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ABSTRACT

The Heterogeneous Effects of Large and Small Minimum Wage Changes on Hours Worked: Evidence Using a Partially Pre-committed Analysis Plan*

In a study of recent minimum wage changes (Clemens and Strain, forthcoming), we demonstrate how analyses of longer-run impacts of policy interventions can be pre-specified as extensions to very short-run analyses. This paper uses this novel methodology to study the effects of minimum wage increases on hours worked. Analyzing CPS and ACS data with the empirical specifications from our partially pre-committed analysis plan, we estimate that relatively large minimum wage increases reduced usual hours worked per week among individuals with low levels of experience and education by just under one hour per week during the decade prior to the onset of the Covid-19 pandemic. Our estimates of the effects of relatively small minimum wage increases vary across data sets and specifications but are, on average, both economically and statistically indistinguishable from zero. We estimate that the elasticity of hours worked with respect to the minimum wage is substantially more negative for large minimum wage increases than for small increases.

JEL Classification: J08, J23, J38

Keywords: minimum wages, hours worked, pre-commitment

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Section I: Introduction

The employment effects of minimum wages have been analyzed in a voluminous literature. This literature has focused largely, though by no means exclusively, on the question of how changes in the minimum wage affect employment levels. But employers of minimum-wage workers have additional margins of adjustment in the face of changes in the statutory wage floor, including the hours per week their employees work.[2] Indeed, given the direct relevance of total hours in standard models of labor input to a firm's production and its associated marginal product, the effect of changes in the minimum wage on hours of work is of first-order importance for our understanding of this policy and of the low-wage labor market.

In this paper, we add to the literature on the minimum wage's effects on the average work hours of relatively young and low-education workers, whose wages are strongly impacted by the minimum wage. A key dimension of our paper's methodology is that it executes analyses that were partially precommitted prior to the public release of several years of the data we analyze.

Specifically, this manuscript's analysis is the second of two sets of analyses to which we precommitted in a paper released in January 2017 (Clemens and Strain, 2017). The first, reflecting the overall emphasis of the literature as described above, focused on the employment probabilities of the individuals in our analysis samples (Clemens and Strain, forthcoming). The

[2] There are many other margins, in addition to employment and hours, across which employers could absorb the higher labor costs associated with minimum wage increases. For a review of this literature, see Clemens (2021). Recent papers by Ku (2021) and Coviello et al (2022) find evidence that worker effort rises in the wake of minimum wage increases, while Clemens and Strain (2020b) provide an illustration of how scheduling practices might respond to higher minimum wages, and papers including Horton (2025) and Clemens, Kahn, and Meer (2021) find evidence that employers alter the mix of workers they recruit and employ in response to minimum wage increases. Through effects on output per hour of work, each of these margins have direct implications for the quantity of labor required to produce a given volume of output. Clemens and Strain (2022) provide evidence that evasion and avoidance are an additional margin through which some firms respond to minimum wage increases.

present analysis extends our earlier analysis by studying their work hours, which is an outcome to which our project had precommitted. Since the present paper's analysis mirrors that of our analysis of the minimum wage's effects on employment, much of the text that follows, including our discussion of the strengths and weaknesses of pre-analysis plans, is taken or adapted from the text of the earlier papers in this project.

Two features of our pre-analysis plan, which is outlined in Section V, merit discussion at the outset, as they are relevant to understanding key dimensions of our findings. First, our pre-analysis plan includes theoretically motivated comparisons of the effects of large vs. small minimum wage increases. Second, we demonstrate how analyses of relatively long-run impacts of policy interventions can be pre-specified as extensions to short-run analyses. In the following section, we further discuss how these dimensions of our study can help to inform the use of pre-analysis plans in non-experimental settings in future work.

Our analysis was spurred by the fact that the past decade of state and federal minimum wage policy created an attractive opportunity to analyze the effects of minimum wage increases on hours worked using a pre-analysis plan.[3] After the Great Recession, there was a pause in both state and federal efforts to increase minimum wages, which was followed by considerable divergence in states' policies. Many states legislated and enacted minimum wage changes that varied substantially in their magnitude. From January 2011 to January 2019, for example, Washington, D.C., California, and New York had increased their minimum wages by 61, 50, and 53 percent, respectively. Wage floors rose more moderately in an additional 24 states and were unchanged in the remainder. The past decade thus provided a suitable opportunity to study the

[3] This paragraph is taken from Clemens and Strain (forthcoming).

effects of both moderate minimum wage changes and historically large minimum wage changes. By contrast, the average increase across the 138 minimum wage increases analyzed by Cengiz *et al.* (2019) averaged just over eight log points.

The results from our pre-analysis plan (see Section VI) are as follows. First, we estimate that relatively large increases in minimum wages reduced usual hours worked per week among individuals with low levels of experience and education by just under one hour per week. Second, our estimates of the effects of moderate minimum wage increases are centered on zero, as are our estimates of the effects of minimum wage increases linked to inflation-indexing provisions. Finally, we find that the effects of large minimum wage changes have increased in magnitude as time has passed since their enacting legislation. Because large cumulative increases were phased in over a number of years, we emphasize that it is not generally feasible to distinguish between the short-and-medium run effects of the initial increments of the legislated increase, on the one hand, and the contemporaneous effects of a large cumulative increase, on the other hand. Overall, the hours elasticities we estimate are similar to the employment elasticities we estimated in our earlier paper.

While most minimum wage research focuses on the extensive margin of employment, a growing number of papers have estimated that minimum wage increases lead to modest or substantial reductions in average and aggregate hours worked among affected workers depending on the sample examined (Zavodny, 2000; Couch and Wittenburg, 2001; Neumark *et al.,* 2004; Sabia, 2009; Jardim *et al.*, 2022; Stewart and Swaffield, 2008; Redmond and McGuinness, 2025; Caliendo *et al*., 2019). These estimated reductions in hours can be small, but are often as large as or larger than estimated employment effects, suggesting that the hours channel is an important margin of adjustment to minimum wage increases. The present paper complements this line of research, finding that hours elasticities in response to recent minimum wage increases are similar to employment elasticities, as analyzed in our earlier work (Clemens and Strain, forthcoming), with hours elasticities in response to larger minimum wage increases being significantly larger and more negative than elasticities in response to smaller increases,.

Although our estimation frameworks are pre-committed, it is nonetheless important to assess their internal validity. To this end, Section VIII presents estimates using the "imputation" estimator of Borusyak, Jaravel, and Spiess (2024), which has attractive properties for our setting. We obtain qualitatively similar results, namely null effects of relatively small minimum wage increases and negative effects that rise over time when states enacted large, multi-phase minimum wage increases.

Our paper proceeds as follows. Section II discusses some of the tradeoffs associated with the use of pre-analysis plans outside of experiments. Section III provides background regarding the minimum wage changes we analyze. Section IV discusses the primary data sources we use. Section V describes our pre-committed estimation frameworks, and Section VI summarizes the results of these pre-committed analyses. Section VII discusses the elasticities implied by the hours and wage impacts we estimate. Section VIII presents estimates from a modern Difference-in-Differences estimator that falls outside of our pre-analysis plan, and Section IX concludes.

Section II: The Design of Pre-Analysis Plans Outside of Experimental Settings

P-hacking poses a substantial threat to the reproducibility of research results. In the context of experimental research, pre-analysis plans are an important solution to the threat of p-hacking. Such plans are rare outside of experiments, however, in large part because it is difficult to implement a "pure" pre-analysis plan for a research project studying longer-term effects of real-world (non-experimental) policy interventions using observational data (Christensen and Miguel, 2018).

Our earlier work (Clemens and Strain, 2017; Clemens and Strain, forthcoming) attempts to design a study that finds a middle ground between the extremes of fully pre-committed analysis and no pre-committed analysis. A goal of this work was to design a study with partial pre-commitment, hopefully retaining substantial gains from reduction in p-hacking while acknowledging the practical benefits of maintaining analytical flexibility in a non-experimental setting. The resulting study design deviates from pure pre-analysis in that it constructs longer-run, pre-committed analyses as extensions to short-run analyses that were not pre-committed.[4] That is, it is a design in which short-run analyses were open ended and were refined by the peer review process (Clemens and Strain, 2018a), and in which long-run analyses were pre-specified as extensions to the short-run analyses.

We quote from Clemens and Strain (forthcoming) to describe the benefits we see from this approach:

> We view the core trade-off we have adopted as attractive for two reasons. First, the pursuit of "pure" pre-analysis plans pushes researchers towards very short-run analyses, which will not tend, by definition, to capture the long-run policy parameters that are more central for policy evaluation. Second, we observe that conventional, flexible explorations of short-run impacts may be crucial for the development of credible research designs on which pre-committed analyses of long-run effects can be built. Because it takes time for researchers to build consensus regarding which research strategies are appropriate for analyzing a novel setting, it may rapidly become too late to propose a "pure" and "credible" pre-analysis plan for analyzing short-run effects. Consequently, we focus on the use of pre-commitment to reduce p-hacking concerns in the development of longer-run analyses.

[4] Readers interested in the development of our pre-analysis plan should turn to the first two papers from our project (Clemens and Strain, 2017, 2018b), as well as the intermediate project milestones in which we incorporated ACS and CPS data from 2016, 2017, and 2018 (Clemens and Strain, 2018a, 2019, 2020a), as well as Clemens and Strain (forthcoming).

A potential threat to any long-run analysis, whether pre-specified or not, is the possibility that economic shocks may create biases that rear their heads in the latter years of an analysis. To the extent that such shocks are standard, e.g., due to normal variations in the strength of contemporaneous macroeconomic fluctuations, we illustrate how robustness checks can be pre-specified. The Covid-19 pandemic illustrates a form of extreme shock that would not be readily addressable through pre-specification. A trade-off we explore in our analysis involves the possibility of pre-specifying narrowly defined degrees of freedom, which relaxes the purity of a pre-analysis plan, but does so in a way that mitigates the risk of a study's failure due to events that could not plausibly have been foreseen. There are advantages, for example, to allowing some degree of pre-specified flexibility on the control variables an analysis might consider, or to allowing regression specifications to adapt to reflect policy variation that could not have been fully anticipated at the time a pre-analysis plan was written. On the other hand, the more flexibility one introduces, the less the analysis is pre-committed.

Section III: Background on State Minimum Wage Changes Between 2011 and 2019

During the years following the Great Recession, there was a pause in both state and federal efforts to increase minimum wages. Subsequently, states diverged substantially in their minimum wage policies. This environment offered an opportunity to conduct relatively transparent labor market analyses using standard program evaluation methods.

Our pre-analysis plan divides states into policy groups based on their minimum wage regimes. A key aspect of our pre-analysis plan is that it incorporates heterogeneity in the minimum wage's effects along dimensions that are of long-standing theoretical interest. Specifically, our analysis plan differentiates between the short- and longer-run effects of minimum wage legislation, between the effects of large and small minimum wage changes, and between the effects of newly legislated minimum wage changes and forecastable changes that are driven by inflation-indexing provisions.

We divide states into four groups designed to track several plausibly relevant differences in their minimum wage regimes. The first group consists of states that enacted no minimum wage changes between January 2013 and the later years of our sample. The second group consists of states that enacted minimum wage changes due to prior legislation that calls for indexing the minimum wage for inflation. The third and fourth groups consist of states that have enacted minimum wage changes through relatively recent legislation. We divide the latter set of states into two groups based on the size of their minimum wage changes and based on how early in our sample they passed the underlying legislation.

Updates to states' minimum wage policies pose challenges to the development of pre-analysis plans. Notably, several of the states that entered our analysis sample with inflation-indexing provisions subsequently enacted minimum wage changes through new statutes. Our approach is thus to present three sets of results. We first present results that hold fixed the policy groupings we adopted in our initial analyses, for which our analysis samples extended through 2015. Second, we present results on samples that exclude states that legislated substantial minimum wage changes after our initial analyses. Third, we present results for which we adjust our groupings of states to account for minimum wage changes enacted as of January 2018.

The maps in Figure 1 present the full divisions of states associated with the policy groupings we use. As shown in the maps, several states shift between the "large" and "small" change groups as we move from the grouping based on changes enacted through January 2015 to the grouping that incorporates changes enacted between January 2015 and January 2018. Figure 2 illustrates the dynamics of the changes in the average effective minimum wage rates across the groupings displayed in Panel A of Figure 1, with Panel A presenting the average level of the nominal minimum wage in each grouping and Panel B presenting the Kaitz Index (i.e., the ratio of the minimum wage to the median wage). While the nominal minimum wage rose non-trivially in our grouping of small increases, the associated Kaitz Index rose modestly (by roughly 0.03) due to contemporaneous growth in median wages. It is only in our grouping of states with large increases that the Kaitz Index rose substantially from baseline to endline (by roughly 0.12). A comparison of Figure 2 with Appendix Figure 2 reveals that updating our groupings of states to reflect minimum wage increases that were passed after the development of our pre-analysis plan has little impact on the endline differences in the minimum wage increases enacted by our groupings of large increases, small increases, and states with no minimum wage changes.

We note that both the "small" and "large" minimum wage changes we analyze are substantial relative to historical minimum wage changes. In our sample, the longer-run increases (meaning those through January 2019) average roughly 25 log points within our "small" group and 35 log points within our "large" group (see Appendix Figure A1). With respect to the bite of these minimum wage increases, we emphasize, as illustrated in Panel B of Figure 1, that the ratio of the minimum wage to the median wage rose substantially in the latter group but modestly in the former group; even the non-trivial nominal increases enacted in our group of "small" minimum wage increases were roughly on pace with growth in median wages.

Section IV: Data Sources

Our primary data sources are the American Community Survey (ACS) and the Current Population Survey (CPS) from the Integrated Public Use Microdata Series (IPUMS).[5] The ACS is the largest publicly available household survey data set containing the information required for our analysis, while the CPS is a common resource for estimating standard employment statistics

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[5] The remainder of this section quotes liberally from the text of this project's previous analyses.

across geographic areas and demographic groups. To create a measure of hours worked that is as consistent as possible from both the ACS and CPS, we create a measure of usual weekly hours worked from both data sources. From the ACS, we use the variable UHRSWORK, which is the total number hours per week that the respondent usually worked in the past 12 months. From the CPS, we use the variable UHRSWORKT, which is the usual number of hours per week the respondent reports being at all jobs, over an unspecified time period.[6] We topcode values of usual hours worked per week in both datasets at 99 hours per week and we set hours worked per week in both datasets to zero for individuals who are not employed.[7]

Table 1 presents summary statistics on the primary ACS samples we analyze (equivalent summary statistics from our CPS samples appear in Table A2). The first sample, described in Columns 1 and 2, consists of individuals ages 16 to 25 with less than a completed high school education. The second sample, described in Columns 3 and 4, consists of all individuals ages 16 to 21. Columns 1 and 3 present data from 2011 to 2013, while Columns 2 and 4 present data from 2015 to 2019. From the baseline to the later years in our sample, hours worked rose for both groups, as did house prices and aggregate per capita incomes.

We supplement the ACS and CPS data with data on macroeconomic covariates. Specifically, we investigate the relevance of departures in economic conditions across our policy groupings, which could bias our estimates, by tracking indicators of the performance of state-level housing markets, state aggregate income per capita, and labor markets.

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[6] Previous studies examining the effects of minimum wages on hours worked have used these variables to define "hours worked" (Berger, Herkenhoff, and Mongey, 2025). We choose these two variables to construct our measures of hours worked because they appear to be the most comparable across the ACS and CPS datasets.

[7] In the CPS, around four percent of individuals in our main analysis samples have the response "hours vary" for the number of usual weekly hours worked. As no similar response exists in the ACS, we code these observations as missing.

Figure 3 presents time series on median house prices (Panel A) and aggregate income (Panel B) across the policy groups we analyze, namely states that enacted large minimum wage increases, small minimum wage increases, inflation-indexed minimum wage increases, and no minimum wage increases. Table 2 summarizes in sample changes in these macroeconomic covariates, as well as in employment and hours worked among prime age adults (ages 26–54).

The house price index reveals that the housing recovery following the Great Recession was strong in states that enacted relatively large minimum wage increases. Median house prices rose by roughly 46 percent in this group of states from the 2011–2013 base period through 2019. They rose by 60 percent in states that indexed their minimum wage rates to inflation. Across states that did not increase their minimum wage rates, house prices rose 35 percent, and in states that enacted small minimum wage increases, median house prices rose by 31 percent. The BEA's income data show that per capita incomes grew roughly $7,500 more in states that enacted relatively large minimum wage changes than in states that enacted no minimum wage changes.[8] Underlying macroeconomic conditions improved to economically and statistically significantly greater degrees in states that enacted large minimum wage changes than in other states.

The employment and weekly hours series for prime age individuals also suggests that underlying economic conditions were stronger in states that enacted minimum wage increases than in states that did not. From the 2011–2013 baseline through 2019, prime age employment grew by an average of 5.3 percentage points and hours worked by an average of 1.62 hours per

[8] Although per capita incomes were not included in this project's initial analysis, the divergence in per capita incomes across groups was quite apparent when we constructed an early version of Panel B of Figure 3 for our analysis of 2011 to 2015 ACS data (Clemens and Strain, 2018b). This is why, consistent with a pre-specified dimension of refinement to our pre-specified regressions, we incorporated per capita income as a control variable for subsequent analyses. Our initial focus on the FHFA housing price index as a macroeconomic control variable was motivated by analyses of the minimum wage increases enacted during the Great Recession (Clemens and Wither, 2019). In that context, there was a strong mapping between the housing market and overall macroeconomy.

week in states that either enacted large minimum wage changes or that indexed their minimum wage rates to inflation. Across states that enacted no minimum wage increases, the prime age employment rate increased by a more modest average of 4.0 percentage points and hours worked grew by 1.24 hours per week.

