraction of the minimum wage workers becomes lower, although it still exceeds that of prime-age workers.

Figure A.3: Distribution of Minimum to Median Wage



Source: CPS-ORG, 1979-2019. All the results are weighted by the CPS earnings weight.

Figure A.3 shows the population weighted distribution of minimum wage to median wages. Most states' minimum-wage-to-median-wage ratio ratios, or in other words, the famous Kaitz index, falls roughly in the range of 0.35 to 0.55, with a longer right tail.

B Expanded Tables and Figures

Appendix B presents the expanded tables and figures. Table B.1 shows the full version of Table 2. Panels A and B are the same with the table in the body, while Panel C shows the employment elasticity with respect to federal minimum wage increases as well as 5-year average effects. First, in the longer run, the effects tend to disappear, as shown in Figure 3. This suggests that employment effects persist only in the short run. Second, responses to the federal level are noisy and negative.

Table B.2 contains the elasticity with respect to minimum wage for each outcome variable in Table 3. Due to the smaller fraction of self-employed workers among the young or older workers, its responses measured by elasticities are much more inflated.

Figure B.1 shows the results in Panel A of Figure 4 one by one, and Figure B.2 shows the extended version of Panel B of Figure 4 with 95-percent confidence intervals.

Table B.1: Expanded Version of Table 2

	Dep var: Employed		
	Age 16-21 (N: 1,428,573)	Age 30-54 (N: 5,770,663)	Age 65-70 (N: 854,730)
	(1)	(2)	(3)
Panel A. Estimation using *NW-type* Specification			
Elasticity w.r.t. Minimum Wage	-0.183***	0.027	0.166+
	(0.051)	(0.016)	(0.086)
Panel B. Estimation using *ADR-type* Specification			
Elasticity w.r.t. Minimum Wage	0.026	0.031**	0.232**
	(0.037)	(0.011)	(0.069)
Panel C. Estimation using *CDLZ-type* Specification			
3Y Average Effects			
Elasticity w.r.t. Minimum Wage	0.023	0.020	0.118*
	(0.067)	(0.019)	(0.058)
Elasticity w.r.t. Minimum Wage (Federal)	0.027	0.004	-0.221
	(0.084)	(0.025)	(0.179)
5Y Average Effects			
Elasticity w.r.t. Minimum Wage	0.042	0.014	0.071
	(0.060)	(0.015)	(0.070)
Elasticity w.r.t. Minimum Wage (Federal)	0.068	0.023	-0.120
	(0.094)	(0.024)	(0.185)

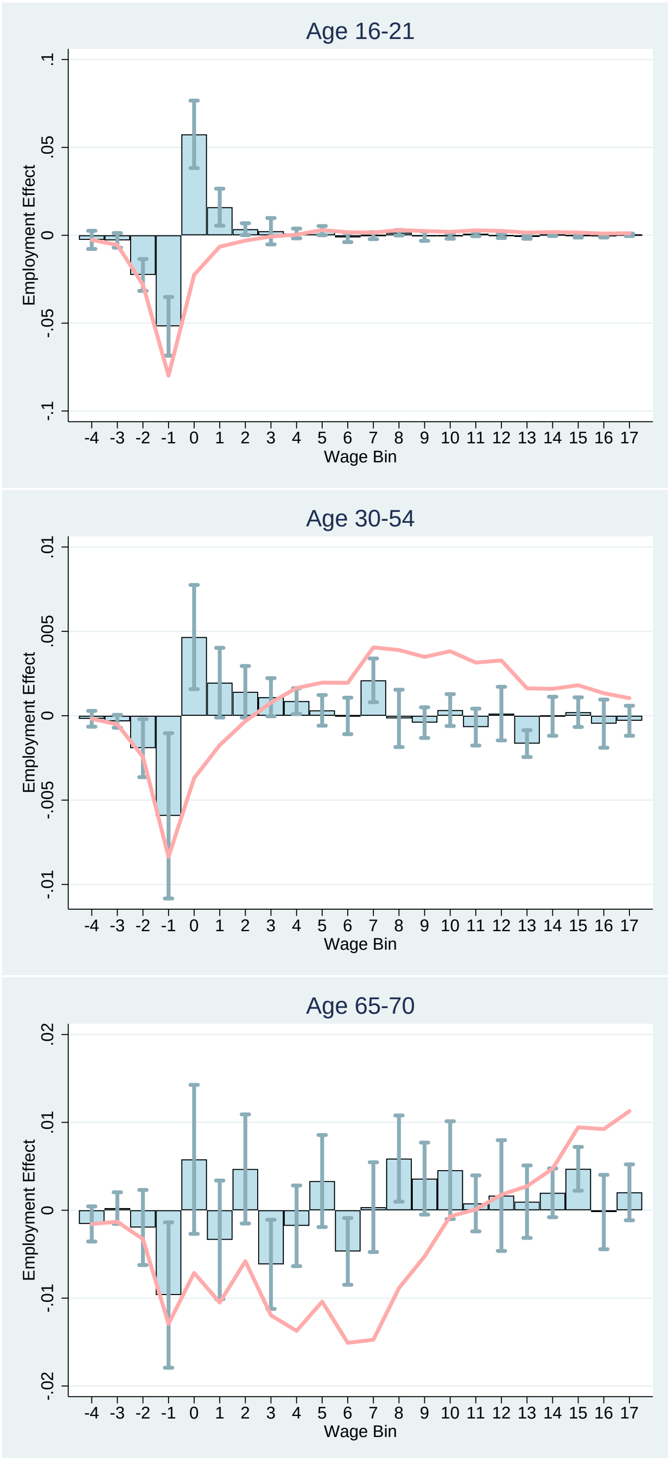
All the results are weighted by the earnings weight (*earnwt*) in CPS-ORG. Robust standard errors are in parentheses and clustered at the state-level. The unit of time is the quarter. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. See note to Table 2 for details.

Table B.2: Expanded Version of Table 3

	Wage/Salary Employment (E) (1)	Unemployed (U) (2)	Self-Employed (S) (3)	All Others (NILF) (4)
Panel A. Age 16-21 (N: 1,428,573)				
Estimation using the *NW-type* Specification				
Semi-Elasticity	-0.083***	-0.001	0.000	0.083**
	(0.023)	(0.011)	(0.002)	(0.029)
Ela w.r.t. MW	-0.183***	-0.010	0.025	0.183**
	(0.051)	(0.135)	(0.168)	(0.063)
Estimation using the *ADR-type* Specification				
Semi-Elasticity	0.012	-0.010	-0.004	0.002
	(0.017)	(0.010)	(0.003)	(0.015)
Ela w.r.t. MW	0.026	-0.119	-0.378	0.005
	(0.037)	(0.117)	(0.280)	(0.032)
Estimation using the *CDLZ-type* Specification				
3Y Average Effects				
Semi-Elasticity	0.010	0.002	0.006*	-0.018
	(0.027)	(0.012)	(0.003)	(0.021)
Ela w.r.t. MW	0.023	0.028	0.732*	-0.035
	(0.067)	(0.179)	(0.301)	(0.041)
Panel B. Age 30-54 (N: 5,770,663)				
Estimation using the *NW-type* Specification				
Semi-Elasticity	0.019	-0.007	0.005	-0.017
	(0.011)	(0.006)	(0.006)	(0.010)
Ela w.r.t. MW	0.027	-0.170	0.053	-0.100
	(0.016)	(0.169)	(0.062)	(0.060)
Estimation using the *ADR-type* Specification				
Semi-Elasticity	0.022**	-0.009	-0.000	-0.013*
	(0.008)	(0.006)	(0.004)	(0.005)
Ela w.r.t. MW	0.031**	-0.231	-0.001	-0.072*
	(0.011)	(0.166)	(0.040)	(0.030)
Estimation using the *CDLZ-type* Specification				
3Y Average Effects				
Semi-Elasticity	0.014	0.002	-0.016**	0.000
	(0.013)	(0.005)	(0.005)	(0.007)
Ela w.r.t. MW	0.020	0.057	-0.169**	0.001
	(0.019)	(0.164)	(0.057)	(0.039)
Panel C. Age 65-70 (N: 854,730)				
Estimation using the *NW-type* Specification				
Semi-Elasticity	0.030+	-0.000	0.033***	-0.063**
	(0.016)	(0.003)	(0.009)	(0.022)
Ela w.r.t. MW	0.166+	-0.002	0.469***	-0.085**
	(0.086)	(0.246)	(0.129)	(0.029)
Estimation using the *ADR-type* Specification				
Semi-Elasticity	0.042**	-0.004	-0.015	-0.024
	(0.012)	(0.004)	(0.011)	(0.014)
Ela w.r.t. MW	0.232**	-0.346	-0.208	-0.032
	(0.069)	(0.381)	(0.154)	(0.020)
Estimation using the *CDLZ-type* Specification				
3Y Average Effects				
Semi-Elasticity	0.025*	-0.004	0.000	-0.021
	(0.012)	(0.004)	(0.011)	(0.018)
Ela w.r.t. MW	0.118*	-0.365	0.003	-0.030
	(0.058)	(0.318)	(0.157)	(0.025)