Table 2 also presents tabulations of usual weekly hours worked in our primary analysis samples. Hours worked among individuals ages 16 to 25 with less than a completed high school education ("Low-Skilled Hours Worked"), as measured in the ACS, expanded 1.10 hours less by 2019 in states that enacted large minimum wage changes than in states that enacted no minimum wage change. In the CPS (Table A4), the measured difference was -1.02 hours. Among all individuals ages 16 to 21, the difference in the ACS is -0.48 hours, while the difference measured in the CPS is -0.27 hours.[9]

Section V: Framework for Estimating the Effects of Minimum Wage Changes

This section presents our regression frameworks for estimating the effects of recent minimum wage increases, following the pre-analysis plan in Clemens and Strain (2017, 2018b). Much of this section's text is thus largely unchanged from these earlier papers.

Our analysis plan adopts a program evaluation approach in which we divide states into groups based on the minimum wage policy changes they legislated early in the time period we analyze. We estimate standard difference-in-differences and triple-difference specifications to identify differential changes in hours worked among relatively low-skilled population groups. Our basic difference-in-differences specification is presented in equation (1):

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[9] Additional tabulations of interest from ACS data, as well as CPS data, appear in Tables A1-A8.

$$Y_{i,s,g(s),t} = \sum_{g(s)\neq 0} \beta_{g(s)} Policy_{g(s)} \times Post_t + \alpha_{1s}\, State_s \; + \; \alpha_{2t}\, Time_t + X_{i,s,t}\, \gamma + \varepsilon_{i,s,t}, \qquad (1)$$

where $Y_{i,s,g(s),t}$ is the number of usual weekly hours worked of individual i, living in state s, which falls in policy category $g(s)$, in year t. We estimate equation (1) on samples restricted to the population groups most likely to be affected by the minimum wage, namely young adults (ages 16 to 21) and individuals ages 16 to 25 with less than a completed high school education (low-skilled). As our sample includes both employed and unemployed individuals, estimates from equation (1) capture both the extensive and intensive margin effects of minimum wages on hours worked.

Equation (1) includes standard controls for sets of state and time fixed effects. The vector X contains sets of control variables that vary across the specifications we estimate. In various specifications, it contains the state median house price index, the log of aggregate state personal income per capita, the state employment rate among individuals with moderately higher skill levels than the individuals in the analysis sample, and individual-level demographic characteristics.

$Policy_{g(s)}$ represents binary indicators for whether a state fits into a given policy group. As discussed above, we differentiate among states that increased their minimum wage rates due to inflation-indexing provisions, states that enacted relatively large statutory increases in total, and states that enacted relatively small statutory increases in total. The omitted group is group $g = 0$, which represents states that did not increase their minimum wage rates.

The coefficients of interest are the $\beta_{g(s)}$ on the interaction between $Policy_{g(s)}$ and $Post_t$. For estimates of equation (1), we treat 2014 as a transition year and thus exclude it from the sample. For this analysis, $Post_t$ is an indicator for observations that occur in 2015, 2016, 2017, 2018, or 2019. $\beta_{g(s)}$ thus describes differential changes in employment from a base period consisting of 2011, 2012, and 2013 through a post period consisting of 2015–2019 for each policy group. In subsequent analysis, we exclude 2014–2018 from the sample so that $\beta_{g(s)}$ describes differential changes in hours worked from the base period of 2011-2013 through a post period consisting of 2019. For a direct comparison of "short" vs. "longer" run effects, we also report summary estimates for specifications in our project's initial analyses for which the post period consisted exclusively of 2015.

The coefficient $\beta_{g(s)}$ is an estimate of the causal effect of states' minimum wage policy changes on usual weekly hours worked under the assumption that hours worked would, in the absence of minimum wage changes, have evolved similarly across the groups of states. We investigate threats to this assumption in multiple ways. First, guided by our pre-analysis plan, we investigate the robustness of our estimates to changing the variables that proxy for variations in economic conditions. We examine robustness to including no such controls, to controlling for the housing market's evolution, to controlling for the log of per capita income, and to controlling for changes in hours worked among individuals in moderately higher-skill groups, which we define as individuals ages 21–30 with high school degrees and individuals ages 31–64 with less than a completed high school degree.

Second, as also in our pre-analysis plan, we estimate the triple-difference model described by equation (2). Notationally, we add the subscript *d(i)* for demographic groups, which distinguishes between the within-state control group and the groups that are "targeted" by minimum wages. Equation (2) augments equation (1) with three sets of two-way fixed effects, namely demographic group-by-time-period effects, group-by-state effects, and state-by-time-period effects. These controls account for differential changes in hours worked across skill groups over time, cross-state differences in the hours worked of the "target" group relative to other skill groups at baseline, and time-varying differences in states' economic conditions:

$$
\begin{aligned}
Y_{i,d(i),s,g(s),t} \; = \; & \sum_{g(s)\neq 0} \beta_{g(s)} Policy_{g(s)} \times Post_t \times Target_{d(i)} + \alpha_{1s}\, State_s + \alpha_{2t}\, Time_t \\
& + \alpha_{3d(i)}\, Target_{d(i)} + \alpha_{4st}\, State_s \times Time_t + \alpha_{5sd(i)}\, State_s \times Target_{d(i)} \\
& + \alpha_{6td(i)}\, Time_t \times Target_{d(i)} + X_{i,s,t}\,\gamma + \varepsilon_{i,s,t}. \qquad (2)
\end{aligned}
$$

The implications of the triple-difference model's state-by-time-period effects depend on which skill groups are included in the sample. The inclusion of state-by-time-period effects enables the specification to control flexibly for economic factors that vary across states and over time. More specifically, they control for such factors as they manifest themselves through hours worked changes among the individuals included in the sample as "within-state control groups." In our triple-difference specifications, the within-state control group consists of prime age adults (ages 26 to 54). Note that this implicitly assumes that hours worked among the "within-state control group" exhibits the same sensitivity to business cycle or other developments as does hours worked among individuals in the target group. In our setting, where prime age hours worked enjoyed greater tailwinds in states that enacted large minimum wage increases, this may thus tend to result in estimates of the minimum wage's effects on hours worked among members of the target group that are modestly biased towards zero.

Third, we step outside of our pre-analysis plan to implement the "imputation" estimator of Borusyak, Jaravel, and Spiess (2024), which has attractive properties that we discuss more fully in Section VIII. A final methodological note involves confidence intervals. Because the point estimates of interest are averages across the sets of difference-in-differences and triple-difference estimates from our pre-analysis plan, we obtain confidence intervals on these estimates through a bootstrapping procedure, which also enables us to estimate confidence intervals for the labor demand elasticities that are implied by our estimates.[10]

Section VI: Regression Estimates of Recent Minimum Wage Changes' Effects

This section presents our estimates of the effects of minimum wage changes on hours worked. As our samples include both employed and unemployed individuals, these estimates capture the effects of minimum wage changes on hours worked at both the extensive and intensive margins. The collection of estimates from our pre-committed analyses can be broken down along the following dimensions: (1) ACS or CPS data; (2) analysis samples consisting of individuals ages 16 to 25 with less than a completed high school education (low-skilled workers) or samples consisting of all individuals ages 16 to 21 (young workers); (3) difference-in-differences specifications described by equation (1) or triple-difference specifications described by equation (2); (4) a "post" period consisting of 2015, 2016, 2017, 2018, and 2019 or a "post" period consisting solely of 2019; (5) the barrier between "large" and "small" changes based on changes enacted through January 2015 or based on changes enacted through January 2018; and (6) including all states in the analysis or omitting states that shift policy categories between January 2015 and January 2019. Results for the full sets of individual specifications are available on request.

We summarize two sets of analyses. In Table 4, we summarize estimates that adhere

[10] Each bootstrap replication reproduces the underlying sample structure by drawing states with replacement after stratifying across the policy groupings. We generated 200 replications and observe that the width of the resulting confidence intervals is little changed by extending the number of replications from 100 to 200.

rigidly to the specifications as implemented in Clemens and Strain (2017). In Table 3, we summarize estimates that incorporate refinements along dimensions that were pre-specified in Clemens and Strain (2017).

Our first finding is that large statutory minimum wage changes are, on average, associated with a differential hours worked decline of -0.73 hours across the full set of specifications we estimate, averaging across our primary analysis samples. The estimates are more negative for the sample consisting of individuals ages 16 to 25 with less than a completed high school education (-0.94 hours) than for the larger sample of all individuals ages 16 to 21 (-0.51 hours).

Second, the results show that the hours worked declines associated with legislation rise as the increases are phased in over time. As shown in Table 3, hours worked effects for 16-25 year olds with less than a completed high school education average -0.38 hours through an endline consisting solely of 2015 and average -1.16 hours estimated through an endline consisting solely of 2019. Equivalent estimates for the "young adult" population ages 16 to 21 are -0.26 and -0.66, respectively. In both instances, these differences are statistically significantly different from zero.

Third, omitting the states that shift policy categories due to minimum wage changes legislated between 2015 and 2018 has modest effects on our results. The point estimate for large statutory increases are slightly smaller and remain statistically distinguishable from zero (see rows labeled "No Switchers").

Fourth, estimates of the effects of minimum wage increases linked to inflation-indexing provisions center on 0. We hypothesize that this results from two factors. First, as shown in Figure 2, the Kaitz Index in these states rose little from baseline to endline. Second, firms' responses to these forecastable minimum wage increases may have occurred closer to the time at which their indexing provisions were first enacted. Fifth, estimates for small statutory minimum wage changes also center on 0, but are highly variable when contrasting estimates from the ACS and CPS, as can be seen in Table A12.[11] The evidence overall implies that the smaller minimum wage changes in our sample have had no detectable impacts on hours worked when considering the intensive and extensive margins.

For individuals ages 16 to 25 with less than a completed high school education, the hours worked effects we estimate for both small and indexed increases are both economically much smaller and statistically differentiable from our estimates for large increases. For all individuals ages 16 to 21, the magnitudes of the hours worked effects differ substantially, but are not as strongly statistically distinguishable across policy groups.

A key final point is that we obtain both qualitatively and quantitatively similar estimates whether we summarize estimates that incorporate pre-specified dimensions of refinement to our sets of specifications or whether we summarize estimates that forego such refinements. This can be seen by comparing the summaries of estimates in Table 3 to those in Table 4.

Section VII: Wage Effects and Implied Elasticities

What do our estimates imply for the elasticity of demand for labor with respect to changes in the minimum wage? Answering this question requires linking the hours worked effects from the previous section with estimated changes in wages. We estimate wage effects of

[11] Two facts lead us to view the differences we observe in our ACS and CPS analyses for states with small minimum wage increases as likely arising from sampling variations rather than differences in survey design. First, we see no differences when comparing ACS and CPS estimates for either the large or indexed minimum wage increases. Second, we observe no meaningful changes in our ACS estimates if we remove the institutionalized group-quarters population from the sample, which accounts for one of the primary differences between the ACS and CPS sampling universes.

recent minimum wage changes using the difference-in-differences models we used to estimate hours worked effects. We summarize these estimates in Tables A9 and A10. We then combine separately estimated hours worked and wage effects to obtain both "own-wage" elasticities and elasticities of hours worked with respect to the minimum wage.

On average across specifications, (see Table A9), we estimate that large minimum wage changes involved minimum wage increases averaging \$2.91, with corresponding estimates for states with small and inflation indexed minimum wage increases of \$1.90 and \$0.94, respectively.[12] With respect to the wages of individuals ages 16 to 25 with less than a completed high school education, workers in states with large minimum wage increases experienced wage increases averaging \$1.64. The corresponding numbers for states with small and inflation indexed minimum wage increases are \$0.92 and \$0.47, respectively. For individuals ages 16 to 21, the corresponding wage increases were of \$1.34, \$0.70, and \$0.33.

Table 5 and Table A11 summarize the key inputs for calculating own wage and minimum wage elasticities with respect to hours worked. We combine our estimated wage and hours worked impacts with the baseline means of each variable so that we can construct the relevant percent changes. We then compute the elasticities of interest as the percent change in hours worked divided by the percent change in the relevant wage. Estimates are, once again, quantitatively similar whether we summarize estimates in which we incorporate pre-specified dimensions of refinement to our sets of specifications or summarize estimates that forego such refinements.

We begin by presenting elasticities averaged across the wage and hours worked effects

[12] Recall that these averages across specifications blend specifications in which the "post" period averages across 2015 to 2019 and specifications in which the "post" period is restricted to 2019 only.

we estimate for the full set of states that increased their minimum wage rates during our sample period. The average elasticities we estimate (i.e., elasticities that do not distinguish between our "large," "small," and "indexer" groupings) are negative. As presented in Table 5, we estimate an own-wage elasticity of -0.12 for individuals ages 16 to 25 with less than a completed high school education and of -0.13 for the sample of all individuals ages 16 to 21. The associated elasticities with respect to the minimum wage are -0.05 and -0.04. These overall elasticity estimates are quite similar to our earlier work's estimated elasticities of employment with respect to the minimum wage. Additionally, they are comparable to employment elasticity estimates from meta-analyses by Neumark and Shirley's (2022) and by Wolfson and Belman (2019) as well as hours elasticities with respect to the minimum wage from Couch and Wittenburg (2001), Neumark *et al.* (2004), and Redmond and McGuinness (2025). The associated elasticities in Table A11 are qualitatively similar.

We next compare elasticities across policy regimes. We find that the elasticities vary dramatically when we compare large minimum wage increases with minimum wage increases that were small or that were forecastable due to their linkage to inflation indexing provisions. For large minimum wage changes, we estimate an own wage elasticity of -0.76 for individuals ages 16 to 25 with less than a completed high school education and of -0.31 for all individuals ages 16 to 21. For small minimum wage changes, we estimate an own-wage elasticity of 0.50 for individuals ages 16 to 25 with less than a completed high school education and of -0.03 for all individuals ages 16 to 21. For inflation-indexed minimum wage changes, we estimate an own-wage elasticity of 0.45 for individuals ages 16 to 25 with less than a completed high school education and of 0.22 for all individuals ages 16 to 21.

Elasticities of usual hours worked with respect to the minimum wage itself follow a quite similar pattern. We again observe larger negative elasticities in response to large minimum wage increases and quite modest and sometimes positive elasticities in response to small minimum wage increases and inflation-indexed minimum wage increases.

Appendix Tables A14, A15, and A16 present summaries of our sets of specifications that do not include time-varying covariates, as they may, in some circumstances, complicate the interpretation of difference-in-difference estimates (Caetano *et al.*, 2022). The resulting hours worked effects and elasticity estimates are similar to those in Tables 5 and A11.

In summary, while the overall elasticities we estimate fall within the consensus range in the literature, we detect economically important heterogeneity with respect to the size of states' minimum wage increases. For large minimum wage changes, we find elasticities that are near the high end or that are more negative than the consensus range, while for smaller minimum wage changes, we find elasticities either within the consensus range or that are more positive.

Section VIII: Results Using a Modern Event Study Difference-in-Differences Estimator

In this section, we present estimates from a modern difference-in-differences estimator that is well suited to our setting. On one level, this analysis can be interpreted as providing the reading of the evidence as we would have developed it if we were executing a fully flexible observational study. More specifically, we present evidence from the imputation difference-in-differences (DiD) estimator of Borusyak, Jaravel, and Spiess (2024), which involves an intuitive, multi-step procedure. First, state fixed effects, time effects, and coefficients on time-varying covariates are estimated on "untreated" observations. Second, the counterfactual outcome for each treated observation is "imputed" using the coefficients from the first step. Third, treatment effects are estimated by comparing and aggregating the realized and counterfactual outcomes for treated units. These treatment effects can be aggregated along a variety of dimensions of interest. In our case, the dimensions of interest include distinguishing across categories of treatment (e.g., "small" vs. "large" increases) and distinguishing between short- and longer-run effects, both of which are key components of our pre-committed analyses.

Within the imputation DiD framework, we provide evidence from two standard specification tests. First, we look to changes in hours worked among groups that are not directly impacted by minimum wages as a conventional falsification test (see Figures A4A, A4B, A5A, and A5B). Panel A reports estimates from a specification that includes no time varying covariates. The estimates reveal that hours worked among prime age adults trended more positively in states that enacted large minimum wage increases than in states that enacted no minimum wage increases, as was evident earlier in Table 2. The associated economic tailwinds would thus tend to bias downward the magnitudes of estimates that take no measures to control for macroeconomic conditions. Panel B incorporates the aggregate income and house price controls we include in a number of regressions from our pre-analysis plan, while panel C additionally incorporates the three-year lags of these variables as well as age and education fixed effects. Both of these specifications yield uniformly economic and statistical null estimates for both the small and large minimum wage increases, and thus pass this falsification check. Second, in analyses of our main samples we check for the presence of divergent pre-existing trends and find no evidence of such trends, as can be seen in Figures 4A and 4B and A3A and A3B.

Figures 4A and 4B report our imputation DiD estimates for the effects of small and large minimum wage changes on hours worked among individuals ages 16 to 21 and among individuals ages 16 to 25 with less than a completed high school education from the ACS and

CPS respectively.[13] As noted above, the estimates to the left of the vertical dashed lines reveal no evidence of concerning divergent pre-existing trends. With respect to subsequent hours worked effects, the evidence is consistent with the estimates obtained using our pre-analysis plan. We find null effects for the states that enacted small minimum wage increases and negative effects for states with large minimum wage increases. The negative estimates for states that enacted relatively large minimum wage increases begin at roughly -0.5 hours per week in the year following the enactment of a state's first minimum wage increase. By four or more years after the enactment of the first increase, the estimate has approached -2 hours worked for individuals ages 16 to 25 with less than a completed high school education from the ACS and -1 hours worked from the CPS and -1 hours worked for the sample of all individuals ages 16 to 21 from the ACS and CPS.

For comparison with estimates from Table 3, imputation DiD estimates can be constructed as simple difference-in-differences or triple-difference style averages (rather than being presented as full event study estimates). Averaging across estimates for the 2015-2019 period, the associated estimates for large minimum wage increases are on the order of -1 hour per week for individuals ages 16-25 with less than a completed high school education and -0.6 hours per week for individuals ages 16-21.

Section IX: Discussion and Conclusion

This paper builds on our earlier work (Clemens and Strain, 2017; 2018b; forthcoming) in presenting the completed results of a four-year, partially pre-committed analysis of minimum

[13] Because states with inflation-indexing regimes were implementing minimum wage increases from the onset of our sample, this and other event study analyses exclude states categorized as indexers in Figure 1 Panel A.

wage changes enacted during the 2010s. Whereas Clemens and Strain (forthcoming) presented completed results for estimated effects on employment, the present paper presents completed results for estimated effects on hours of work. As emphasized here and in our earlier work, our partially precommitted analysis plan differentiates between the effects of large and small minimum wage increases, as well as between their short- and longer-run effects. To our knowledge, these dimensions of our partially pre-committed analysis plan are methodologically novel with respect to their focus on using pre-committed dimensions of heterogeneity to examine the predictions of economic models in an analysis of non-experimental data.

During the time period we study, we estimate that relatively large minimum wage increases had substantial, negative effects on usual weekly hours worked among individuals with low levels of experience and education. By contrast, our estimates of the effects of relatively small minimum wage increases are centered on zero. The implied elasticities are similar to the elasticities we obtained in our earlier analysis of employment. Relative to existing research on the employment effects of minimum wages, these estimates imply elasticities that are near the high end or larger than the consensus range in response to large minimum wage increases. Our estimates are either within the consensus range or more positive than the consensus range in response to small minimum wage increases.

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Figures and Tables

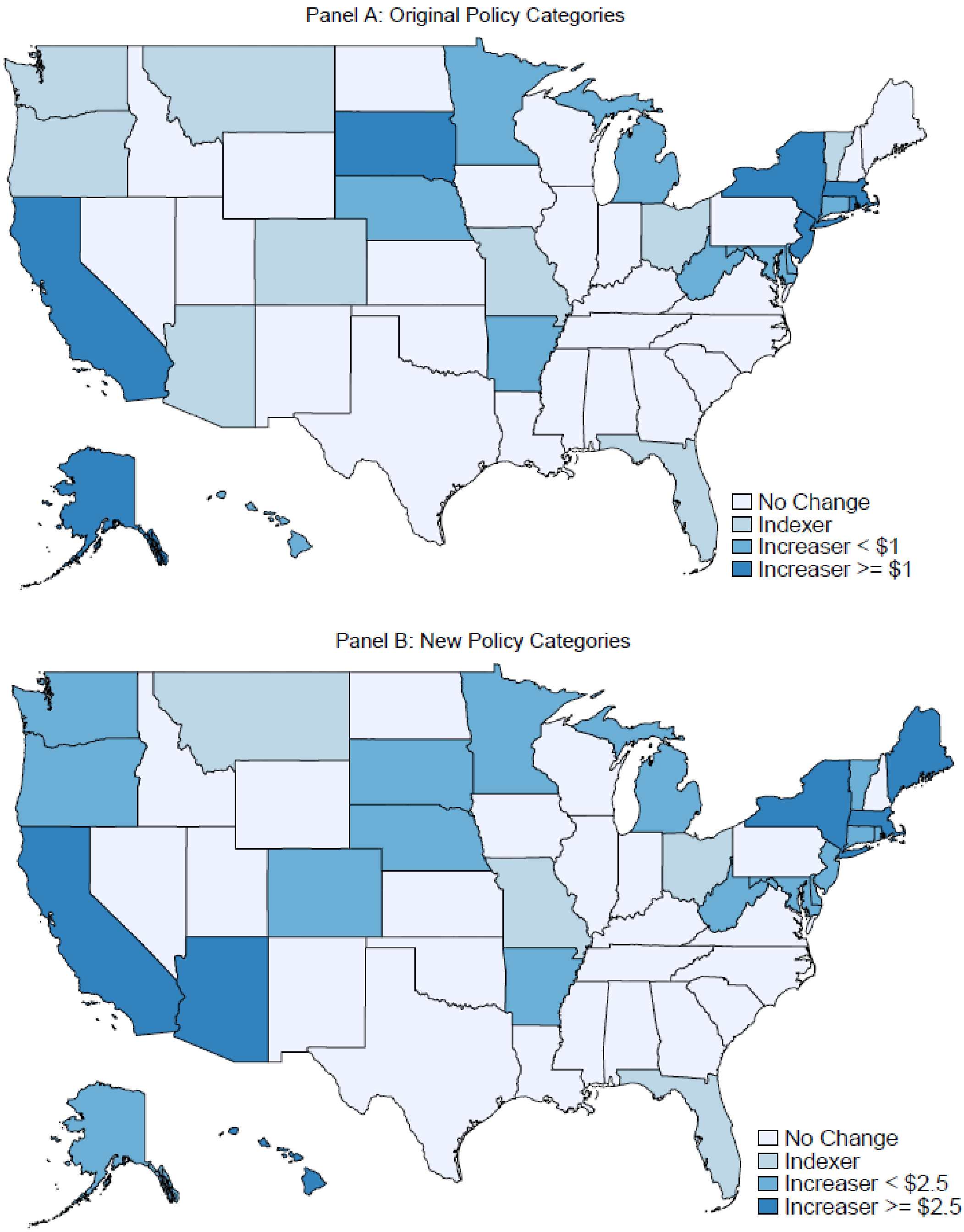

Figure 1. States in Original and New Minimum Wage Policy Categories: Panel A displays the states in our original policy categories defined using minimum wage changes between 2013 and 2015. Panel B displays the states in our new policy categories defined using indexed and statutory minimum wage increases between January 2013 and January 2018. Indexers are states that index their minimum wage to inflation. Data on minimum wage indexing provisions come from the National Council of State Legislatures. Data on minimum wage changes come from the U.S. Department of Labor.

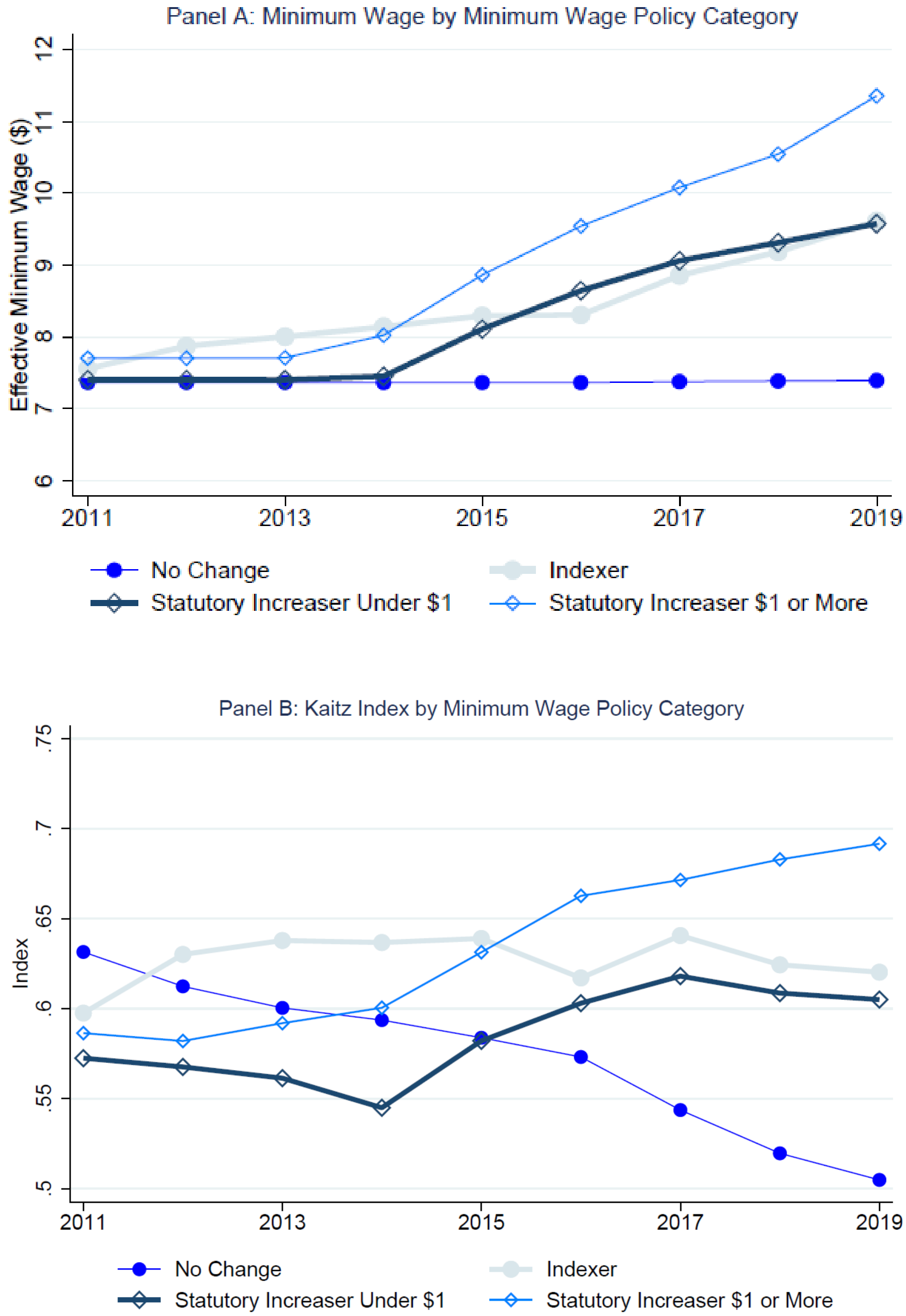

Figure 2. Average Minimum Wage and Kaitz Index Across Policy Categories: Panel A plots the average annual effective minimum wage for states in each of our four policy categories from January 2011 to January 2019. Panel B plots the average Kaitz index for states in each of our four policy categories from January 2011 to January 2019. We calculate median hourly wages from the CPS ORG using all employed individuals ages 16 and over who do not have imputed wage rates. For individuals paid by the hour, we use the reported hourly wage. For individuals not paid by the hour, we calculate an hourly wage using their reported weekly earnings divided by their reported usual hours worked per week. States are defined as statutory increasers under $1 if the combined statutory increase in their minimum wage between January 2013 and January 2015 was under $1. States are defined as statutory increasers of $1 or more if the combined statutory increase in their minimum wage was $1 or greater. Indexers are states that index their minimum wage to inflation. The effective minimum wage is defined as the maximum of the state and federal minimum wage. Data on minimum wage rates come from the U.S. Department of Labor. Data on minimum wage policies come from the National Conference of State Legislatures. Averages are weighted by population.

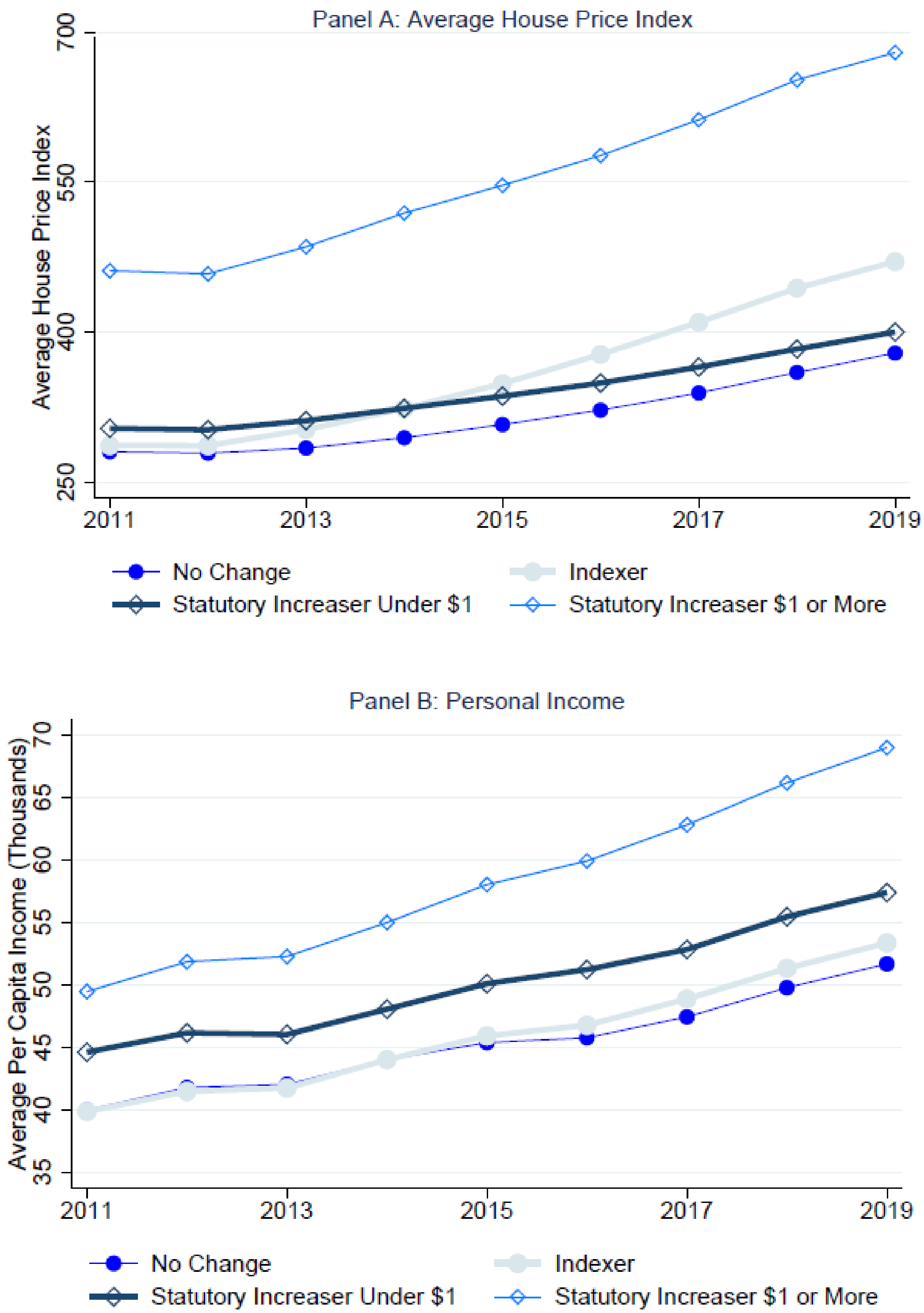

Figure 3. Macroeconomic Time Series Across Policy Categories: Panel A plots the average housing price index variable for each of our four policy categories from 2011 to 2019. Housing price index data come from the Federal Housing Finance Agency. Panel B plots average per capita income for each of our four policy categories from 2011 to 2019. Data on average per capita income come from the Bureau of Economic Analysis. States are defined as statutory increasers under $1 if the combined statutory increase in their minimum wage between January 2013 and January 2015 was under $1. States are defined as statutory increasers of $1 or more if the combined statutory increase in their minimum wage was $1 or greater. Indexers are states that index their minimum wage to inflation. Averages are weighted by population

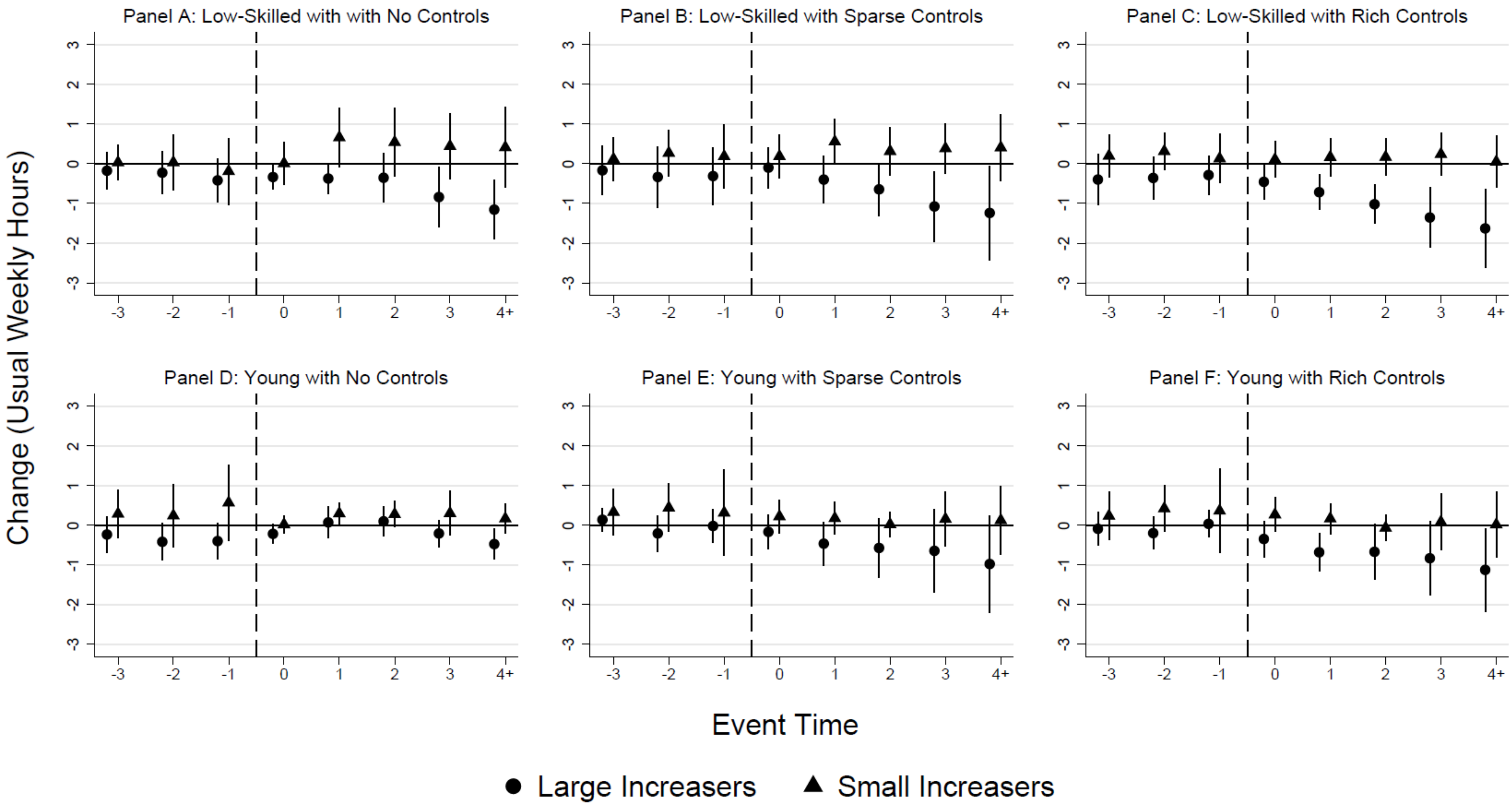

Figure 4A. Event Studies of Changes in Usual Weekly Hours Worked in the ACS Following Large and Small Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code the first treatment year as the year in which a state's first statutory minimum wage increase took effect. We compare estimates for large vs. small increases as defined in the main text. Panels A, B, and C plot coefficients for low-skilled individuals defined as individuals ages 16–25 without a completed high school education. Panels D, E, and F plot coefficients for young individuals defined as all individuals ages 16–21. The samples are from the ACS. Regressions with "no controls" include state and year fixed effects. Regressions with "sparse controls" include state and year fixed effects, as well as the log of annual average state per capita income and the annual average state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log annual average per capita income and the state annual average house price index house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