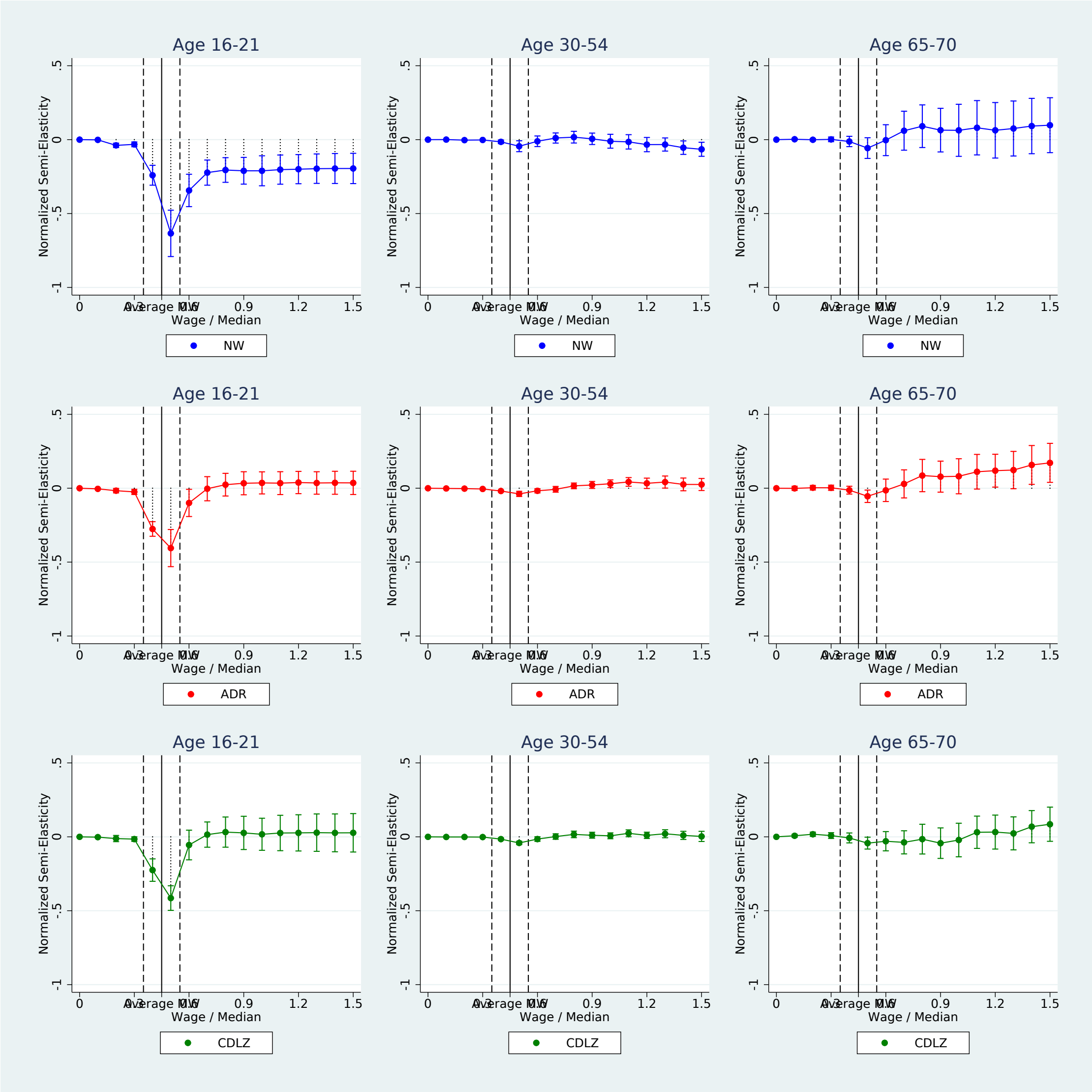
Robust standard errors are in parentheses and clustered at the state level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. See notes to Table 2 for more details.

Figure B.1: Results using Bunching Approach by Age



Each bar shows the employment effects on the wage bin normalized by the employment-to-population ratio of each age group before the treatment. The red line shows the cumulative effects up to that wage bin.

Figure B.2: Expanded version of Figure 4



The blue, green, and red dots show the estimates for the young (16-21), prime-age (30-54), and elderly (65-70), respectively. Each bar shows a 95 percent confidence interval. See text for details. The black solid line shows the average minimum wage-median wage ratio (approximately 45 percent of the median wage), and the black dotted lines show the 5th and 95th percentiles of the minimum to median ratio, respectively.

C Effects on Other Labor Market Outcomes

Examining the effects on the number of jobs may not provide a comprehensive picture of the effects on the labor market, since other labor market outcomes may also respond to the minimum wages. This subsection explores other important labor market outcomes such as wages and hours, using three baseline specifications.

Table C.1 shows the effects of minimum wages on log hourly wages and log weekly working hours. All the reported coefficients are elasticities of hourly wages with respect to minimum wages, in other words, $\hat{\beta}$ from equations (1) and (2) for Panels A and B and $\sum_{\tau=0}^{2} \hat{\beta}_{\tau} - \sum_{\tau=-3}^{-1} \hat{\beta}_{\tau}$ divided by minimum wage change for Panel C.

The positive effects of minimum wages on the hourly wage of the affected are well-established in the literature. Consistent with the literature, column (1) of Table C.1 reports positive and significant effects on the hourly wage of young workers. Hourly wage elasticity with respect to minimum wage falls in the [0.1, 0.2] interval, which is consistent with the consensus in the literature (Belman and Wolfson, 2014, Ch 5). The estimates in column (3) are positive but close to zero and insignificant, as expected from the small share of minimum wage workers among prime-age workers.

The results in column (5) also show that the effects on older workers' hourly wage are close to zero, conditional on working. There are several explanations for the zero wage effects. First, although a larger fraction of older workers earn minimum wage compared to prime-age workers, it is still much lower than that of teenagers. Therefore, the zero wage effects could be a result of a smaller fraction of minimum wage workers. Second, given the small positive effects reported in the previous subsection, a higher minimum wage may increase the fraction of lower wage workers, which would lead to insignificant or even negative wage effects among those who work. Finally, higher minimum wages may move workers from high-paying jobs with longer hours to low-paying jobs with shorter-hours.

In Appendix D.2, I conduct several analyses to answer this question. However, it is not clear which explanation makes sense. If a smaller bite of the minimum wage is the reason for zero wage effects, wage effects should be larger for subgroups with larger fraction of minimum wage workers. In Appendix Figure D.5, I show the fraction of minimum wage workers by education and age, analogous to Figure 2. This shows that approximately 40 percent of older workers without a high school diploma earn less than or equal to 120 percent of the effective minimum wage. However, as shown in Appendix Table D.6, wage effects are not larger for this group, which provides less support for the explanation. If positive employment effects and compositional shifts are the reason for the zero wage effects, groups with positive employment effects will show lower wage effects. This is also not true in the analysis by education level. Therefore, it is not clear why the wage effects are smaller.

Table C.1: Effects of Minimum Wages on Wages and Hours

	Sample: Employed					
	Age 16-21		Age 30-54		Age 65-70	
	Log Hourly Wages	Log Weekly Hours	Log Hourly Wages	Log Weekly Hours	Log Hourly Wages	Log Weekly Hours
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Estimation using *NW-type* Specification						
Elasticity w.r.t. Minimum Wage	0.128***	-0.090**	0.006	-0.000	-0.024	-0.021
	(0.024)	(0.027)	(0.021)	(0.010)	(0.051)	(0.033)
Obs	655,520	622,277	3,887,157	3,817,307	144,503	138,456
Panel B. Estimation using *ADR-type* Specification						
Elasticity w.r.t. Minimum Wage	0.190***	0.023	0.009	-0.010*	0.027	0.041
	(0.021)	(0.031)	(0.016)	(0.005)	(0.044)	(0.053)
Observations	655,520	622,275	3,887,157	3,817,307	144,461	138,406
Panel C. Estimation using *CDLZ-type* Specification						
3Y Average Effects						
Elasticity w.r.t. Minimum Wage	0.164***	0.032	0.014	0.002	0.057	0.024
	(0.022)	(0.027)	(0.016)	(0.007)	(0.065)	(0.038)
Elasticity w.r.t. Minimum Wage (Federal)	-0.032	0.053	0.003	-0.010	0.074	0.035
	(0.046)	(0.039)	(0.023)	(0.011)	(0.096)	(0.087)
5Y Average Effects						
Elasticity w.r.t. Minimum Wage	0.152***	0.061+	0.017	0.002	0.057	0.020
	(0.023)	(0.036)	(0.014)	(0.007)	(0.054)	(0.037)
Elasticity w.r.t. Minimum Wage (Federal)	-0.015	0.051	0.012	-0.012	0.070	0.049
	(0.047)	(0.048)	(0.024)	(0.011)	(0.088)	(0.075)
Obs	655,520	622,277	3,887,157	3,817,307	144,503	138,456

Columns (1), (3), and (5) report elasticities of hourly wages with respect to minimum wages, and columns (2), (4), and (6) report elasticities of working hours with respect to minimum wages. Robust standard errors are in parentheses and clustered at the state level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. See notes to Table 2 for more details.

Hours of work is another important labor market outcome. The results in column (2) and (4) show negative effects on young workers from the NW-type specification and zero effects on prime-age workers. Focusing on older workers, the results in columns (6) suggest that a minimum wage does not change the weekly working hours of employed workers. In summary, conditional on working, a higher minimum wage does not alter the labor market characteristics of older workers, although it increases their employment.

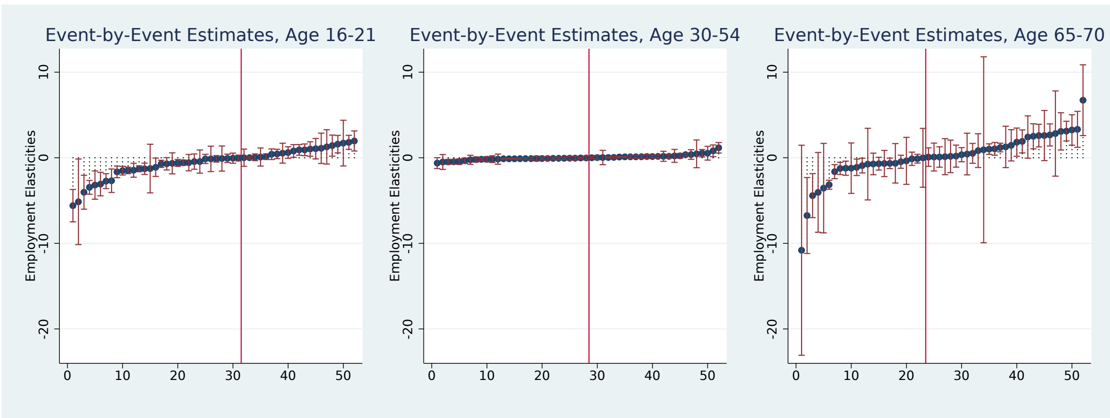
D Robustness Check and Heterogeneity of Employment Effects

This section presents more detailed results regarding the employment effects analysis in section 5.1.

D.1 Event-by-Event Estimates

Figure D.1 first presents event-by-event estimates for 52 'clean' treatments. Events are aligned by the size of the elasticities, and the red vertical line shows the place of zero. In the case of the prime-age, estimates are generally much smaller. In the case of the young and the elderly, some of the estimates become noisy and larger in magnitude, possibly due to the lack of observations. This analysis, however, also shows that for more of the events, the elderly employment elasticities are positive.

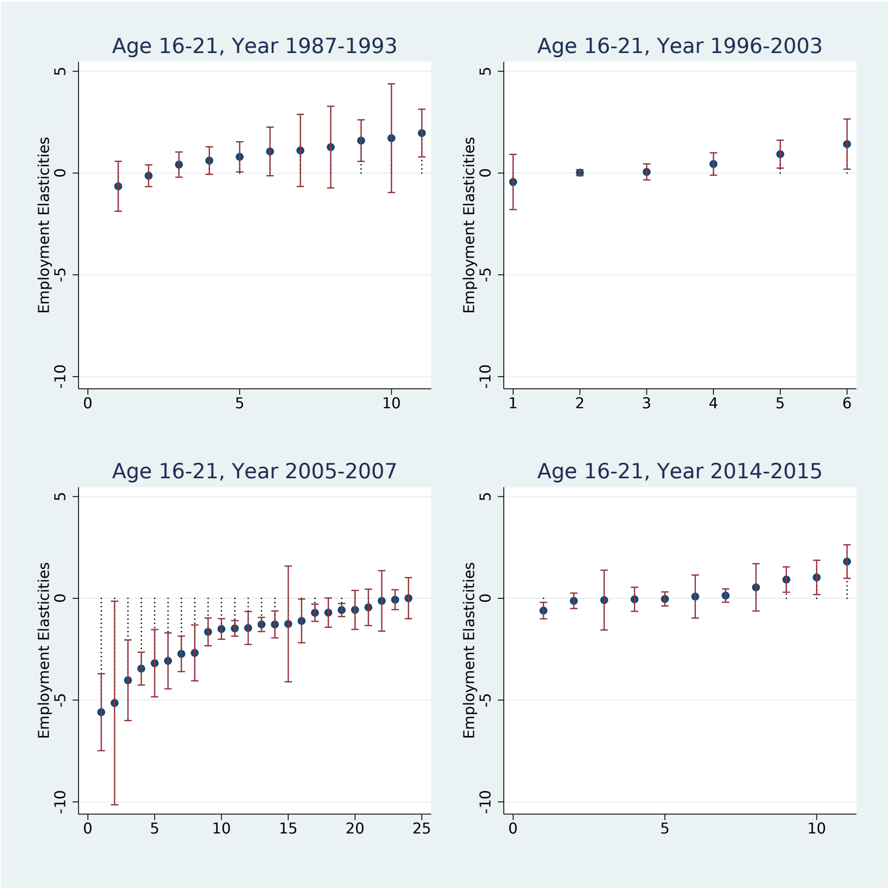
Figure D.1: Event-by-Event Estimates



Each dot shows the point estimates of employment elasticity with respect to minimum wage, and each bar shows 95 percent confidence interval. Red vertical line is located between the smallest positive estimates and the largest negative estimates.

Figures D.2 through D.4 show the event-by-event estimates, classified by the time. Most state-level minimum wage increases are clustered in certain periods, providing a natural way of classification. I classify them into 4 time periods: 1987-1993, 1996-2003, 2005-2007, and 2014-2015. Events after 2015 are excluded since I do not have their full 8-year window observations. This shows that, in general, negative effects are more prominent for minimum wage increases during the Great Recession, as shown by Clemens and Wither (2019). In contrast, from the late 80s to the early 90s, effects tend to be more positive.

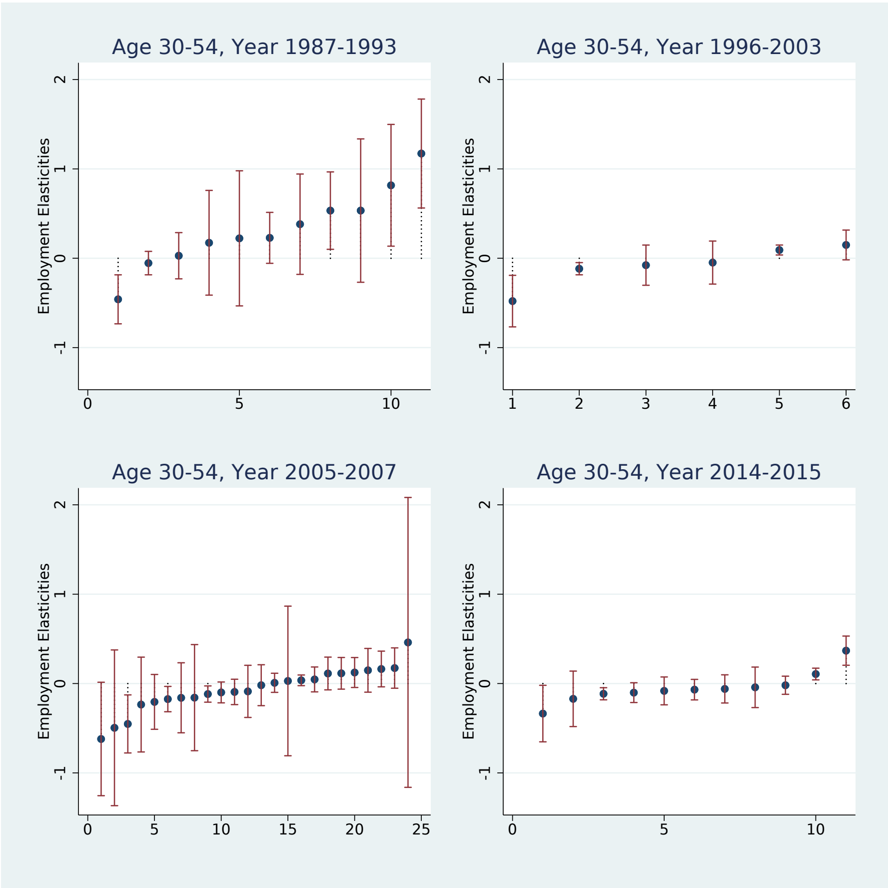
Figure D.2: Event-by-Event, Young (16-21)



Each dot shows the point estimates of employment elasticity with respect to minimum wage, and each bar shows 95 percent confidence interval.

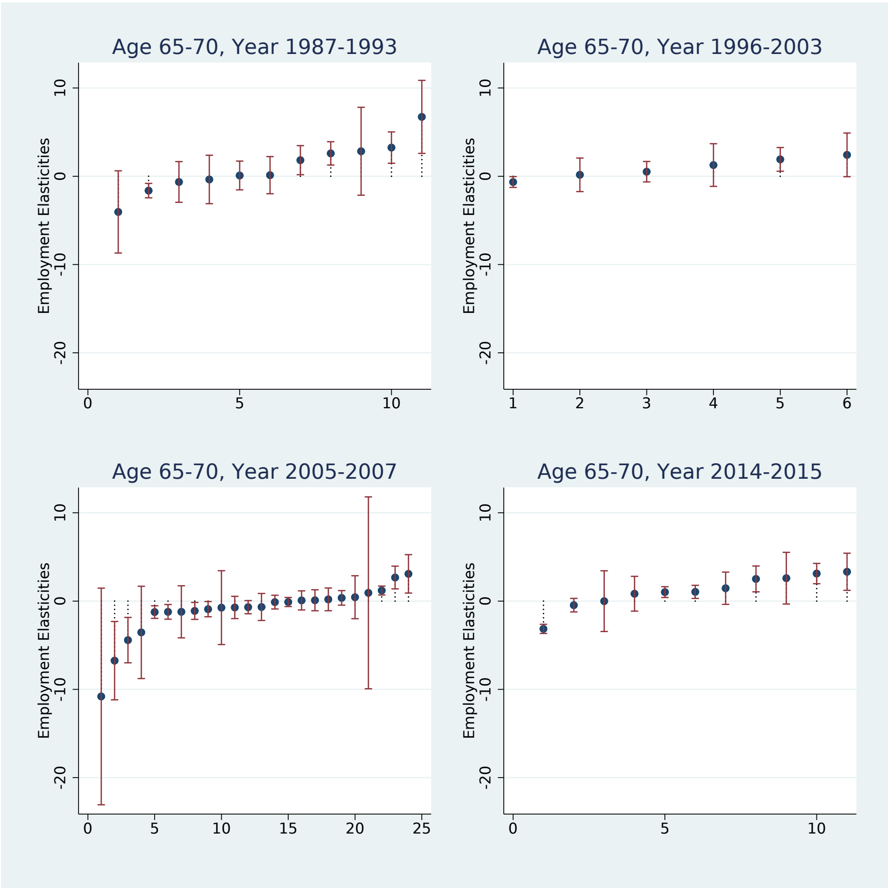
In recent periods, employment elasticities with respect to the minimum wages of prime-age workers are close to zero and often negative. In contrast, in the case of older populations. estimates tend to be more positive and often significantly different from zero. This is especially interesting for several reasons. First, as shown in Appendix Figure A.2, the hourly wage of older workers is higher in this period. This may support the analysis in section 5.2, which reports positive employment effects on workers above the minimum. Second, although the average hourly wages of prime-age and older workers become closer in this period, they are affected differently. Third, this period sees relatively more frequent minimum wage changes, hence identification exploits more variation. The effects of recent minimum wage changes require future study.