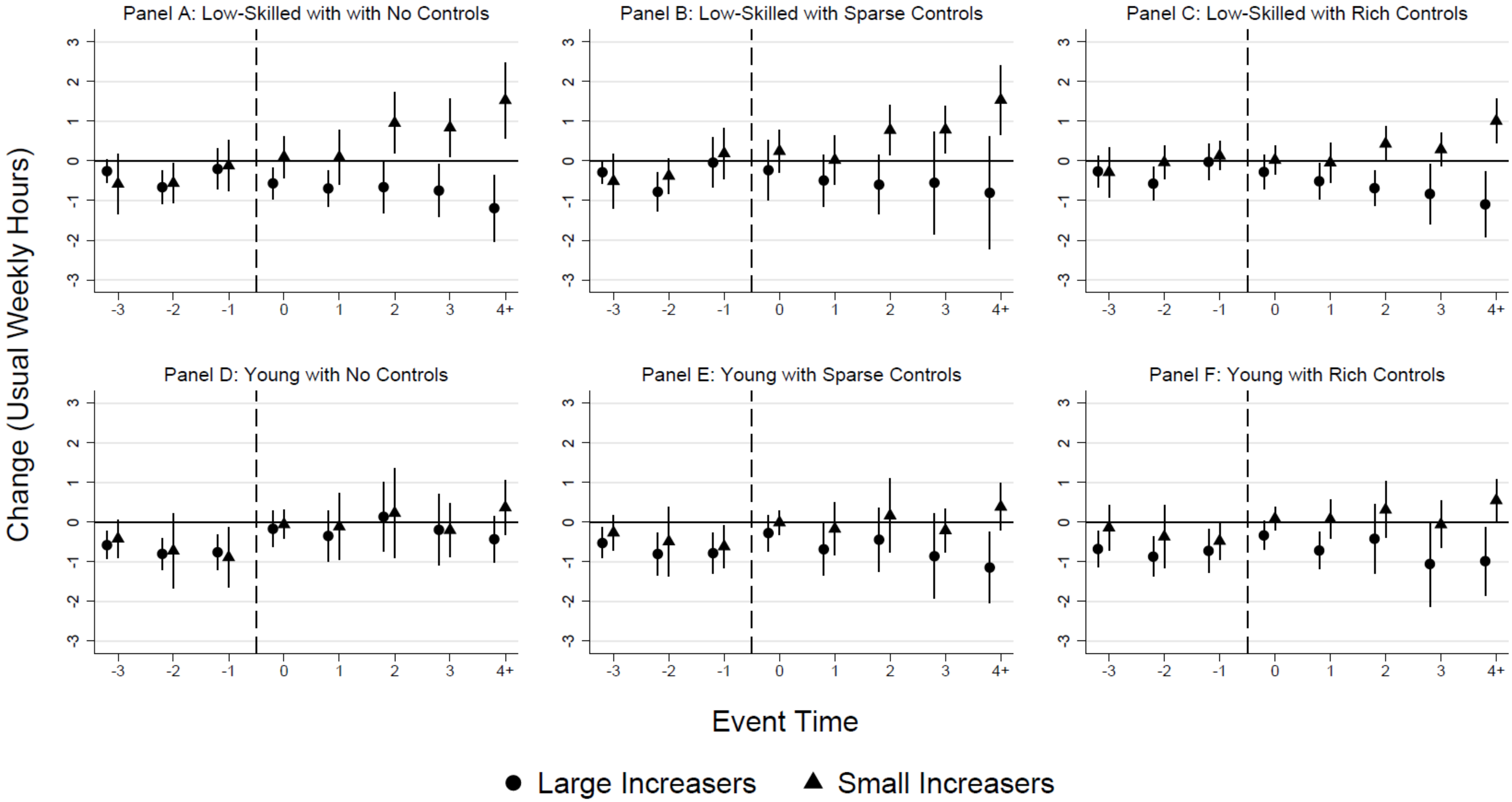

Figure 4B. Event Studies of Changes in Usual Weekly Hours Worked in the CPS Following Large and Small Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code the first treatment year as the year in which a state's first statutory minimum wage increase took effect. We compare estimates for large vs. small increases as defined in the main text. Panels A, B, and C plot coefficients for low-skilled individuals defined as individuals ages 16–25 without a completed high school education. Panels D, E, and F plot coefficients for young individuals defined as all individuals ages 16–21. The samples are from the CPS. Regressions with "no controls" include state and year-month fixed effects. Regressions with "sparse controls" include state and year-month fixed effects, as well as the log of quarterly state per capita income and the quarterly state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log annual average per capita income and the state annual average house price index house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

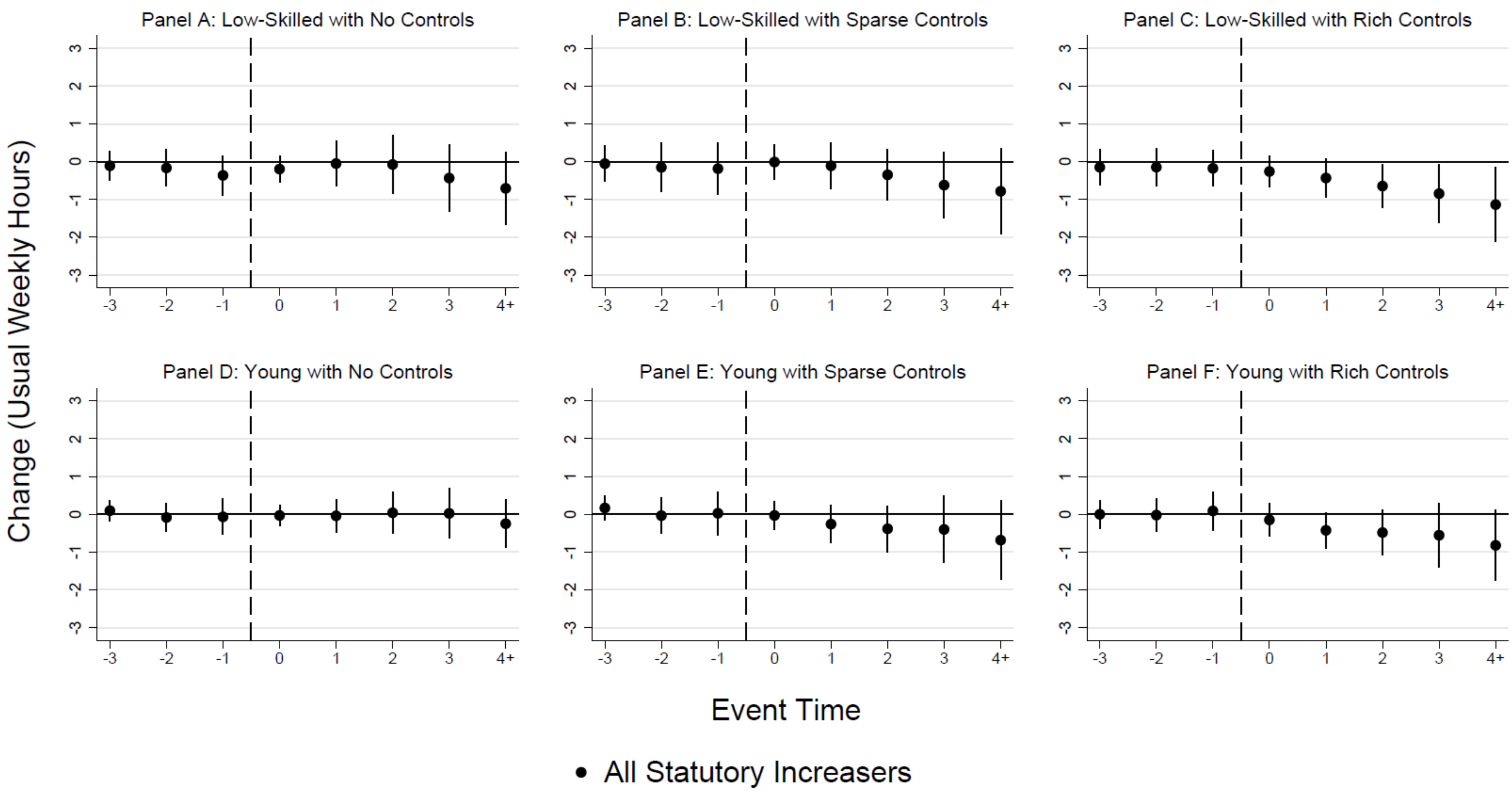

Figure B6A. Event Studies of Changes in Usual Weekly Hours Worked in the ACS Following Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code the first treatment year as the year in which a state's first statutory minimum wage increase took effect. Panels A, B, and C plot coefficients for low-skilled individuals defined as individuals ages 16–25 without a completed high school education. Panels D, E, and F plot coefficients for young individuals defined as all individuals ages 16–21. The samples are from the ACS. Regressions with "no controls" include state and year fixed effects. Regressions with "sparse controls" include state and year fixed effects, as well as the log of annual average state per capita income and the annual average state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log per capita income and the house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

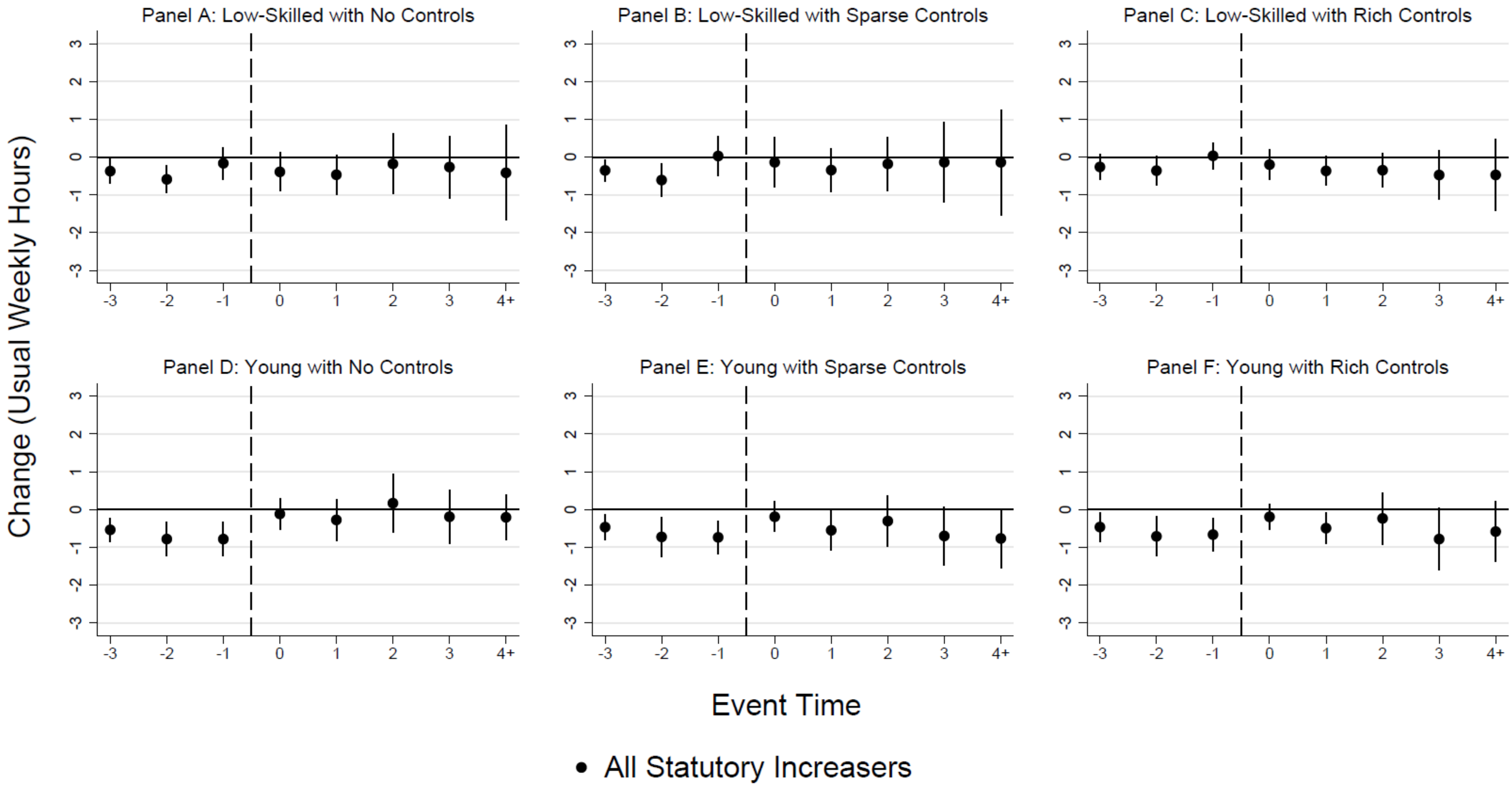

Figure B6B. Event Studies of Changes in Usual Weekly Hours Worked in the CPS Following Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code the first treatment year as the year in which a state's first statutory minimum wage increase took effect. Panels A, B, and C plot coefficients for low-skilled individuals defined as individuals ages 16–25 without a completed high school education. Panels D, E, and F plot coefficients for young individuals defined as all individuals ages 16–21. The samples are from the CPS. Regressions with "no controls" include state and year-month fixed effects. Regressions with "sparse controls" include state and year-month fixed effects, as well as the log of quarterly state per capita income and the quarterly state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log per capita income and the house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

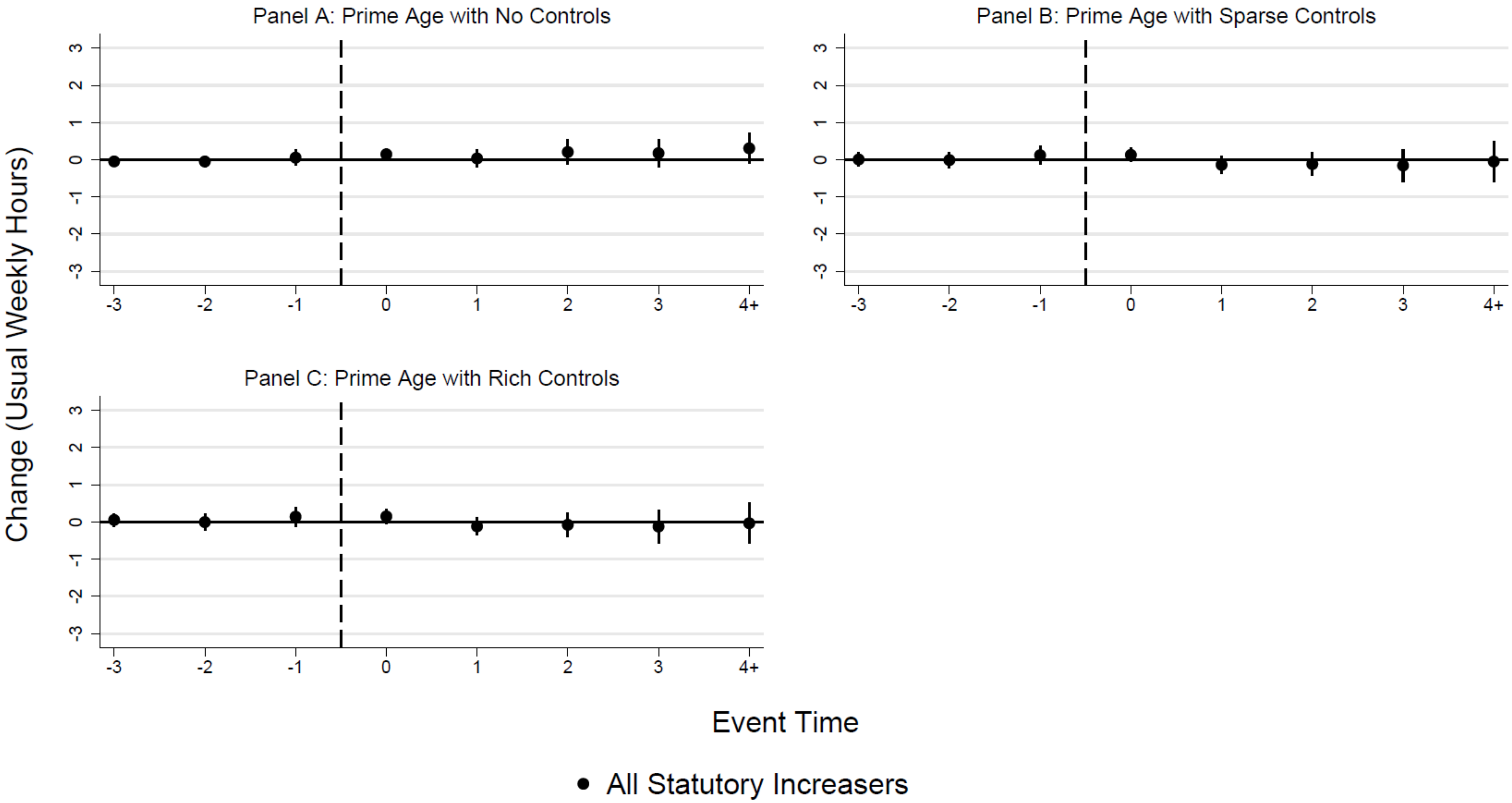

Figure B10A. Event Studies of Changes in Prime Age Usual Weekly Hours Worked From the ACS Following Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code first treatment year as the year in which a state's first statutory minimum wage increase took effect. Panels A, B, and C plot coefficients for prime age individuals defined as individuals ages 26–54. The samples are from the ACS. Regressions with "no controls" include only state and year fixed effects and no time-varying covariates. Regressions with "sparse controls" include state and year fixed effects, as well as the log of annual average state per capita income and the annual average state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log annual average per capita income and the state annual average house price index house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