Figure D.3: Event-by-Event, Prime-Age (30-54)



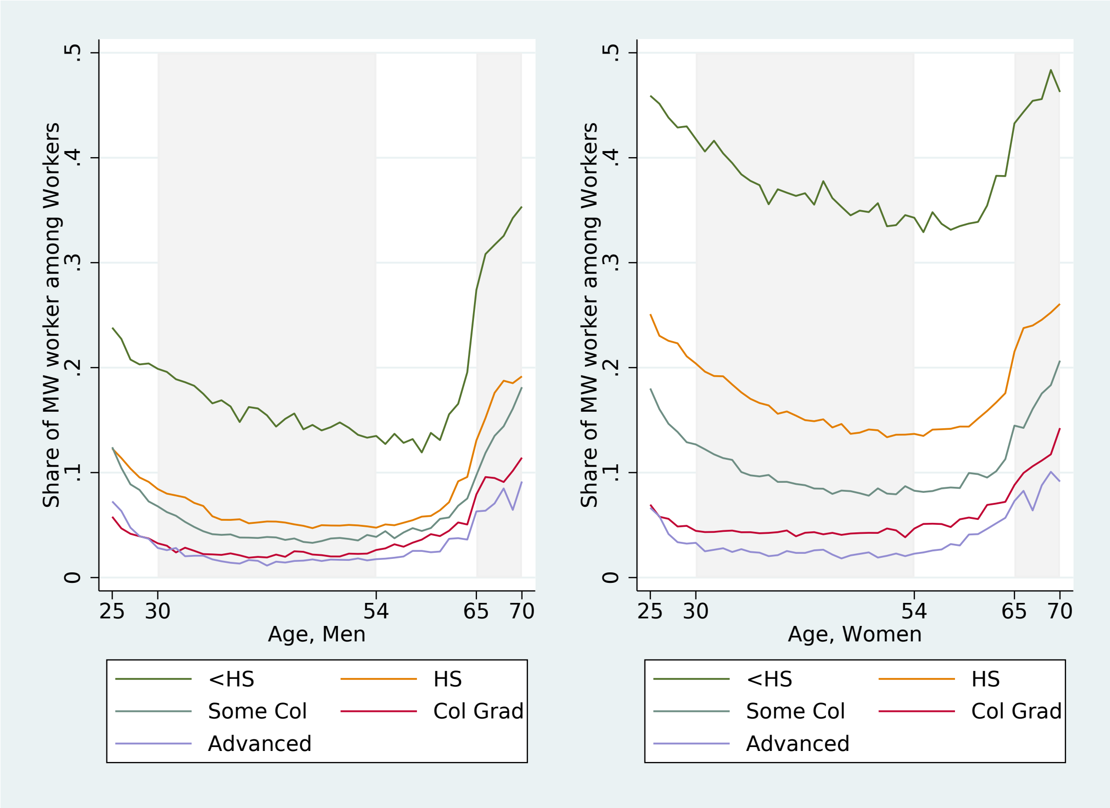
Each dot shows the point estimates of employment elasticity with respect to minimum wage, and each bar shows 95 percent confidence interval.

Figure D.4: Event-by-Event, Elderly (65-70)



Each dot shows the point estimates of employment elasticity with respect to minimum wage, and each bar shows 95 percent confidence interval.

Figure D.5: Share of Minimum Wage Workers, by Age and Education



Source: CPS-ORG, 1979-2019. All the results are weighted by the CPS earnings weight. Minimum wage workers are defined as those whose hourly wage is the effective minimum wage * 1.2 or lower.

D.2 Heterogeneity by Education

This subsection addresses heterogeneity based on education. Figure D.5 shows the fraction of minimum wage workers among workers by age and education. It resembles Figure 1, but starts from 25 since analyzing workers with higher education below age 25 is hardly meaningful. There are two notable observations. First, the fraction of minimum wage workers shows an increasing trend from age 60, and the increase becomes dramatic from age 65 for all education levels. This finding is consistent with the analysis for all workers in Figure 1, but Figure D.5 shows that it is not limited to low-educated workers and applies to workers of all education levels, including those with advanced degrees. Among workers aged 65-70, the fraction of minimum wage workers is approximately 10 percent for those who have a bachelor's degree or higher. Second, although increasing trends are common for everyone, they are more dramatic for workers without a bachelor's degree. In the case of high school dropouts, the fraction of minimum wage workers exceeds 30 percent after age 65.

Table D.1: Employment Effects by Education, Age 16-21

	Dep var: Employed Sample: Age 16-21 High School Dropouts (1)	 High School Graduates (2)	 Some College (3)	 College Degree or Above (4)
Panel A. Estimation using *NW-type* Specification				
Elasticity w.r.t. Minimum Wage	-0.316***	-0.035	-0.216***	0.146
	(0.087)	(0.039)	(0.059)	(0.196)
Obs	716,626	325,030	377,878	7,610
Panel B. Estimation using *ADR-type* Specification				
Elasticity w.r.t. Minimum Wage	0.023	0.138**	-0.053	0.146
	(0.072)	(0.041)	(0.053)	(0.196)
Obs	716,626	325,030	377,878	7,610
Panel C. Estimation using *CDLZ-type* Specification				
3Y Average Effects				
Elasticity w.r.t. Minimum Wage	-0.079	0.118*	0.051	-0.180
	(0.122)	(0.055)	(0.062)	(0.323)
Elasticity w.r.t. Minimum Wage (Federal)	0.142	0.013	-0.061	0.368
	(0.134)	(0.086)	(0.086)	(0.486)
5Y Average Effects				
Elasticity w.r.t. Minimum Wage	-0.015	0.114*	0.044	-0.116
	(0.126)	(0.044)	(0.050)	(0.272)
Elasticity w.r.t. Minimum Wage (Federal)	0.149	0.040	0.027	0.552
	(0.133)	(0.090)	(0.100)	(0.362)
Obs	716,632	325,583	378,570	7,610

All the results are weighted by the CPS earnings weight. Standard errors are in parentheses and clustered at the state-level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. See note to Table 2.

Figure D.5 motivates analysis in this section. Based on the observation in Figure D.5, I divide the population into four groups: High school dropouts, high school graduates, some college, and bachelor's degree or above. Tables D.1 through D.3 show the heterogeneity of employment effects by education level for the young, prime-age, and elderly, respectively.

Table D.1 shows the results for young workers. Column (4) is included for completeness but does not appear to deliver meaningful findings given the small sample size. Although the overall patterns differ across the specifications, all the specifications show that the results are more negative for high school dropouts and workers with some college education. A large portion of workers with some college education in this population may not have completed their schooling. Hence, these workers may be susceptible to adjustments responding to higher minimum wages.

Table D.2 shows the same results for prime-age workers. Most of the estimates of employment elasticities with respect to minimum wage fall in the range of [-0.05, 0.05],

Table D.2: Employment Effects by Education, Age 30-54

	Dep var: Employed Sample: Age 30-54			
	High School Dropouts	High School Graduates	Some College	College Degree or Above
	(1)	(2)	(3)	(4)
Panel A. Estimation using *NW-type* Specification				
Elasticity w.r.t. Minimum Wage	0.202***	0.036	-0.001	-0.017
	(0.048)	(0.023)	(0.017)	(0.013)
Obs	729,309	1,905,989	1,477,447	1,657,918
Panel B. Estimation using *ADR-type* Specification				
Elasticity w.r.t. Minimum Wage	0.040	0.047*	0.049*	0.011
	(0.046)	(0.020)	(0.023)	(0.016)
Obs	729,264	1,905,989	1,477,445	1,657,916
Panel C. Estimation using *CDLZ-type* Specification				
3Y Average Effects				
Elasticity w.r.t. Minimum Wage	0.044	0.020	0.015	0.023
	(0.037)	(0.027)	(0.016)	(0.021)
Elasticity w.r.t. Minimum Wage (Federal)	0.041	0.039	0.006	-0.030
	(0.080)	(0.033)	(0.034)	(0.029)
5Y Average Effects				
Elasticity w.r.t. Minimum Wage	0.002	0.034+	0.015	0.002
	(0.037)	(0.020)	(0.014)	(0.016)
Elasticity w.r.t. Minimum Wage (Federal)	0.110	0.040	0.020	-0.006
	(0.105)	(0.033)	(0.030)	(0.027)
Obs	729,309	1,905,989	1,477,447	1,657,918

All the results are weighted by the CPS earnings weight. Standard errors are in parentheses and clustered at the state-level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. See note to Table 2.

Table D.3: Employment Effects by Education, Age 65-70

	Dep var: Employed Sample: Age 65-70			
	High School Dropouts	High School Graduates	Some College	B.A or Above
	(1)	(2)	(3)	(4)
Panel A. Estimation using *NW-type* Specification				
Elasticity w.r.t. Minimum Wage	0.162	0.200+	-0.000	0.066
	(0.172)	(0.110)	(0.096)	(0.094)
Obs	226,463	293,819	163,429	171,019
Panel B. Estimation using *ADR-type* Specification				
Elasticity w.r.t. Minimum Wage	0.014	0.234+	0.242+	0.265+
	(0.233)	(0.133)	(0.143)	(0.141)
Observations	226,457	293,819	163,396	170,974
Panel C. Estimation using *CDLZ-type* Specification				
3Y Average Effects				
Elasticity w.r.t. Minimum Wage	0.428*	0.132	0.045	0.105
	(0.194)	(0.128)	(0.140)	(0.112)
Elasticity w.r.t. Minimum Wage (Federal)	-0.590+	-0.102	-0.241	-0.146
	(0.340)	(0.244)	(0.275)	(0.285)
5Y Average Effects				
Elasticity w.r.t. Minimum Wage	0.190	0.127	0.009	0.073
	(0.212)	(0.119)	(0.162)	(0.109)
Elasticity w.r.t. Minimum Wage (Federal)	-0.274	-0.204	-0.048	0.014
	(0.343)	(0.250)	(0.258)	(0.244)
Obs	226,463	293,819	163,429	171,019

All the results are weighted by the CPS earnings weight. Standard errors are in parentheses and clustered at the state-level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. See note to Table 2.

although some are statistically different from zero. The only exception is high school dropouts using the NW-type specification, and interestingly, this result shows positive employment elasticity.

In Table D.3, although heterogeneity analysis is not highly robust to the choice of specification, none of the results show evidence of disemployment effects. Even high-school dropouts whose share of minimum wage workers is above 30 percent do not show disemployment effects. However, specifications do not provide robust evidence on who is more positively affected by employment. High school graduates are the group all three specifications show relatively similar estimates in the [0.1, 0.25] interval. Except for this group, the results differ by specification. The NW-type specification and CDLZ-type specifications tend to show larger positive effects on lower-educated workers, and the ADR-type specification shows the opposite result.

Results so far suggest the following. Although a larger fraction of the elderly, especially less-educated workers, earn minimum wages, there is no evidence of disemployment effects suggested by standard neoclassical theory. Results instead suggest small positive effects, but these effects may not be limited to the least-skilled workers who are more likely to earn minimum wages.

Next Tables D.4 through D.6 show the effects on hourly wages. Table D.4 shows the positive wage elasticities for all the specifications in columns (1) and (3), with larger and clearer effects on the wages of those who do not have a high school diploma. The effects in columns (2) and (3) are smaller in Panel A, while Panels B and C show larger and clearer effects on hourly wages.

Table D.5 shows the effects on hourly wages of prime-age workers. Somewhat surprisingly, the effects on less-educated workers are generally negative in Panel A, while they are closer to zero in the other specifications. Together with Figure 4, this may cast some doubts on the validity of this specification.

Finally, Table D.6 shows the effects on older workers. One goal of this analysis is to determine why the effects on the hourly wage of older workers are close to zero. As mentioned in section 5.2, there are several explanations: (1) only a small fraction of workers are affected; (2) positive employment responses increase the fraction of lower-wage workers; and (3) workers may move to lower-wage part-time jobs.

As discussed above and shown in Figure D.5, the fraction of minimum wage workers among wage/salary workers is substantial for high school dropouts. The sample average of the share of minimum wage workers among high school dropouts in wage/salary jobs is 0.38. Given that the same ratio for the young workers is approximately 50 percent, this bite is not small. If a smaller 'bite' is the culprit of the zero wage effects, we can expect to see clearer effects for this group. In column (1) of Table D.6, however, this is

Table D.4: Effects on Hourly Wage by Education, Age 16-21

	Dep var: ln Hourly Wages Sample: Age 16-21, employed			
	High School Dropouts	High School Graduates	Some College	College Degree or Above
	(1)	(2)	(3)	(4)
Panel A. Estimation using *NW-type* Specification				
Elasticity w.r.t. Minimum Wage	0.221***	0.055+	0.084*	0.178
	(0.022)	(0.032)	(0.035)	(0.166)
Obs	236,184	200,898	213,581	4,572
Panel B. Estimation using *ADR-type* Specification				
Elasticity w.r.t. Minimum Wage	0.270***	0.153***	0.135***	0.631+
	(0.029)	(0.032)	(0.032)	(0.325)
Observations	236,077	200,284	212,930	3,538
Panel C. Estimation using *CDLZ-type* Specification				
3Y Average Effects				
Elasticity w.r.t. Minimum Wage	0.192***	0.168***	0.139***	0.131
	(0.033)	(0.026)	(0.027)	(0.251)
Elasticity w.r.t. Minimum Wage (Federal)	-0.039	-0.093	0.017	-0.306
	(0.057)	(0.062)	(0.060)	(0.592)
5Y Average Effects				
Elasticity w.r.t. Minimum Wage	0.173***	0.152***	0.141***	0.115
	(0.034)	(0.029)	(0.026)	(0.196)
Elasticity w.r.t. Minimum Wage (Federal)	0.006	-0.072	0.010	-0.275
	(0.053)	(0.064)	(0.056)	(0.479)
Obs	236,184	200,898	213,581	4,572

All the results are weighted by the CPS earnings weight. Standard errors are in parentheses and clustered at the state-level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. See note to Table 2.

Table D.5: Effects on Hourly Wage by Education, Age 30-54

	Dep var: ln Hourly Wages Sample: Age 30-54, employed			
	High School Dropouts	High School Graduates	Some College	College Degree or Above
	(1)	(2)	(3)	(4)
Panel A. Estimation using *NW-type* Specification				
Elasticity w.r.t. Minimum Wage	-0.130***	-0.046*	-0.040*	0.058+
	(0.028)	(0.022)	(0.019)	(0.033)
Obs	385,325	1,256,552	1,029,024	1,216,256
Panel B. Estimation using *ADR-type* Specification				
Elasticity w.r.t. Minimum Wage	0.006	0.002	-0.003	0.027
	(0.041)	(0.025)	(0.021)	(0.024)
Observations	384,679	1,256,552	1,029,010	1,216,230
Panel C. Estimation using *CDLZ-type* Specification				
3Y Average Effects				
Elasticity w.r.t. Minimum Wage	0.069*	0.025	0.008	0.012
	(0.031)	(0.021)	(0.020)	(0.023)
Elasticity w.r.t. Minimum Wage (Federal)	-0.053	0.003	0.016	-0.003
	(0.063)	(0.029)	(0.034)	(0.035)
5Y Average Effects				
Elasticity w.r.t. Minimum Wage	0.073**	0.026	0.011	0.017
	(0.026)	(0.019)	(0.019)	(0.018)
Elasticity w.r.t. Minimum Wage (Federal)	0.016	0.018	0.035	-0.010
	(0.068)	(0.025)	(0.032)	(0.038)
Obs	385,325	1,256,552	1,029,024	1,216,256

All the results are weighted by the CPS earnings weight. Standard errors are in parentheses and clustered at the state-level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. See note to Table 2.

Table D.6: Effects on Hourly Wage by Education, Age 65-70

	Dep var: ln Hourly Wages Sample: Age 65-70, employed			
	High School Dropouts	High School Graduates	Some College	College Degree or Above
	(1)	(2)	(3)	(4)
Panel A. Estimation using *NW-type* Specification				
Elasticity w.r.t. Minimum Wage	-0.066	-0.033	0.023	-0.071
	(0.069)	(0.047)	(0.058)	(0.069)
Obs	25,607	47,344	31,831	39,721
Panel B. Estimation using *ADR-type* Specification				
Elasticity w.r.t. Minimum Wage	0.040	0.143*	0.145	-0.118
	(0.168)	(0.069)	(0.089)	(0.087)
Observations	23,770	46,608	30,265	38,256
Panel C. Estimation using *CDLZ-type* Specification				
3Y Average Effects				
Elasticity w.r.t. Minimum Wage	0.171	0.130+	0.311*	-0.174
	(0.115)	(0.067)	(0.148)	(0.145)
Elasticity w.r.t. Minimum Wage (Federal)	0.162	-0.165	0.026	0.223
	(0.192)	(0.156)	(0.188)	(0.206)
5Y Average Effects				
Elasticity w.r.t. Minimum Wage	0.177+	0.132*	0.258+	-0.164
	(0.101)	(0.058)	(0.135)	(0.122)
Elasticity w.r.t. Minimum Wage (Federal)	0.141	-0.111	0.001	0.196
	(0.211)	(0.142)	(0.162)	(0.170)
Obs	25,607	47,344	31,831	39,721

All the results are weighted by the CPS earnings weight. Standard errors are in parentheses and clustered at the state-level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. See note to Table 2.

not the case. In general, wage effects are not larger for the high-school dropouts. Middle-skilled workers such as high school graduates or those with some college education may experience larger effects, if there is any difference.