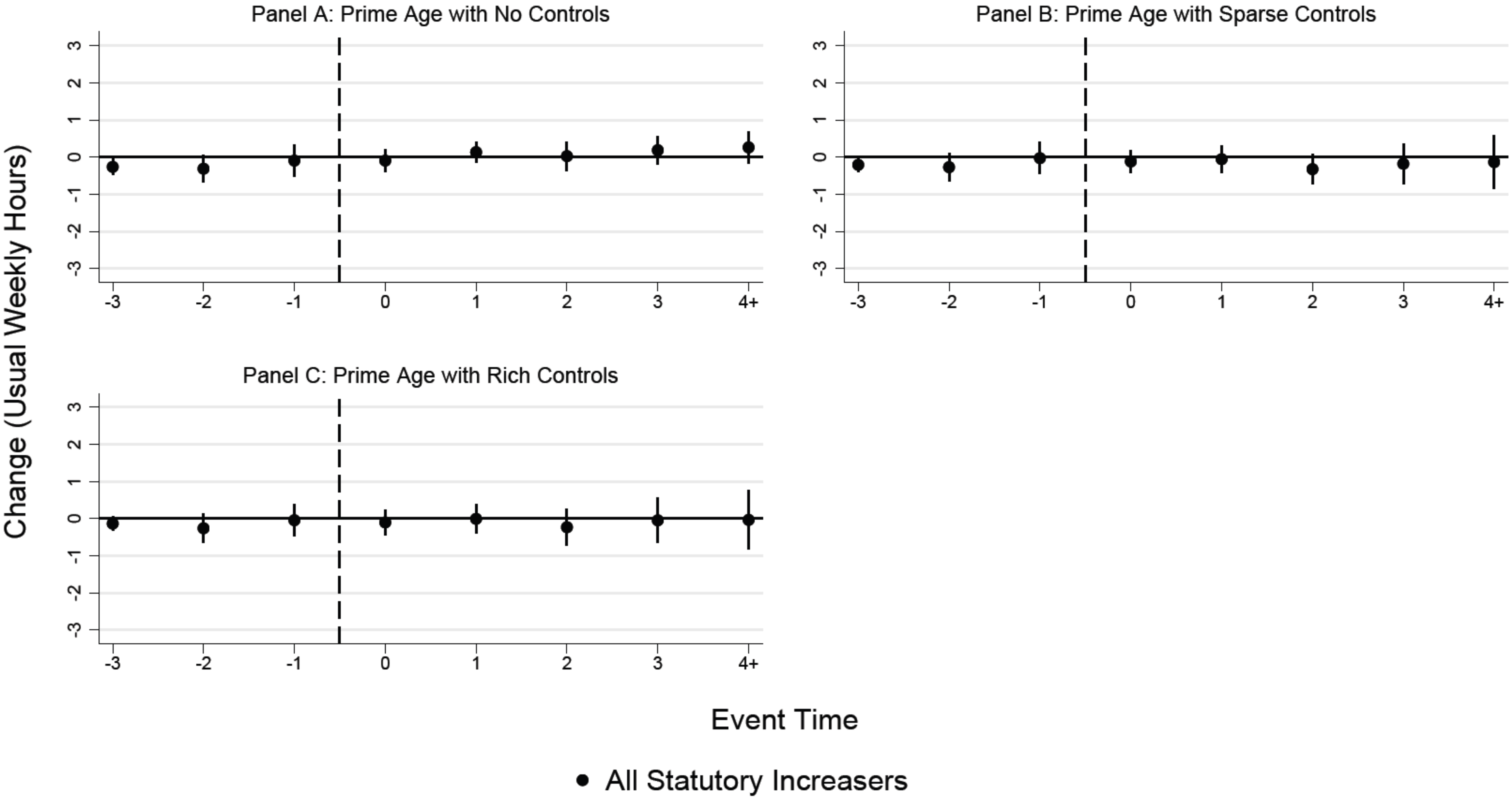

Figure B10B. Event Studies of Changes in Prime Age Usual Weekly Hours Worked From the CPS Following Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code first treatment year as the year in which a state's first statutory minimum wage increase took effect. Panels A, B, and C plot coefficients for prime age individuals defined as individuals ages 26–54. The samples are from the CPS. Regressions with "no controls" include only state and year-month fixed effects and no time-varying covariates. Regressions with "sparse controls" include state and year fixed effects, as well as the log of quarterly average state per capita income and the quarterly state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log annual state per capita income and the state annual average house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

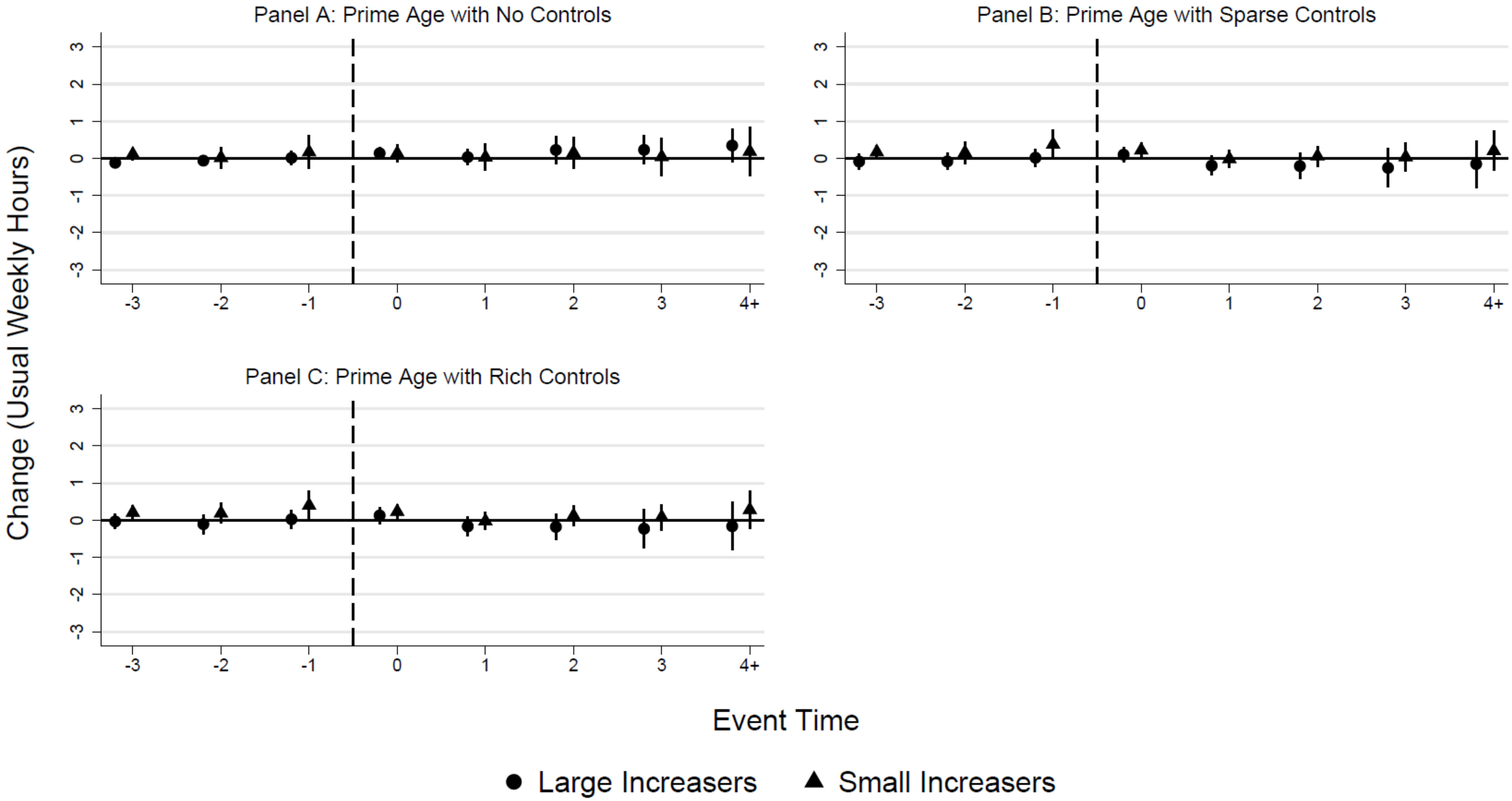

Figure B11A. Event Studies of Changes in Prime Age Usual Hours Weekly Worked From the ACS Following Large and Small Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code first treatment year as the year in which a state's first statutory minimum wage increase took effect. We compare estimates for large vs. small increases as defined in the main text. Panels A, B, and C plot coefficients for prime age individuals defined as individuals ages 26–54. The samples are from the ACS. Regressions with "no controls" include only state and year fixed effects and no time-varying covariates. Regressions with "sparse controls" include state and year fixed effects, as well as the log of annual average state per capita income and the annual average state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log annual state per capita income and the house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

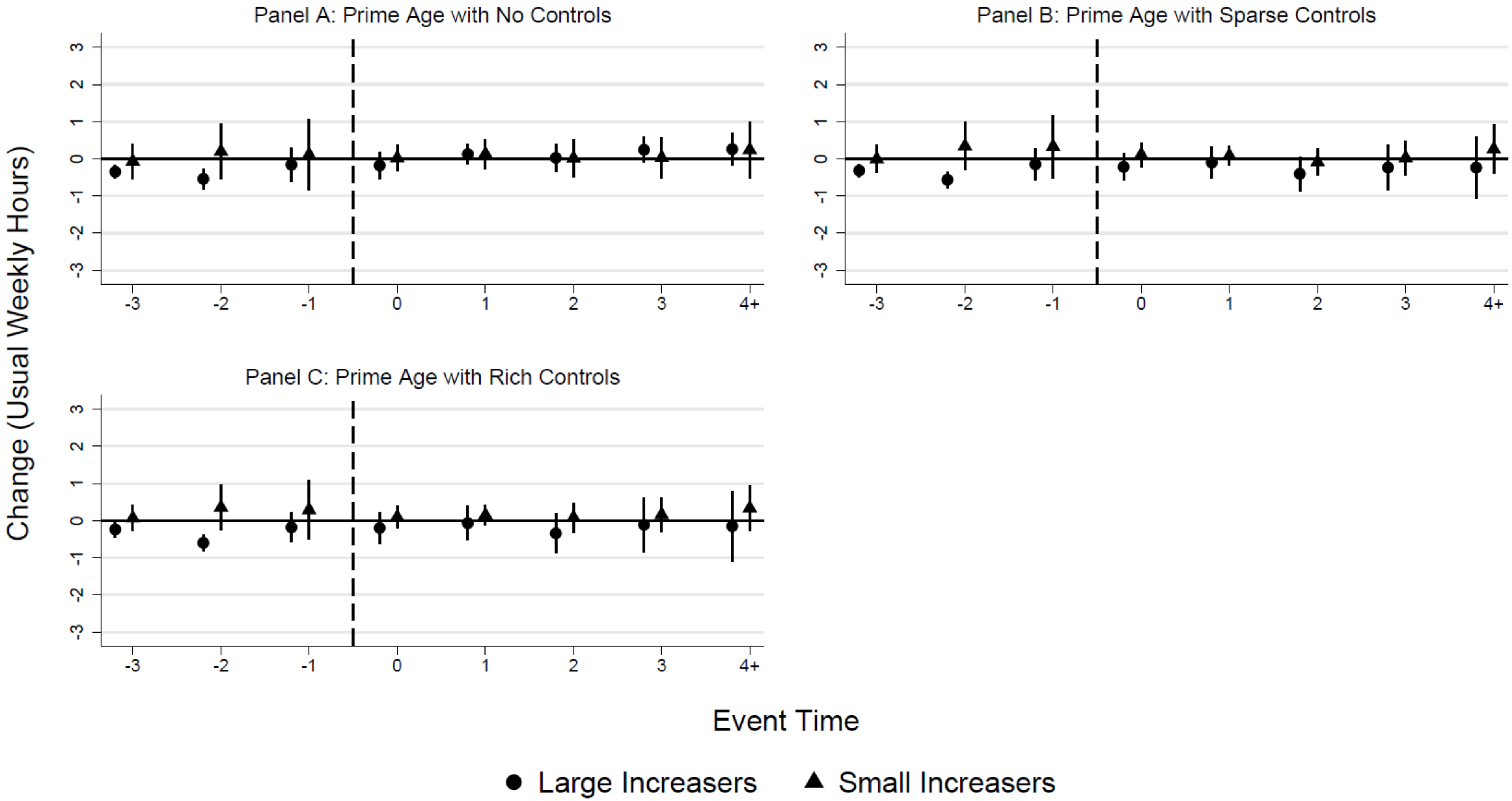

Figure B11B. Event Studies of Changes in Prime Age Usual Weekly Hours Worked From the CPS Following Large and Small Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code first treatment year as the year in which a state's first statutory minimum wage increase took effect. We compare estimates for large vs. small increases as defined in the main text. Panels A, B, and C plot coefficients for prime age individuals defined as individuals ages 26–54. The samples are from the CPS. Regressions with "no controls" include only state and year-month fixed effects and no time-varying covariates. Regressions with "sparse controls" include state and year-month fixed effects, as well as the log of quarterly state per capita income and the quarterly state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log annual state per capita income and the annual average house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

Table 1. Sample Summary Statistics Usual Hours Worked: ACS Data for 2011-2013 and 2015-2019

	(1)	(2)	(3)	(4)
Years	2011-2013	2015-2019	2011-2013	2015-2019
Skill Groups	Ages 16 to 25 w/ < High School		Ages 16 to 21	
Usual Hours Worked	8.017	8.474	13.67	14.96
	(14.09)	(13.89)	(16.22)	(16.55)
Age	17.90	17.63	18.58	18.54
	(2.444)	(2.253)	(1.704)	(1.703)
Black	0.166	0.155	0.153	0.147
	(0.372)	(0.362)	(0.360)	(0.354)
High School Degree	0	0	0.343	0.358
	(0)	(0)	(0.475)	(0.479)
Some College Education	0	0	0.247	0.242
	(0)	(0)	(0.431)	(0.428)
House Price Index	325.9	413.3	330.4	419.8
	(99.86)	(133.1)	(101.6)	(135.9)
Income Per Capita ($1000s)	43.81	51.82	44.04	52.24
	(6.270)	(8.524)	(6.364)	(8.665)
Effective Minimum Wage ($)	7.531	8.398	7.536	8.450
	(0.422)	(1.341)	(0.424)	(1.371)
Observations	346,135	519,374	774,438	1,235,967

Notes: This table reports summary statistics for our two sample groups. Columns 1 and 2 report averages and standard errors (in parenthesis) of each of the variables for our subsample of low-skilled individuals, defined as individuals ages 16 to 25 with less than a high school education. Columns 3 and 4 report averages and standard errors (in parenthesis) for our subsample of young adult individuals, defined as individuals ages 16 to 21. Entries for usual weekly hours worked, age, race, and education summarize data from the American Community Survey (ACS). The house price index variable uses data from the Federal Housing Finance Agency (FHFA). The income per capita variable uses data from the Bureau of Economic Analysis (BEA). The effective minimum wage variable uses data from the Bureau of Labor Statistics (BLS).

Table 2. Unadjusted Differences in Usual Weekly Hours Worked Across Policy Regimes Using ACS Data and $1 Cutoff

	(1)	(2)	(3)	(4)
	2011-2013	2019	Change	Change Relative to Non-Increasers
Young Adult Hours Worked				
Non-Increasers	14.38	16.11	1.74	
Indexers	13.95	15.95	2.00	0.26
Increase < $1	14.86	16.20	1.34	-0.40
Increase >= $1	11.64	12.90	1.25	-0.48
Low-Skilled Hours Worked				
Non-Increasers	8.62	9.36	0.74	
Indexers	7.84	9.26	1.42	0.68
Increase < $1	8.16	8.87	0.71	-0.03
Increase >= $1	6.90	6.54	-0.36	-1.10
Prime Age Hours Worked				
Non-Increasers	33.07	34.31	1.24	
Indexers	32.42	34.06	1.64	0.40
Increase < $1	33.44	34.66	1.22	-0.02
Increase >= $1	32.17	33.76	1.59	0.35
Prime Age Employment				
Non-Increasers	0.751	0.791	0.040	
Indexers	0.746	0.797	0.051	0.011
Increase < $1	0.768	0.812	0.044	0.004
Increase >= $1	0.748	0.802	0.054	0.014
House Price Index				
Non-Increasers	279.8	377.3	97.5	
Indexers	291.1	466.6	175.5	
Increase < $1	303.6	397.1	93.5	78.0
Increase >= $1	465.6	679.2	213.6	-4.0
Income per Capita ($1000s)				116.1
Non-Increasers	41.21	51.50	10.29	
Indexers	40.96	53.10	12.14	1.85
Increase < $1	45.44	57.23	11.79	1.50
Increase >= $1	51.04	68.86	17.82	7.53

Notes: This table reports usual weekly hours worked for each our of our four policy groups (non-increasers, indexers, increase < $1, and increase >= $1) broken out across three types of individuals: young adults, low-skilled, and prime age. Young adults are defined as individuals ages 16 to 21. Low-skilled adults are those ages 16 to 25 without a completed high school education. Prime age adults are defined as individuals between the ages of 26 and 54. This table also reports mean values of economic control variables (house price index and income per capita) for each of our four policy groups calculated using our sample of young adults. The income per capita variable uses BEA data, and the house price index variable uses FHFA data. Column 1 reports the average value between 2011 and 2013 for each row, column 2 reports the average value in 2019, and column 3 reports the difference between the two. Column 4 reports the change in the average value for each row relative to the relevant non-increaser value. Averages are weighted by state population.