However, it is also not clear whether the increased portion of lower wage workers could explain the zero wage effects results. A composition change would imply that large employment effects cause lower wage effects; hence one would expect to see negative relationships between the wage and employment effects. In Table D.3, patterns are not highly consistent across the methods, but larger employment effects are found among high school graduates. However, this group shows larger wage effects in Table D.6. Therefore, it is not clear why wage effects are smaller for older workers.

D.3 Heterogeneity by Employment Status in the Previous Year

In Tables D.7 through D.9, I use the 2-year panel nature of the CPS-ORG. To construct longitudinal data using the CPS-ORG, I use household identifier variables (*hhid, hhnum*, and *lineno*) together with the month of the interview and state identifiers. Although this set of variables is standard in the literature (see Lefgren and Madrian, 1999), it often creates multiple matches. Although it is possible to overcome this issue for the period after 2004 (see Chung, 2022 for more detail), I rely on the standard method for consistency. Fewer than 0.3 percent of the total observations have this problem. Approximately 70 percent of the total observations are matched.

Using matched observations, I classify them into two groups: those who worked in the first year and those who did not. Then I estimate the minimum wage effects on each group. However, since I am conditioning on the first-year labor market outcomes and use the second-year labor market outcomes as a dependent variable, using a standard event-study design with an 8-year window may create a problem. Since past minimum wage increases may affect the first-year labor market outcomes, I may end up with conditioning on the results. To avoid this problem, I modify the specification as follows and focus on the short-run changes.

$$y_{ista} = \beta I_{st} + X'_{ista}\gamma + \phi_{sa} + \phi_{ta} + \Omega_{st} + \varepsilon_{ista} \tag{D.1}$$

Here I_{st} captures the state-level minimum wage increases between two interviews. Hence, I estimate the short-run adjustments in labor market outcomes by comparing the labor market outcomes of those who experience large increases and those who do not. Again, the effects are converted into elasticity.

Table D.7 through D.9 show the results for observations who did and did not work in the previous year separately, for the young, prime-age and elderly, respectively. The employment-to-population ratio is much lower for those who did not work in the first

Table D.7: Minimum Wage Effects by Previous Employment Status, Age 16-21

	Outcome: Employment		
	All Matched	Do Not Work in the 1st Year	Work in the 1st Year
	(1)	(2)	(3)
Panel A. Estimation using the *NW-type* Specification			
$\ln MW$	-0.095**	-0.057*	-0.044
	(0.029)	(0.024)	(0.032)
Elasticity w.r.t. Minimum Wage	-0.200**	-0.199*	-0.059
	(0.060)	(0.085)	(0.043)
Obs	345,545	200,843	144,662
Panel B. Estimation using the *ADR-type* Specification			
$\ln MW$	0.024	-0.008	0.054
	(0.033)	(0.031)	(0.054)
Elasticity w.r.t. Minimum Wage	0.051	-0.028	0.071
	(0.070)	(0.109)	(0.071)
Obs	345,244	200,530	144,471
Panel C. Estimation using the *CDLZ-type* Specification			
I_{st}	-0.004	-0.002	0.001
	(0.005)	(0.007)	(0.006)
1Y Elasticity w.r.t. Minimum Wage	-0.076	-0.067	0.009
	(0.084)	(0.207)	(0.063)
Obs	345,545	200,843	144,662

Robust standard errors are in parentheses and clustered at the state-level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. Panel C includes indicators for small increases and large federal level increases, together with demographic controls, as in Table 2 and state-age and time-age specific fixed effects. Panels A and B include the same set of variables as in Table 2. See note to Table 2 for detail.

year. I present both coefficients and elasticities to avoid the potential risk of exaggerating very small changes.

In Tables D.7 and D.9, the effects tend to be more negative in column (2), which suggests more negative effects on inflows into employment, consistent with Gopalan et al. (2021). The results are again very different in Table D.9, in column (1), the effects on all the matched observations show elasticity in the bound of [0.1, 0.3], similarly to the results in Table 2. In later columns, in all the specifications, positive responses measured by elasticity are clear for entrants ([0.3, 0.7]) rather than incumbents ([-0.1, 0.1]), although the sizes of the coefficients themselves are often reversed and estimates are generally imprecise, possibly due to the smaller sample size. In the case of those who did not work in the first year, the second year average employment rate is just approximately 4 percent, while the same ratio for those who worked in the last year is above 70 percent. This suggests that a higher minimum wage may foster unretirement behavior. However, the estimates are highly noisy and suffer from insufficient observations, necessitating further research.

Table D.8: Minimum Wage Effects by Previous Employment Status, Age 30-54

	Outcome: Employment		
	All Matched	Do Not Work in the 1st Year	Work in the 1st Year
	(1)	(2)	(3)
Panel A. Estimation using the *NW-type* Specification			
$\ln MW$	0.005	-0.013	0.002
	(0.014)	(0.011)	(0.007)
Elasticity w.r.t. Minimum Wage	0.007	-0.066	0.002
	(0.020)	(0.057)	(0.008)
Obs	1,974,017	598,087	1,375,930
Panel B. Estimation using the *ADR-type* Specification			
$\ln MW$	0.015+	-0.036*	0.003
	(0.009)	(0.015)	(0.007)
Elasticity w.r.t. Minimum Wage	0.022+	-0.183*	0.003
	(0.013)	(0.076)	(0.008)
Obs	1,974,017	598,063	1,375,928
Panel C. Estimation using the *CDLZ-type* Specification			
I_{st}	0.002	-0.003	0.000
	(0.002)	(0.002)	(0.001)
1Y Elasticity w.r.t. Minimum Wage	0.020	-0.132	0.004
	(0.026)	(0.087)	(0.009)
Obs	1,974,017	598,087	1,375,930

Robust standard errors are in parentheses and clustered at the state-level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. Panel C includes indicators for small increases and large federal level increases, together with demographic controls, as in Table 2 and state-age and time-age specific fixed effects. Panels A and B include the same set of variables as in Table 2. See note to Table 2 for detail.

Table D.9: Minimum Wage Effects by Previous Employment Status, Age 65-70

	Outcome: Employment		
	All Matched	Do Not Work in the 1st Year	Work in the 1st Year
	(1)	(2)	(3)
Panel A. Estimation using the *NW-type* Specification			
$\ln MW$	0.044*	0.013	0.018
	(0.019)	(0.008)	(0.031)
Elasticity w.r.t. Minimum Wage	0.242*	0.362	0.025
	(0.102)	(0.224)	(0.042)
Obs	319,243	253,331	65,912
Panel B. Estimation using the *ADR-type* Specification			
$\ln MW$	0.050*	0.024+	-0.033
	(0.019)	(0.014)	(0.064)
Elasticity w.r.t. Minimum Wage	0.275*	0.674+	-0.046
	(0.108)	(0.395)	(0.087)
Obs	319,243	253,331	65,630
Panel C. Estimation using the *CDLZ-type* Specification			
I_{st}	0.003	0.003+	0.007
	(0.004)	(0.002)	(0.009)
1Y Elasticity w.r.t. Minimum Wage	0.117	0.650+	0.080
	(0.178)	(0.339)	(0.111)
Obs	319,243	253,331	65,912

Robust standard errors are in parentheses and clustered at the state-level. +, *, **, *** are statistically significant at 10%, 5%, 1%, and 0.1%, respectively. Panel C includes indicators for small increases and large federal level increases, together with demographic controls, as in Table 2 and state-age and time-age specific fixed effects. Panels A and B include the same set of variables as in Table 2. See note to Table 2 for detail.

E Note on the Bunching Approach

This section applies a brand-new tool in the minimum wage literature: the bunching approach proposed by Cengiz et al. (2019). The basic idea of the method is related to the bunching. Labor economists have long recognized that a substantial fraction of workers are clustered at the exact minimum (e.g. DiNardo et al., 1996). If the minimum wage is increased, some of the jobs below the new minimum wage level will be eliminated and some portion of those will be recovered at the level exactly at or slightly above the new minimum wage level, creating a bunching at the new minimum. Then, employment effects can be identified by comparing the size of missing and excess jobs near the minimum wages and the size of missing jobs and excess jobs can be obtained by comparison with a hypothetical distribution. This method is useful to decompose the overall employment effects into bin-by-bin effects and observe where the effects occur.

In practical estimation, the key issue is how to construct a hypothetical distribution. Cengiz et al. (2019) relies on states that do not experience minimum wage increases. Therefore, we are in the difference-in-differences framework. To estimate it, they use an event-study design using state-level minimum wage increases. The unit of observation is the employment-to-population ratio by \$0.25 wage bin. A more detailed discussion is provided in Cengiz et al. (2019).

$$\frac{E_{sjt}}{N_{st}} = \sum_{\tau=-3}^{4} \sum_{k=-4}^{17} \alpha_{\tau k} I_{sjt}^{\tau k} + \mu_{sj} + \rho_{jt} + \Omega_{sjt} + \varepsilon_{sjt} \tag{E.1}$$

Equation (E.1) represents the regression specification. Unlike previous estimates, the unit of analysis is state-period-wage-bin level aggregates. E_{sjt} shows an estimate of the number of employees of state s, time t and wage bin j. The first component of the RHS shows the treatment dummies. $I_{sjt}^{\tau k}$ is equal to 1 if the increased minimum wage τ years from period t and the wage bin is in the interval k and $k+1$ dollars relative to the new one. I define 'treatment' as minimum wage increases larger than \$0.50 in 2019 USD, as in equation (3). μ_{sj} and ρ_{jt} captures state-by-wage-bin effects and period-by-wage-bin effects. Ω includes controls such as small and federal level minimum wage increases.[22] Following Cengiz et al. (2019) to obtain precise information on hourly wages, workers with imputed information are excluded, unlike in the analysis in other parts of the paper.

There are several issues related to estimating the number of workers. To estimate the number of workers and residents, I rely on the CPS earnings weight *earnwt*, as in Cengiz et al. (2019). The sum of *earnwt* in the raw CPS-ORG across all years is equal to 12 times total population, so I can estimate the population at the state-quarter level

[22] Here, I try to keep the details as close to Cengiz et al. (2019) as possible. Unlike equation (3), Ω include indicators for wage bins within the $[MW, MW+4]$ and $[MW-4, MW]$ for a year before the increase (*pre*), 2-3 years before the increase (*early*), and for five years after the increases (*post*). In sum, I include six ({early, pre, post} $\times$ {above, below}) for small and federal minimum wage increases.

very precisely by summing them across quarters and dividing this by 3. But since we exclude all imputed workers, the number of workers is underestimated. To correct for this issue, Cengiz et al. (2019) relies on additional information from Quarterly Census of Employment and Wages (QCEW) data. Specifically, Cengiz et al. (2019) calculates $\frac{E_{sjt}}{N_{st}} = \frac{E^{CPS}_{sjt}}{E^{CPS}_{st}} * \frac{E^{QCEW}_{st}}{N^{CPS}_{st}}$, where superscript CPS shows estimates using CPS information and $QCEW$ represents information from the QCEW, respectively. If the distribution of excluded observation is unrelated to wage bin and working time status, this method can provide reliable information for estimating the number of workers in the wage bin. I follow this procedure and multiply the number of workers by $\frac{E^{QCEW}_{st}}{E^{CPS}_{st}}$.

The employment effects are estimated as follows. Note that the dependent variable is employment-to-population ratio by wage bin. Therefore, the estimates $\alpha_{\tau k}$ will capture the effects of minimum wage increase τ years from period t and k dollars from the wage bin on the share of workers in that cell in percentage point terms. The change in the employment-to-population share between time -1 (year prior to the minimum wage increases) and year τ is calculated by $\alpha_{\tau k} - \alpha_{-1k}$ and it will show the change in number of workers per capita in that wage cell. It is normalized by calculating $\Delta a_{\tau k} = \frac{\alpha_{\tau k} - \alpha_{-1k}}{\overline{EPOP}_{-1}}$ where $\overline{EPOP}_{-1}$ is average employment-to-population ratio of treated states of the year prior to the minimum wage increases, corresponding to $\bar{y}_{-1}$ in equation (3). Therefore, $\Delta\alpha_{\tau k}$ implies changes in the number of jobs in the wage bin and working times relative to the total workforce. The average effects on k wage for the following five years is $\Delta a_k = \frac{1}{5}\sum_{\tau=0}^{5}\Delta a_{\tau k}$.

Although there are numerous advantages to this approach, it has serious shortcomings. Since it decomposes the workforce into 117 wage bins, we need a very large sample with precise information on hours. The CPS-ORG meets the criteria for the overall low-wage workforce, but even the CPS-ORG is small for a variety of subgroups such as elderly. Consequently, a large portion of wage bins do not contain any observations. Specific results using the bunching approach are in Figure 4 and Figure B.1.

F Note on the Nested-CES Production Function

In the competitive labor market, the wage of each type of worker equals the marginal product. Therefore, from the production function described in section 6.2, we have:

$$
\begin{aligned}
\ln w_y &= \ln[(1-\alpha)AK^{\alpha}L^{-\alpha}] + \tfrac{1}{\sigma_p}\ln(L) + \ln\theta_{np} + [-\tfrac{1}{\sigma_p} + \tfrac{1}{\sigma}]\ln(L_{np}) + \ln\theta - \tfrac{1}{\sigma}\ln L_y \\
\ln w_o &= \ln[(1-\alpha)AK^{\alpha}L^{-\alpha}] + \tfrac{1}{\sigma_p}\ln(L) + \ln\theta_{np} + [-\tfrac{1}{\sigma_p} + \tfrac{1}{\sigma}]\ln(L_{np}) + \ln(1-\theta) - \tfrac{1}{\sigma}\ln L_o \\
\ln w_p &= \ln[(1-\alpha)AK^{\alpha}L^{-\alpha}] + \tfrac{1}{\sigma_p}\ln(L) + \ln(1-\theta_{np}) - \tfrac{1}{\sigma_p}\ln L_p
\end{aligned}
$$

From young and older workers' wages, this can be expressed as:

$$\ln(w_y/w_o) = \ln(\theta/(1-\theta)) - \frac{1}{\sigma}\ln(L_y/L_o)$$

Rearrange it. Then, obtain equation (4).

For comparison, from young and prime-age workers' wages,

$$
\begin{aligned}
\ln(w_y/w_p) &= \ln(\theta_{np}/(1-\theta_{np})) + \tfrac{1}{\sigma_p}\ln(L_{np}/L_p) + \ln\theta - \tfrac{1}{\sigma}\ln(L_y/L_{np}) \\
&= \ln(\theta_{np}/(1-\theta_{np})) + [\tfrac{1}{\sigma_p} + \tfrac{1}{\sigma}]\ln(L_{np}/L_p) + \ln\theta - \tfrac{1}{\sigma}\ln(L_y/L_p)
\end{aligned}
$$

Therefore, without proper control of the relative workforce between prime- and non-prime-age workers, regression of the relative wage between young and prime-age workers on the relative employment between the young and prime-age cannot be interpreted as a parameter in the production function.

G Note on the Simulated Wage Instrument

This section explains how I calculate the simulated wage instrument based on DiNardo et al. (1996)'s "tail pasting" approach. Specifically, the simulated average wage is calculated as follows.

Let base year be 0 and comparison year be 1. Define the minimum wage at base year be MW_0 and comparison year be MW_1. Let $MW^L = \max\{MW_0, MW_1\}$. For the wage distribution above the MW^L, I use the base year's wage distribution and calculate the conditional average.[23] For the wage distribution below the MW^L, I use the wage distribution of the comparison year and calculate the conditional average. Then, I calculate the simulated average wage by the weighted sum of these two conditional averages using the base year's fraction of workers above and below the MW^L as weights. This is in line with the method in DiNardo et al. (1996) with some simplifications.

Specifically, I assume that wage distribution above MW^L is not affected by the minimum wage, and that wage distribution below the MW^L is determined by the real value of the minimum wage. Then, for wages above MW^L,

$$[1 - \boldsymbol{I}(w \leq MW^L)]f(w|t = 0, MW_0) = [1 - \boldsymbol{I}(w \leq MW^L)]f(w|t = 0; MW_1)$$

where $f(w|t)$ is the probability density function of the wages at time t. $f(w|t = 0, MW_0)$ is the actual wage distribution at time 0, and $f(w|t = 0, MW_1)$ is a counterfactual wage distribution at time 0 if minimum wage is changed to MW_1. Additionally, for a wage below MW^L,

$$[\boldsymbol{I}(w \leq MW^L)]f(w|t = 1; MW_1) = [\boldsymbol{I}(w \leq MW^L)]\psi(MW_1)f(w|t = 0; MW_1)$$

where ψ is a reweighting function defined below. Then, the counterfactual wage density will be

$$\begin{aligned} f(w|t = 0; MW_1) &= \boldsymbol{I}(w \leq m_L)\psi(MW_1)f(w|t = 1; MW_1) \\ &\quad +[1 - \boldsymbol{I}(w \leq MW^L)]f(w|t = 0; MW_0) \end{aligned}$$

Using this counterfactual wage distribution, a simulated average wage can be obtained from

$$\begin{aligned} E[w|t = 0; MW_1] &= \int wf(w|t = 0; MW_1)dw \\ &= \int \boldsymbol{I}(w \leq MW^L)\psi(MW_1)wf(w|t = 1; MW_1)dw \\ &\quad + \int [1 - \boldsymbol{I}(w \leq MW^L)]wf(w|t = 0; MW_0)dw \\ &= \psi(MW_1)P(w_1 \leq MW^L)E[w|t = 1, w \leq MW^L; MW_1] \\ &\quad +P(w_0 > MW^L)E[w|t = 0, w > MW^L; MW_0] \end{aligned}$$

where the reweighting function $\psi(MW_1)$ is equal to $\dfrac{P(w_0 \leq MW^L)}{P(w_1 \leq MW^L)}$. The reweighting function will adjust for the difference in the fraction of workers below MW^L to ensure

[23] As mentioned above, in practice I use 1.2 times maximum of the minimum wage for the threshold.

that the counterfactual wage density integrates to 1.[24]

Do these simulated wages match the fluctuations in actual wages well? I show the evolution of the actual and simulated average wage over time using two example states: California and Michigan. Figure G.1 shows the evolution of the two average wages together with the real minimum wages.