Table 3. Summary of Usual Weekly Hours Worked Regression Results

Panel A: Low-Skilled Workers	(1)	(2)	(3)	(4)
Sample	All	All	All	All
Policy Group	All Change	Large	Small	Indexer
$1 Cutoff; Post Period 2015-2019	-0.01	-0.77	0.43	0.30
	[-0.42,0.38]	[-1.17,-0.09]	[-0.29,0.95]	[-0.13,0.69]
$1 Cutoff; Post Period 2015	0.06	-0.38	0.09	0.48
	[-0.30,0.43]	[-0.66,0.28]	[-0.66,0.64]	[0.05,0.80]
$1 Cutoff; Post Period 2019	-0.12	-1.16	0.58	0.20
	[-0.66,0.38]	[-1.82,-0.40]	[-0.49,1.35]	[-0.33,0.65]
$1 Cutoff; No Switchers; Post Period 2015-2019	-0.03	-0.76	0.43	0.24
	[-0.48,0.40]	[-1.18,-0.09]	[-0.36,0.94]	[-0.18,0.67]
$1 Cutoff; No Switchers; Post Period 2019	-0.15	-1.16	0.59	0.13
	[-0.73,0.33]	[-1.82,-0.46]	[-0.57,1.31]	[-0.42,0.64]
$2.5 Cutoff; Post Period 2019	-0.18	-0.84	0.18	0.11
	[-0.76,0.38]	[-1.61,0.24]	[-0.79,0.94]	[-0.44,0.56]
Overall Average Effects	-0.10	-0.94	0.44	0.19
	[-0.65,0.37]	[-1.69,-0.06]	[-0.59,1.23]	[-0.31,0.66]
Panel B: Young Workers	(1)	(2)	(3)	(4)
Sample	All	All	All	All
Policy Group	All Change	Large	Small	Indexer
$1 Cutoff; Post Period 2015-2019	-0.07	-0.42	-0.03	0.25
	[-0.49,0.19]	[-1.08,-0.00]	[-0.71,0.43]	[-0.12,0.54]
$1 Cutoff; Post Period 2015	-0.08	-0.26	-0.16	0.19
	[-0.50,0.26]	[-0.82,0.31]	[-0.85,0.40]	[-0.19,0.52]
$1 Cutoff; Post Period 2019	-0.15	-0.66	0.05	0.17
	[-0.65,0.15]	[-1.37,-0.33]	[-0.64,0.55]	[-0.34,0.48]
$1 Cutoff; No Switchers; Post Period 2015-2019	-0.13	-0.44	-0.03	0.08
	[-0.50,0.14]	[-1.02,-0.02]	[-0.64,0.46]	[-0.25,0.48]
$1 Cutoff; No Switchers; Post Period 2019	-0.23	-0.71	0.05	-0.02
	[-0.65,0.10]	[-1.45,-0.32]	[-0.57,0.57]	[-0.37,0.90]
$2.5 Cutoff; Post Period 2019	-0.14	-0.33	-0.18	0.08
	[-0.64,0.23]	[-0.79,0.27]	[-0.89,0.30]	[-0.34,0.68]
Overall Average Effects	-0.14	-0.51	-0.03	0.11
	[-0.61,0.18]	[-1.23,0.03]	[-0.72,0.51]	[-0.33,0.55]

Notes: This table presents averages across estimates from the regression analyses in our pre-analysis plan. The underlying estimates are estimates of β (g(s)) from either equation (1) or equation (2). They are thus estimates of the change in usual weekly hours worked among individuals in our analysis samples from states that increased their minimum wages relative to individuals in states that did not increase their minimum wages. The numbers in brackets below each average are the lower and upper bound of the 95 percent confidence interval generated by bootstrapping the estimated average. The key dimensions along which we average the estimates (e.g., contrasting time periods, contrasting the "Low-Skill" and "Young" samples, or contrasting the effects of "Large" increases, "Small" increases, and the inflation-indexed minimum wage changes enacted by the "Indexer" group) are clearly labeled in the body of the table. The grouping of states we describe as "$1 Cutoff" corresponds with the grouping in Panel A of Figure 1, which is the grouping from our original pre-analysis plan. The grouping of states we describe as "$2.5 Cutoff" corresponds with the grouping in Panel B of Figure 1 which reflects minimum wage changes enacted after we developed our pre-analysis plan. (Note that the inclusion of estimates involving updated groupings was, itself, specified in our pre-analysis plan.) The "$1 Cutoff Post Period 2015" results were not part of the pre-analysis plan and are thus not included in the "Overall Average Effects" calculations. Panel A includes individuals 16 to 25 with less than a completed high school education and Panel B includes all individuals ages 16 to 21.

Table 4. Summary of Usual Weekly Hours Worked Regression Results Using Specifications from Clemens and Strain (2017)

Panel A: Low-Skilled Workers	(1)	(2)	(3)	(4)
Sample	All	All	All	All
Policy Group	All Change	Large	Small	Indexer
Original Categories				
Post Period 2015-2019	0.05	-0.64	0.46	0.33
	[-0.40,0.46]	[-1.10,-0.01]	[-0.27,1.01]	[-0.16,0.76]
Post Period 2015	0.08	-0.34	0.10	0.48
	[-0.31,0.43]	[-0.65,0.31]	[-0.64,0.67]	[0.05,0.80]
Post Period 2019	-0.06	-1.03	0.63	0.21
	[-0.68,0.48]	[-1.82,-0.22]	[-0.43,1.41]	[-0.40,0.68]
Overall Average Effects	-0.01	-0.83	0.55	0.27
	[-0.60,0.46]	[-1.68,-0.07]	[-0.33,1.30]	[-0.33,0.73]
Panel B: Young Workers	(1)	(2)	(3)	(4)
Sample	All	All	All	All
Policy Group	All Change	Large	Small	Indexer
Original Categories				
Post Period 2015-2019	-0.06	-0.38	-0.01	0.22
	[-0.48,0.22]	[-1.03,0.03]	[-0.67,0.47]	[-0.16,0.56]
Post Period 2015	-0.11	-0.31	-0.16	0.14
	[-0.52,0.25]	[-0.81,0.34]	[-0.82,0.39]	[-0.26,0.47]
Post Period 2019	-0.16	-0.67	0.09	0.09
	[-0.65,0.14]	[-1.36,-0.31]	[-0.60,0.55]	[-0.47,0.43]
Overall Average Effects	-0.11	-0.52	0.04	0.15
	[-0.63,0.18]	[-1.24,-0.02]	[-0.67,0.54]	[-0.40,0.52]

Notes: This table presents averages across estimates from the regression analyses in our pre-analysis plan. The underlying estimates are calculated from regression equation (3) from Clemens and Strain (2017). They are thus estimates of the change in usual weekly hours worked among individuals in our analysis samples from states that increased their minimum wages relative to individuals in states that did not increase their minimum wages. They are thus estimates of the change in the employment rate among individuals in our analysis samples from states that increased their minimum wages relative to individuals in states that did not increase their minimum wages. The numbers in brackets below each average are the lower and upper bound of the 95 percent confidence interval generated by bootstrapping the estimated average. The key dimensions along which we average the estimates (e.g., contrasting time periods, contrasting the "Low-Skilled" and "Young" samples, or contrasting the effects of "Large" increases, "Small" increases, and the inflation-indexed minimum wage changes enacted by the "Indexer" group) are clearly labeled in the body of the table. The grouping of states we describe as "Original" corresponds with the grouping in Panel A of Figure 1, which is the grouping from our original pre-analysis plan. The "Post Period 2015" results were not part of the pre-analysis plan and are thus not included in the "Overall Average Effects" calculations. Panel A includes individuals 16 to 25 with less than a completed high school education and Panel B includes all individuals ages 16 to 21.

Table 5. Summary of Elasticities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Group	Low-Skilled	Low-Skilled	Low-Skilled	Low-Skilled	Young	Young	Young	Young
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
Panel A: Usual Weekly Hours Worked								
Overall Average Effects	-0.10	-0.94	0.44	0.19	-0.14	-0.51	-0.03	0.11
Mean in 2011-2013 Baseline	7.49	6.90	8.16	7.84	13.10	11.64	14.86	13.95
Change from Baseline (%)	-1.33	-13.57	5.45	2.47	-1.09	-4.39	-0.20	0.79
Panel B: Minimum Wages								
Overall Average Effects	1.92	2.91	1.90	0.94	1.92	2.92	1.91	0.94
Mean in 2011-2013 Baseline	7.69	7.72	7.41	7.80	7.68	7.71	7.41	7.81
Change from Baseline (%)	24.93	37.71	25.63	12.06	25.00	37.80	25.81	11.98
Panel C: Hourly Wages								
Overall Average Effects	1.01	1.64	0.92	0.47	0.79	1.34	0.70	0.33
Mean in 2011-2013 Baseline	8.77	9.19	8.45	8.55	9.20	9.54	8.96	8.98
Change from Baseline (%)	11.51	17.85	10.90	5.45	8.57	14.05	7.78	3.64
Elasticity of Hourly Wage w.r.t Minimum Wage	0.46	0.47	0.43	0.45	0.34	0.37	0.30	0.30
Panel D Elasticities								
Own Wage	-0.12	-0.76	0.50	0.45	-0.13	-0.31	-0.03	0.22
	[-0.94,0.42]	[-1.67,-0.05]	[-0.95,1.35]	[-2.66,5.42]	[-0.73,0.16]	[-1.38,0.02]	[-0.98,0.50]	[-2.02,1.72]
Minimum Wage	-0.05	-0.36	0.21	0.20	-0.04	-0.12	-0.01	0.07
	[-0.34,0.22]	[-0.70,-0.02]	[-0.27,0.64]	[-0.42,0.91]	[-0.19,0.06]	[-0.36,0.01]	[-0.19,0.14]	[-0.23,0.38]

Notes: This table reports average usual weekly hours and wage effects for each minimum wage policy group and skill group along with own-wage and minimum wage elasticities. The numbers in brackets below each elasticity are the lower and upper bound of the 95 percent confidence interval generated by bootstrapping the estimated elasticity. The baseline mean for the usual weekly hours panel comes from the ACS and the overall average effects on usual weekly hours are calculated from regression estimates on data from the ACS and CPS. The baseline mean and estimated overall average effects on hourly wages come from the basic monthly CPS. The baseline mean and estimated overall average effects on hourly wages come from the CPS ORG. Averages in the "mean in 2011-2013 baseline" rows are calculated using our original policy categories, while those in the "overall average effects rows" use results generated on both the original and new policy categories. Low-Skilled individuals are ages 16 to 25 with less than a completed high school education and young individuals are ages 16 to 21. Average effects for usual weekly hours (panel A), minimum wages (panel B), and hourly wages (panel C) are taken from Tables 3 and A9. The hourly wage elasticity with respect to the minimum wage is the percentage change in average hourly wages from the baseline period of 2011-2013 divided by the percentage change in minimum wages from 2011-2013. The own-wage elasticity for each policy-skill group is the estimated usual weekly hours effect divided by the percentage change in average hourly wages from the baseline period of 2011-2013 and the minimum wage elasticity is the estimated usual weekly hours effect divided by the percentage change in the minimum wage from 2011-2013.

Online Appendix A: Additional Tables and Figures

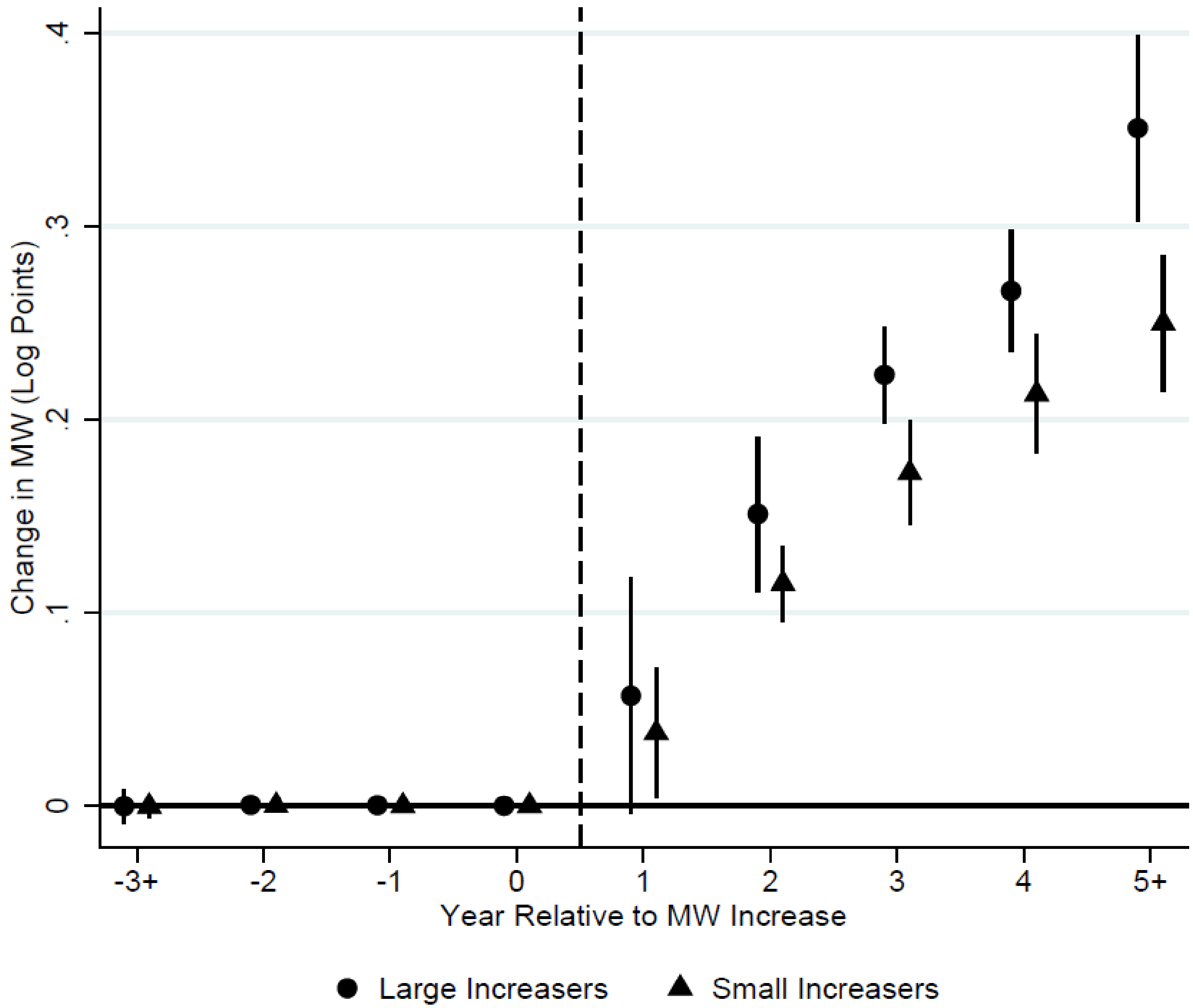

Figure A1. Changes in State Effective Minimum Wage Following Initial Statutory Minimum Wage Increases: This figure displays coefficients from the "stacked event study" estimator described by equation (5). The dependent variable is the log of the minimum wage. Event Time is defined such that year "1" corresponds with the year during which a given state enacted its first minimum wage change due to legislation passed during our sample period. We compare estimates for large vs. small increasers as defined in Panel A of Figure 1. Regressions include state and year fixed effects. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