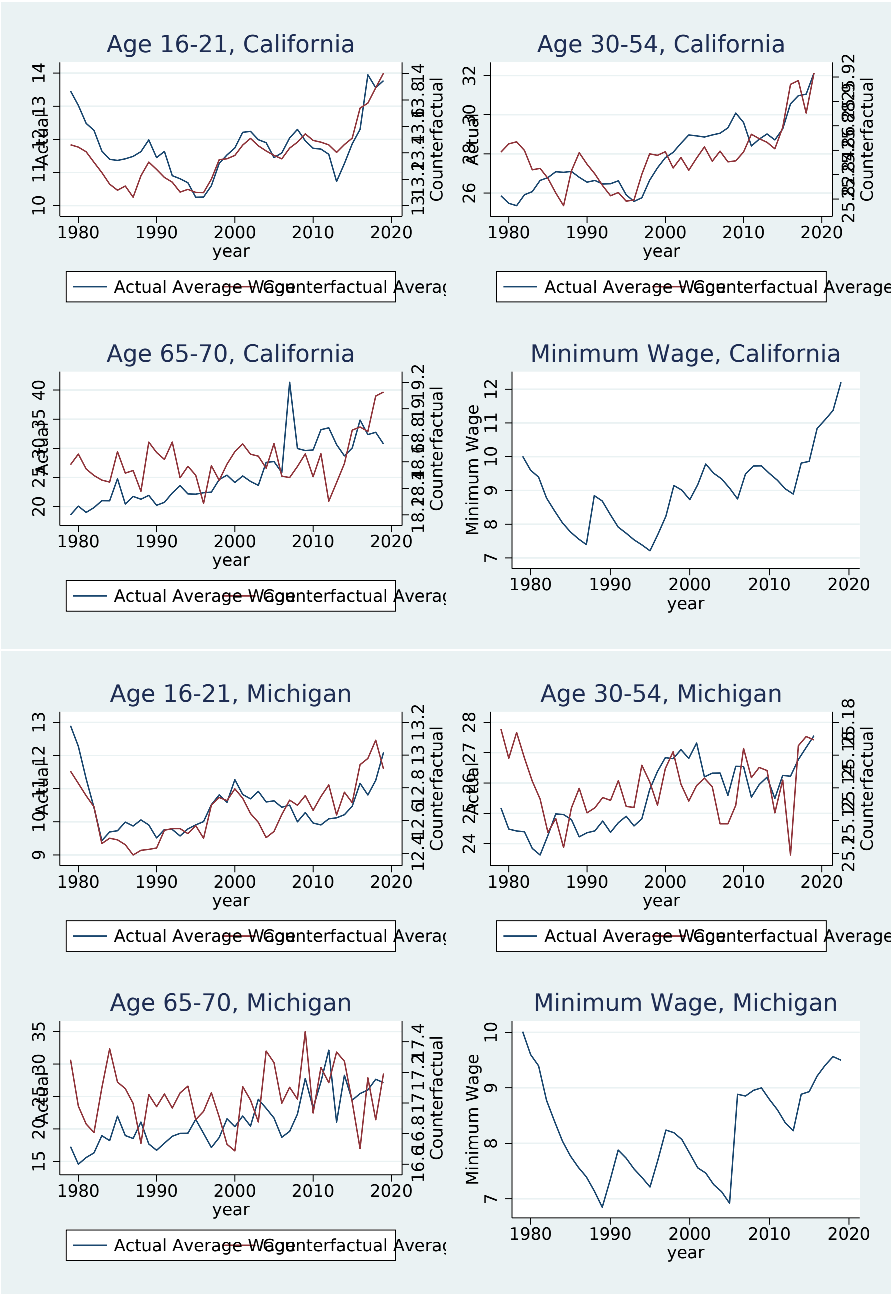
First the counterfactual wage fluctuates much less than the actual wage rates. By way of construction, the simulated wage rate holds the wage above the minimum wage constant. Therefore, especially for workers such as prime-age workers whose fraction affected by the minimum wage is small, it fluctuates little. On the other hand, if a larger fraction of workers is affected by the minimum wages, it fluctuates relatively more.

In Figure G.1, for young workers, trends closely follow those of the actual wage with little fluctuations. Note that the left axis shows the actual wage and the right axis shows the simulated wage. In contrast, the simulated wage rate deviates from the trends in actual wage much more for prime-age or older workers. For instance, in Michigan, the real value of the minimum wage dropped significantly in the 1980s and was relatively stable by the mid 2000s. Movement in the simulated wages of prime-age workers reflect these trends in minimum wages. The actual wages of prime-age workers, however, were relatively stable in the 1980s and 1990s and then experienced a sharp increase in around 2000.

The explanatory power of these simulated wages for actual wages comes from the fact that the simulated wages successfully follow the trend in one particular group - young workers. Since the average wage rate of young workers is greatly affected by the minimum wage, and the simulated wage rate can capture this, the actual relative wage rate between the young workers and the other groups can be explained by the simulated relative wage rate between the groups.

[24] The original method in DiNardo et al. (1996) also adjusts for the difference in observable characteristics. I do not apply that process. Since I use state-age or state-age-industry level as my unit of analysis, the sample size for each unit is much smaller. Therefore I use the simpler approach.

Figure G.1: Evolution of Actual and Simulated Wage, California and Michigan



H Distribution of Industry across Ages

This subsection examines how similar industry distribution of workers in different ages are. For that purpose, I use the index of congruence used by Welch (1999) and Borjas (2003). The index for any two groups k and l is defined by

$$G_{kl} = \frac{\sum_c (q_{kc} - \bar{q}_c)(q_{lc} - \bar{q}_c)/\bar{q}_c}{\sqrt{(\sum_c (q_{kc} - \bar{q}_c)^2/\bar{q}_c)(\sum_c (q_{lc} - \bar{q}_c^2/\bar{q}_c)}}$$

where q_{hc} implies the portion of workers employed in industry c among group $h(= k, l)$ workers, and $\bar{q}_c$ is the fraction of the entire workforce employed in the industry. The index has a value of 1 if workers in two groups have identical industry distribution and -1 if they are employed in completely different industries.

Table H.1 shows the index of congruence across age and education groups. Overall, industry distribution of the young, prime-age, and elderly are different. $G_{young,prime} = -0.976, G_{young,elderly} = -0.106$ and $G_{prime,elderly} = -0.096$. It starts to show some similarity as decomposing them into education groups. The industry distribution of young workers by education groups are very similar with each other, suggesting that they are close substitutes. The elderly without high school diplomas are the group whose industry distribution is the most similar with the young workers ($G = 0.356$), followed by the elderly with high school diplomas ($G = 0.288$). The same index with prime-age high school dropouts is 0.232 and high school graduates is -0.118. It suggests that at least the less educated elderly have some potential to be substitutes to the young workers.

There are other interesting patterns in Table H1. The Index of Congruence shows that industry distribution of the better educated elderly is relatively similar to that of prime-age workers, unlike the less-educated elderly. The index between older workers with advanced degrees and prime-age workers with advanced degrees is even 0.924.

Panels B and C in Table H1 show the index for full-time and part-time workers.[25] Industry distribution of full-time young workers becomes much more similar to that of low-educated prime-age and elderly workers. G between the young apd prime-age and older high-school dropouts become 0.574 and 0.545, respectively. However, part-time young workers work in relatively different industries. It might be the result of the disproportionately high fraction of young part-time workers in 'Leisure and Hospitality' (32.7 percent) and 'Wholesale and Retail Trade' (30 percent).

In sum, there are some possibilities that the less-educated elderly could be a closer substitute for the young workers, compared to less-educated prime-age workers. The indexes are higher for full-time workers who drive the positive employment effects.

[25] $\bar{q}_c$ is calculated only by using full-time and part-time workers, respectively.

Table H.1: Index of Congruence in Industry across Age and Education Groups

		Young	Prime-Age (Age 30-54)					
		All	All	<HS	HSG	Some Col	Col Grad	Advanced
			Panel A. All Workers					
Young (Age 16-21)	All	-	-0.976	0.232	-0.118	-0.762	-0.635	-0.547
Elderly (Age 65-70)	All	-0.106	-0.096	-0.370	-0.473	0.024	0.185	0.379
	<HS	0.356	-0.412	0.575	0.139	-0.534	-0.597	-0.349
	HSG	0.288	-0.413	-0.136	-0.016	-0.113	-0.257	-0.232
	SC	-0.132	-0.028	-0.607	-0.413	0.300	0.365	0.288
	CG	-0.371	0.212	-0.753	-0.674	0.355	0.726	0.661
	Adv.	-0.422	0.328	-0.556	-0.723	0.225	0.582	0.924
			Panel B. Full-Time Workers					
Young (Age 16-21)	All	-	-0.948	0.574	0.291	-0.609	-0.642	-0.648
Elderly (Age 65-70)	All	-0.290	0.076	-0.439	-0.606	0.101	0.328	0.594
	<HS	0.545	-0.461	0.838	0.350	-0.605	-0.716	-0.438
	HSG	0.270	-0.338	0.057	0.283	0.097	-0.378	-0.326
	SC	-0.319	0.127	-0.704	-0.438	0.549	0.488	0.348
	CG	-0.539	0.288	-0.830	-0.786	0.375	0.825	0.699
	Adv.	-0.549	0.361	-0.589	-0.821	0.084	0.574	0.936
			Panel C. Part-Time Workers					
Young (Age 16-21)	All	-	-0.976	-0.050	-0.684	-0.938	-0.867	-0.773
Elderly (Age 65-70)	All	-0.653	0.487	0.179	0.770	0.417	0.320	0.168
	<HS	-0.255	0.135	0.705	0.626	-0.065	-0.165	-0.212
	HSG	-0.350	0.152	0.103	0.708	0.115	-0.005	-0.168
	SC	-0.611	0.439	-0.032	0.687	0.445	0.343	0.152
	CG	-0.718	0.600	-0.235	-0.532	0.638	0.617	0.422
	Adv.	-0.884	0.904	-0.179	0.307	0.901	0.928	0.924

See text for details. The number in each cell shows the similarity in industry distribution across groups of workers. -1 means that workers are working in a completely different set of industries, and 1 means that the industry distribution is identical. All results are weighted by CPS earnings weight (*earnwt*) variable.