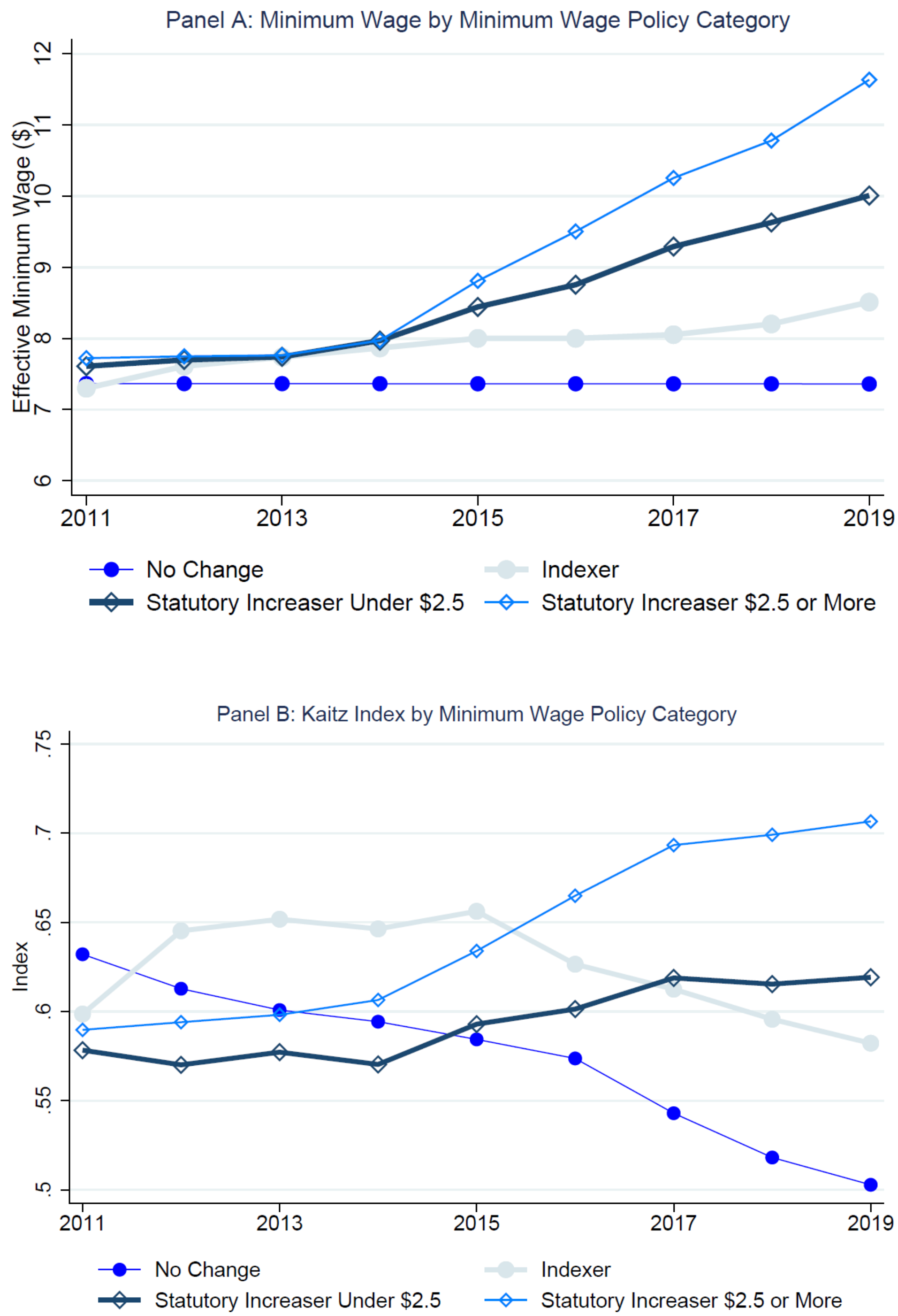

Figure A2. Average Minimum Wage and Kaitz Index Across New Policy Categories: Panel A plots the average annual effective minimum wage for states in each of our four policy categories from January 2011 to January 2019. Panel B plots the average Kaitz index for states in each of our four policy categories from January 2011 to January 2019. We calculate median hourly wages from the CPS ORG using all employed individuals ages 16 and over who do not have imputed wage rates. For individuals paid by the hour, we use the reported hourly wage. For individuals not paid by the hour, we calculate an hourly wage using their reported weekly earnings divided by their reported usual hours worked per week. States are defined as statutory increasers under $2.5 if the combined statutory increase in their minimum wage between January 2013 and January 2018 was under $2.5. States are defined as statutory increasers of $2.5 or more if the combined statutory increase in their minimum wage was $2.5 or greater. Indexers are states that index their minimum wage to inflation. The effective minimum wage is defined as the maximum of the state and federal minimum wage. Data on minimum wage rates come from the U.S. Department of Labor. Data on minimum wage policies come from the National Conference of State Legislatures. Averages are weighted by state population.

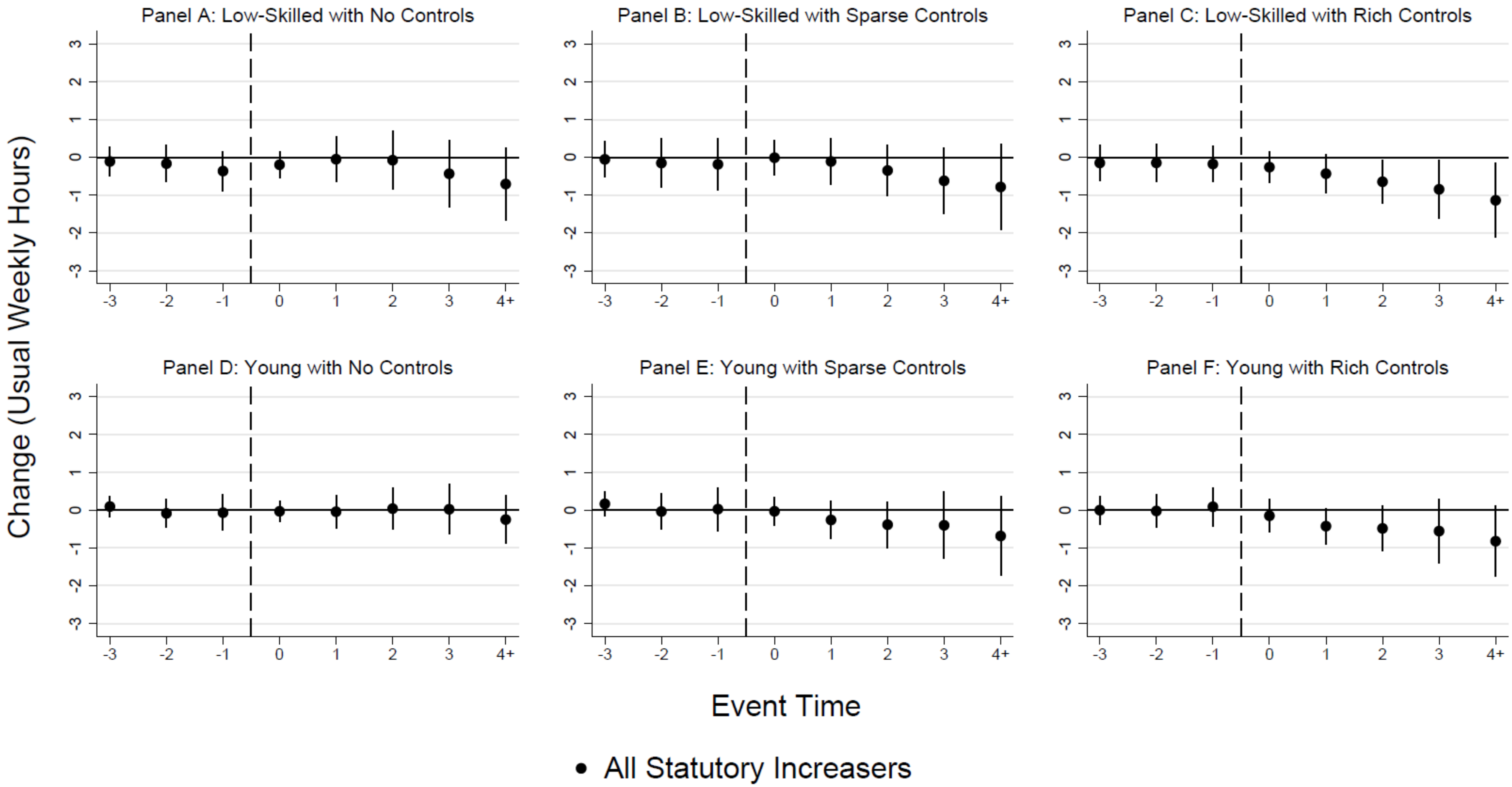

Figure A3A. Event Studies of Changes in Usual Weekly Hours Worked in the ACS Following Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code the first treatment year as the year in which a state's first statutory minimum wage increase took effect. Panels A, B, and C plot coefficients for low-skilled individuals defined as individuals ages 16–25 without a completed high school education. Panels D, E, and F plot coefficients for young individuals defined as all individuals ages 16–21. The samples are from the ACS. Regressions with "no controls" include state and year fixed effects. Regressions with "sparse controls" include state and year fixed effects, as well as the log of annual average state per capita income and the annual average state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log per capita income and the house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

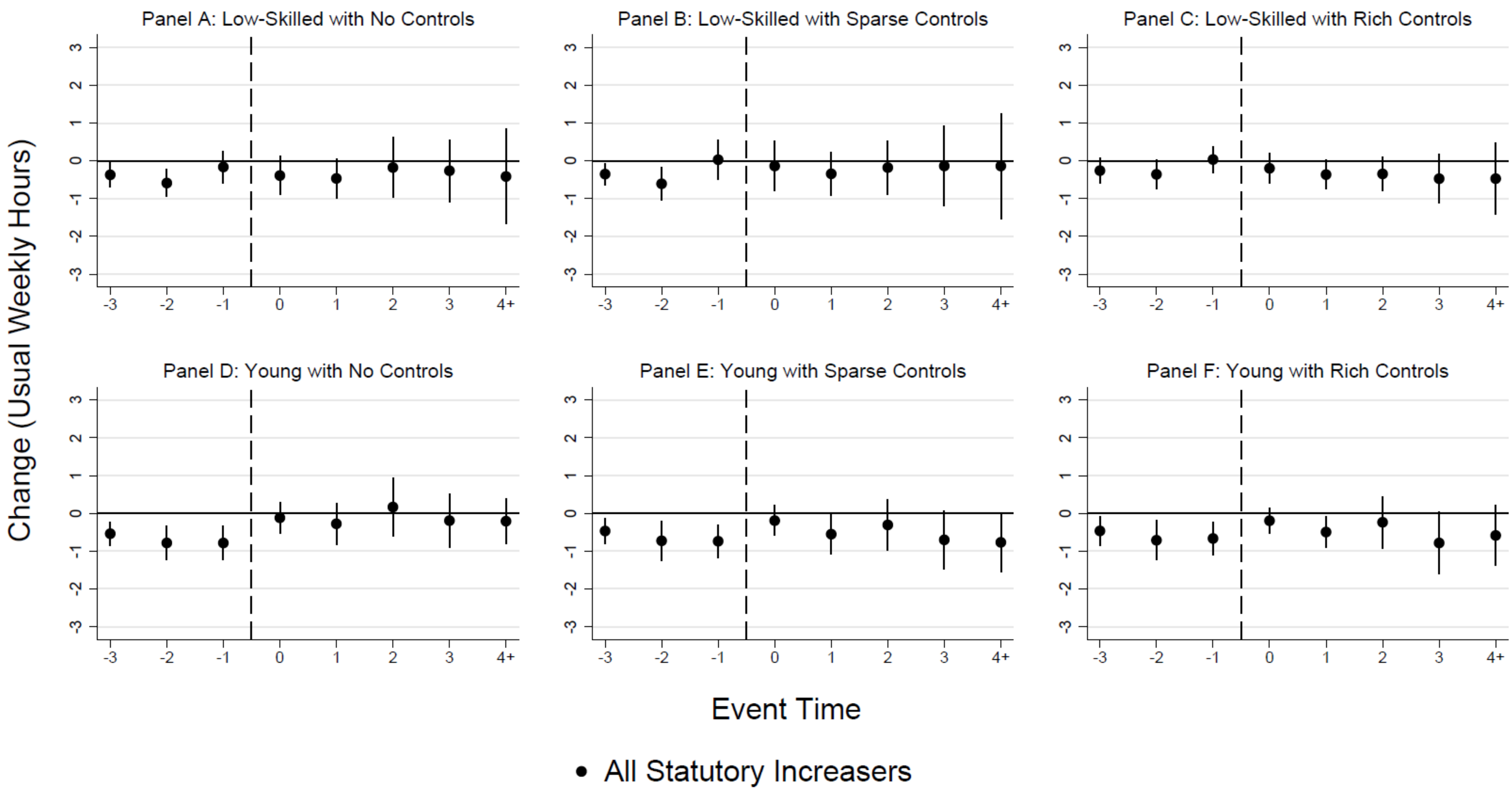

Figure A3B. Event Studies of Changes in Usual Weekly Hours Worked in the CPS Following Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code the first treatment year as the year in which a state's first statutory minimum wage increase took effect. Panels A, B, and C plot coefficients for low-skilled individuals defined as individuals ages 16–25 without a completed high school education. Panels D, E, and F plot coefficients for young individuals defined as all individuals ages 16–21. The samples are from the CPS. Regressions with "no controls" include state and year-month fixed effects. Regressions with "sparse controls" include state and year-month fixed effects, as well as the log of quarterly state per capita income and the quarterly state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log per capita income and the house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

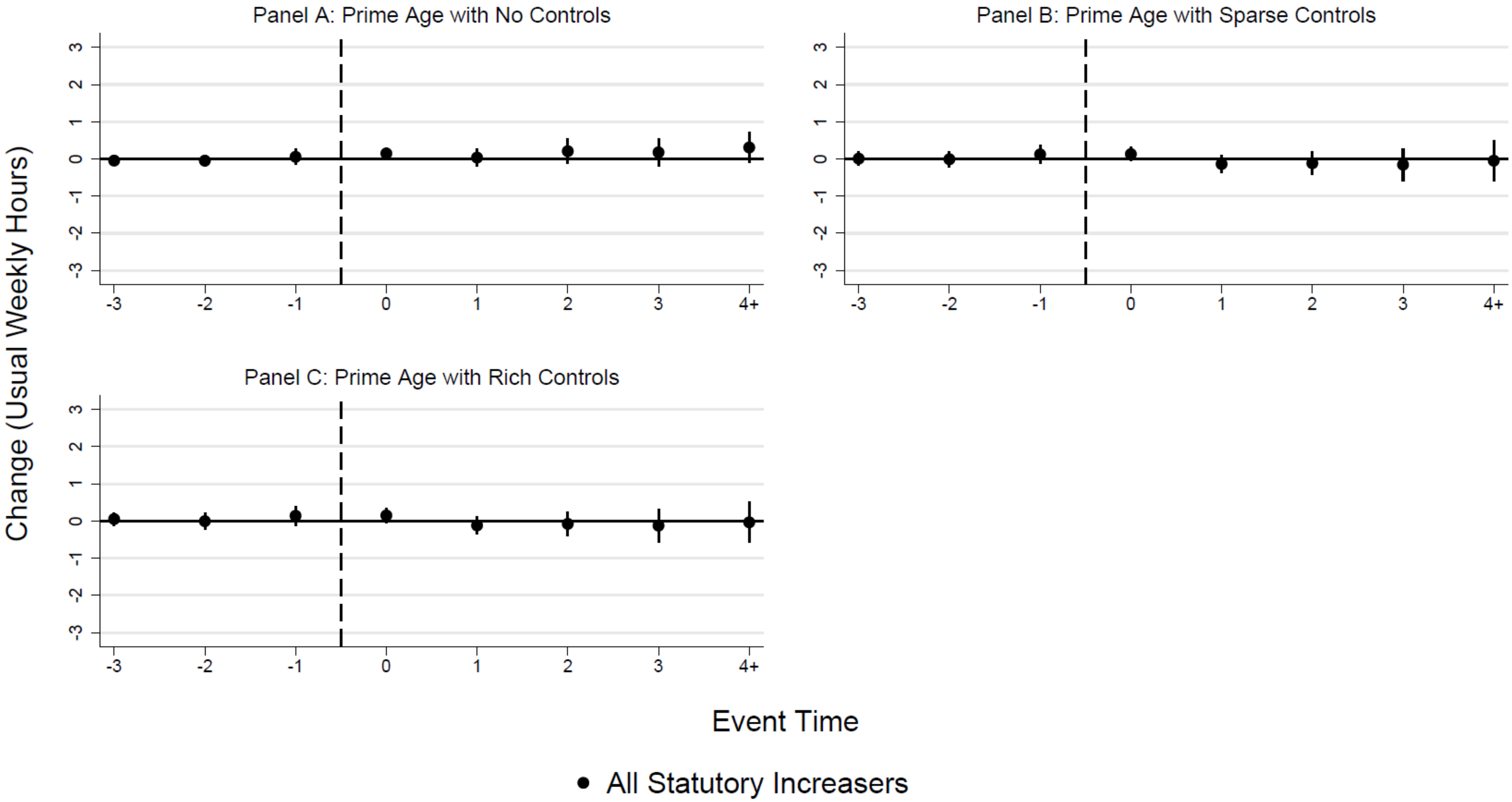

Figure A4A. Event Studies of Changes in Prime Age Usual Weekly Hours Worked From the ACS Following Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code first treatment year as the year in which a state's first statutory minimum wage increase took effect. Panels A, B, and C plot coefficients for prime age individuals defined as individuals ages 26–54. The samples are from the ACS. Regressions with "no controls" include only state and year fixed effects and no time-varying covariates. Regressions with "sparse controls" include state and year fixed effects, as well as the log of annual average state per capita income and the annual average state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log annual average per capita income and the state annual average house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

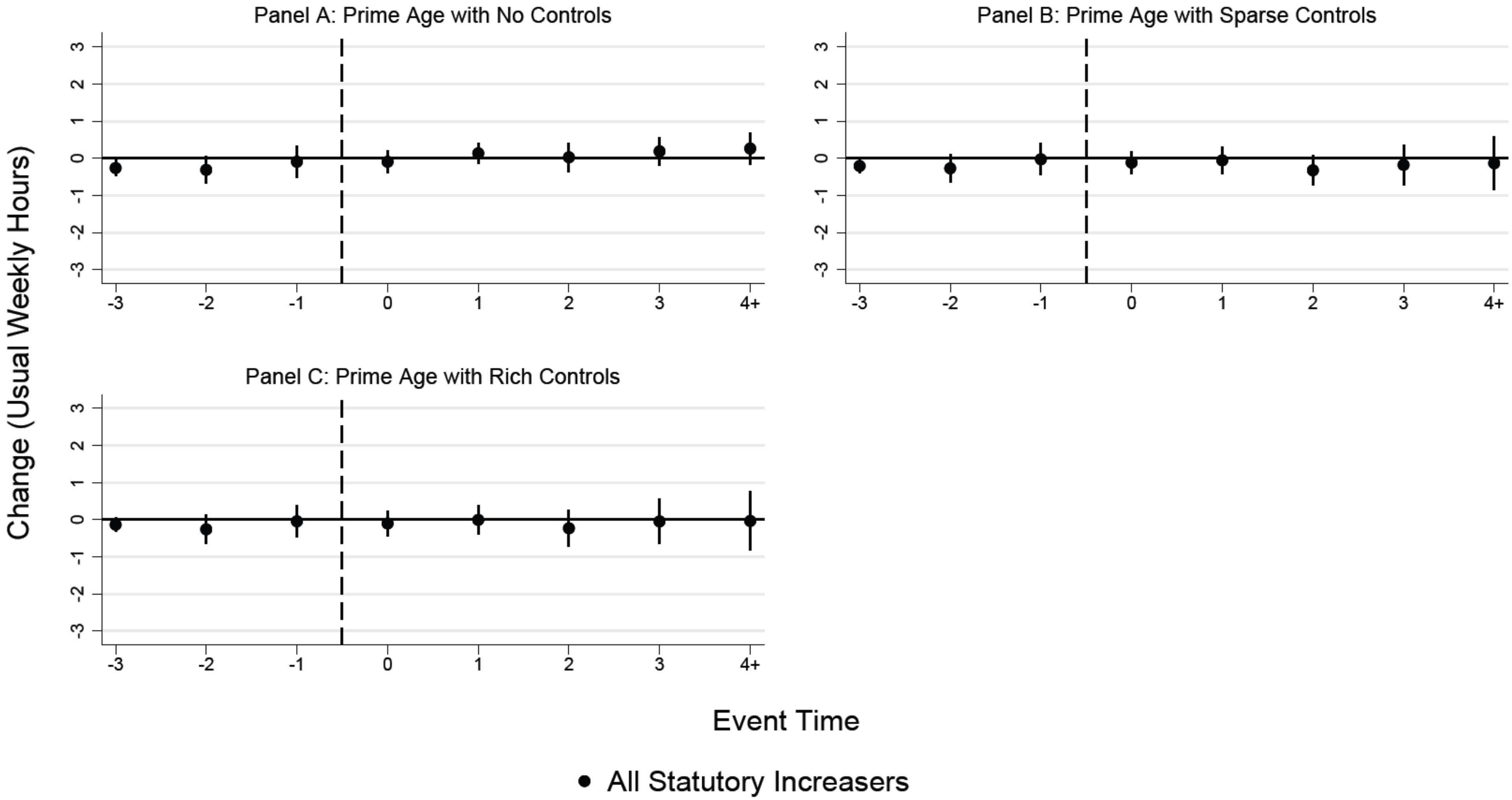

Figure A4B. Event Studies of Changes in Prime Age Usual Weekly Hours Worked From the CPS Following Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code first treatment year as the year in which a state's first statutory minimum wage increase took effect. Panels A, B, and C plot coefficients for prime age individuals defined as individuals ages 26–54. The samples are from the CPS. Regressions with "no controls" include only state and year-month fixed effects and no time-varying covariates. Regressions with "sparse controls" include state and year fixed effects, as well as the log of quarterly average state per capita income and the quarterly state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log annual state per capita income and the state annual average house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

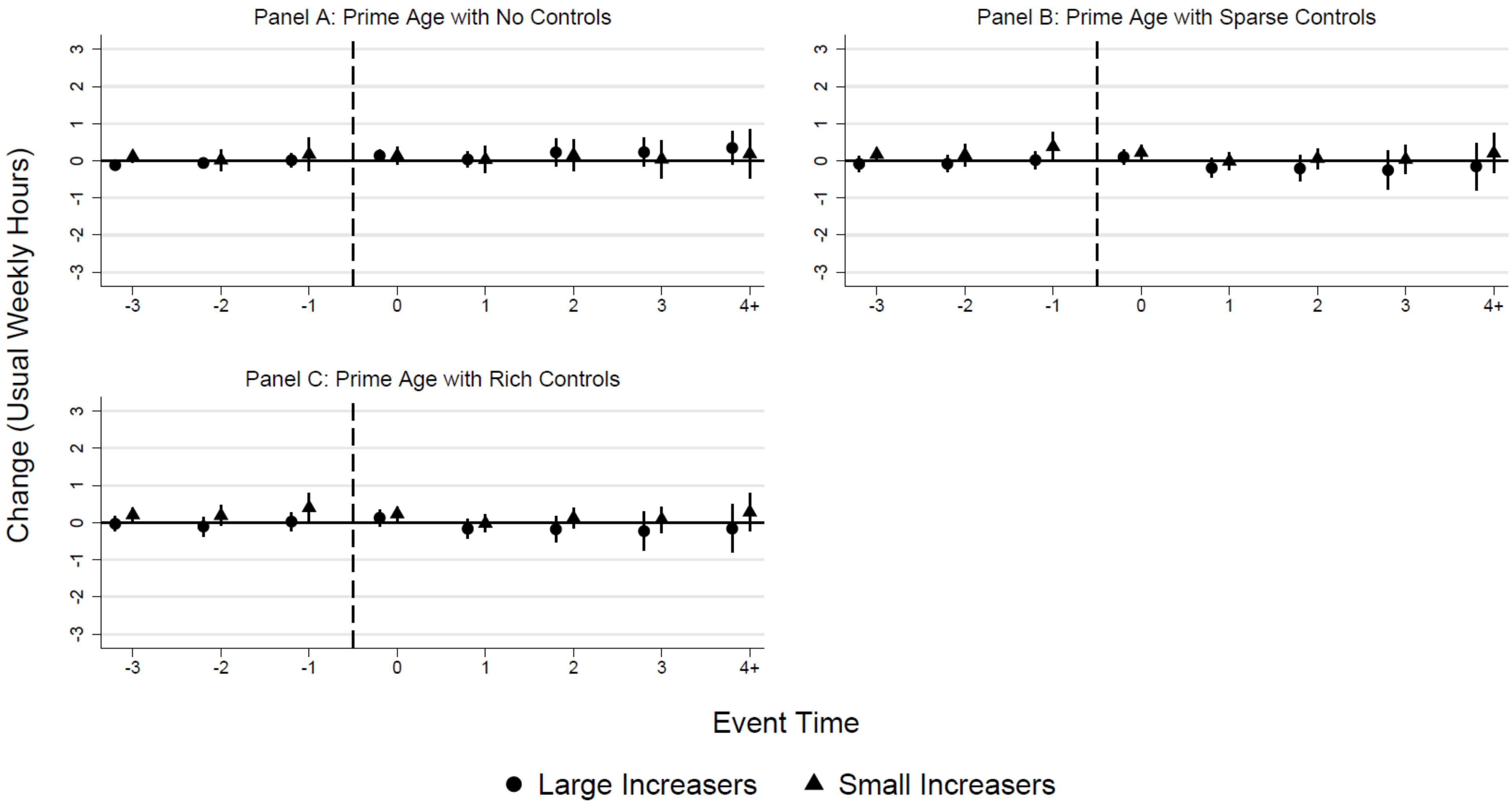

Figure A5A. Event Studies of Changes in Prime Age Usual Hours Weekly Worked From the ACS Following Large and Small Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code first treatment year as the year in which a state's first statutory minimum wage increase took effect. We compare estimates for large vs. small increases as defined in the main text. Panels A, B, and C plot coefficients for prime age individuals defined as individuals ages 26–54. The samples are from the ACS. Regressions with "no controls" include only state and year fixed effects and no time-varying covariates. Regressions with "sparse controls" include state and year fixed effects, as well as the log of annual average state per capita income and the annual average state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log annual state per capita income and the house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

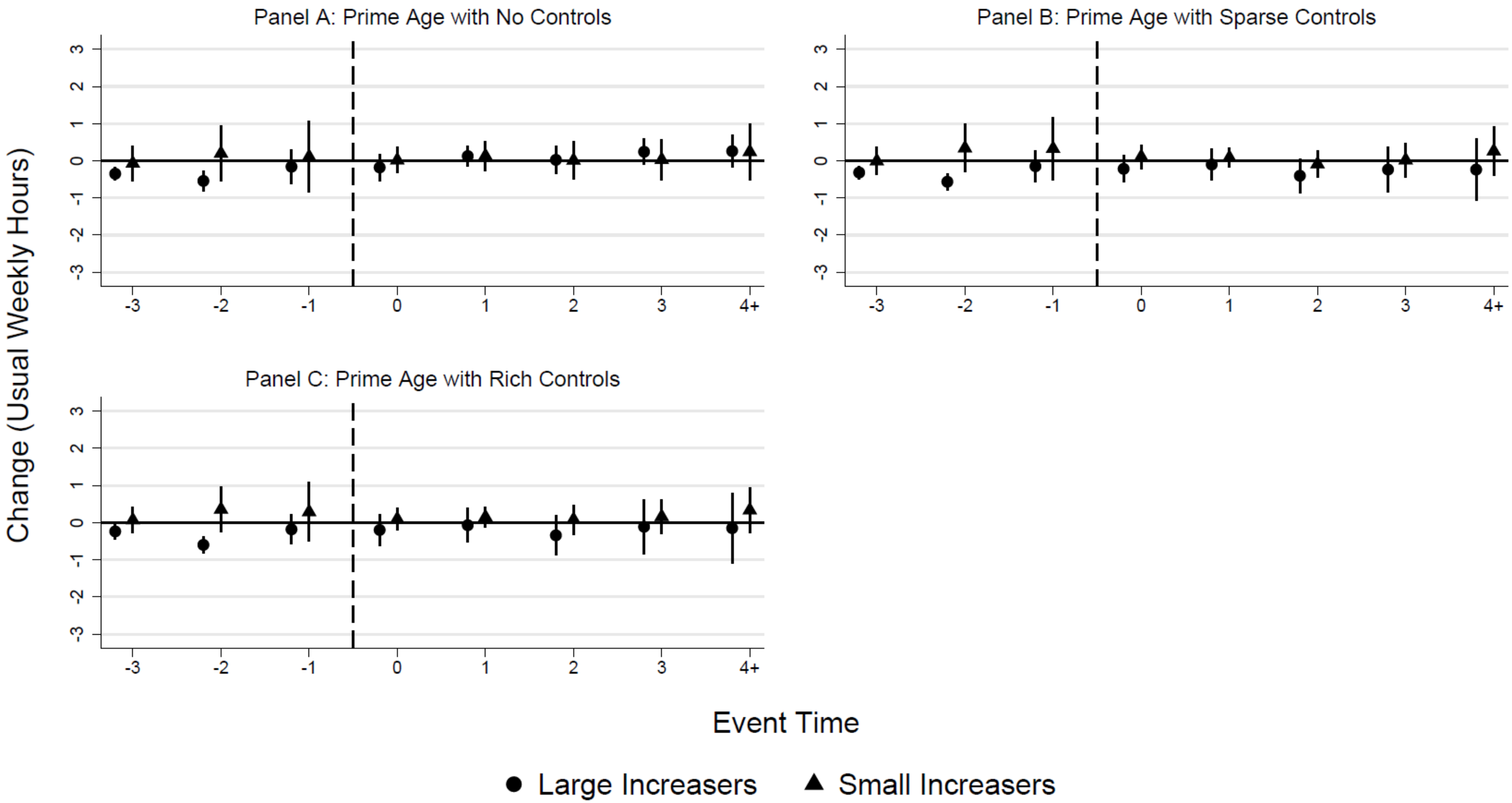

Figure A5B. Event Studies of Changes in Prime Age Usual Weekly Hours Worked From the CPS Following Large and Small Statutory Minimum Wage Increases Using the BJS Imputation Estimator: This figure displays coefficients obtained using the imputation estimator proposed by Borusyak, Jaravel, and Spiess (2024) (BJS). For the BJS estimator, we code first treatment year as the year in which a state's first statutory minimum wage increase took effect. We compare estimates for large vs. small increases as defined in the main text. Panels A, B, and C plot coefficients for prime age individuals defined as individuals ages 26–54. The samples are from the CPS. Regressions with "no controls" include only state and year-month fixed effects and no time-varying covariates. Regressions with "sparse controls" include state and year-month fixed effects, as well as the log of quarterly state per capita income and the quarterly state house price index. Regressions with "rich controls" include all controls in the sparse controls regressions plus the three-year lag of log annual state per capita income and the annual average house price index, as well as a dummy variable for each education group and age. Error bars denote 95 percent confidence intervals around each estimated coefficient. Standard errors are clustered by state.

Table A1. Sample Summary Statistics Usual Hours Worked: ACS Data for 2011-2013 and 2019

	(1)	(2)	(3)	(4)
Years	2011-2013	2019	2011-2013	2019
Skill Groups	Ages 16 to 25 w/ < High School		Ages 16 to 21	
Usual Weekly Hours Worked	8.017	8.675	13.67	15.34
	(14.09)	(13.83)	(16.22)	(16.61)
Age	17.90	17.53	18.58	18.54
	(2.444)	(2.155)	(1.704)	(1.696)
Black	0.166	0.148	0.153	0.146
	(0.372)	(0.355)	(0.360)	(0.353)
High School Degree	0	0	0.343	0.368
	(0)	(0)	(0.475)	(0.482)
Some College Education	0	0	0.247	0.240
	(0)	(0)	(0.431)	(0.427)
House Price Index	325.9	460.9	330.4	466.9
	(99.86)	(143.2)	(101.6)	(146.1)
Income Per Capita ($1000s)	43.81	56.10	44.04	56.45
	(6.270)	(8.965)	(6.364)	(9.118)
Effective Minimum Wage ($)	7.531	8.899	7.536	8.960
	(0.422)	(1.812)	(0.424)	(1.837)
Observations	346,135	98,302	774,438	243,315

Notes: This table reports summary statistics for our two sample groups. Columns 1 and 2 report averages and standard errors (in parenthesis) of each of the variables for our subsample of low-skilled individuals, defined as individuals ages 16 to 25 with less than a high school education. Columns 3 and 4 report averages and standard errors (in parenthesis) for our subsample of young adult individuals, defined as individuals ages 16 to 21. Entries for usual weekly hours worked, age, race, and education summarize data from the American Community Survey (ACS). The house price index variable uses data from the Federal Housing Finance Agency (FHFA). The income per capita variable uses data from the Bureau of Economic Analysis (BEA). The effective minimum wage variable uses data from the Bureau of Labor Statistics (BLS).

Table A2. Sample Summary Statistics Usual Hours Worked: CPS Data for 2011-2013, 2015-2019

	(1)	(2)	(4)	(5)
Years	2011-2013	2015-2019	2011-2013	2015-2019
Skill Groups	Ages 16 to 25 w/ < High School		Ages 16 to 21	
Usual Weekly Hours Worked	5.476	5.958	9.121	10.54
	(12.45)	(12.52)	(14.96)	(15.78)
Age	17.97	17.73	18.50	18.47
	(2.423)	(2.243)	(1.730)	(1.734)
Black	0.164	0.156	0.155	0.150
	(0.370)	(0.363)	(0.362)	(0.357)
High School Degree	0	0	0.223	0.234
	(0)	(0)	(0.416)	(0.424)
Some College Education	0	0	0.299	0.290
	(0)	(0)	(0.458)	(0.454)
House Price Index	327.8	413.9	331.8	419.9
	(100.8)	(132.5)	(102.5)	(135.0)
Income Per Capita ($1000s)	43.91	51.88	44.15	52.30
	(6.338)	(8.513)	(6.420)	(8.597)
Effective Minimum Wage ($)	7.535	8.416	7.541	8.461
	(0.423)	(1.344)	(0.426)	(1.366)
Observations	197,386	287,097	365,354	546,414

Notes: This table reports summary statistics for our two sample groups. Columns 1 and 2 report averages and standard errors (in parenthesis) of each of the variables for our subsample of low-skilled individuals, defined as individuals ages 16 to 25 with less than a high school education. Columns 3 and 4 report averages and standard errors (in parenthesis) for our subsample of young adult individuals, defined as individuals ages 16 to 21. Entries for usual weekly hours worked, age, race, and education summarize data from the Current Population Survey (CPS). The house price index variable uses data from the Federal Housing Finance Agency (FHFA). The income per capita variable uses data from the Bureau of Economic Analysis (BEA). The effective minimum wage variable uses data from the Bureau of Labor Statistics (BLS).

Table A3. Sample Summary Statistics Usual Hours Worked: CPS Data for 2011-2013 and 2019

	(1)	(3)	(4)	(6)
Years	2011-2013	2019	2011-2013	2019
Skill Groups	Ages 16 to 25 w/ < High School		Ages 16 to 21	
Usual Weekly Hours Worked	5.476	5.989	9.121	10.96
	(12.45)	(12.40)	(14.96)	(15.98)
Age	17.97	17.62	18.50	18.47
	(2.423)	(2.118)	(1.730)	(1.729)
Black	0.164	0.153	0.155	0.149
	(0.370)	(0.360)	(0.362)	(0.356)
High School Degree	0	0	0.223	0.239
	(0)	(0)	(0.416)	(0.427)
Some College Education	0	0	0.299	0.291
	(0)	(0)	(0.458)	(0.454)
House Price Index	327.8	460.9	331.8	465.6
	(100.8)	(143.2)	(102.5)	(144.8)
Income Per Capita ($1000s)	43.91	56.14	44.15	56.40
	(6.338)	(8.962)	(6.420)	(9.044)
Effective Minimum Wage ($)	7.535	8.919	7.541	8.971
	(0.423)	(1.810)	(0.426)	(1.826)
Observations	197,386	51,409	365,354	101,036

Notes: This table reports summary statistics for our two sample groups. Columns 1 and 2 report averages and standard errors (in parenthesis) of each of the variables for our subsample of low-skilled individuals, defined as individuals ages 16 to 25 with less than a high school education. Columns 3 and 4 report averages and standard errors (in parenthesis) for our subsample of young adult individuals, defined as individuals ages 16 to 21. Entries for usual weekly hours worked, age, race, and education summarize data from the Current Population Survey (CPS). The house price index variable uses data from the Federal Housing Finance Agency (FHFA). The income per capita variable uses data from the Bureau of Economic Analysis (BEA). The effective minimum wage variable uses data from the Bureau of Labor Statistics (BLS).

Table A4. Unadjusted Differences in Usual Hours Worked Across Policy Regimes Using CPS Data, 2019 Post Period, and $1 Cutoff

	(1)	(2)	(3)	(4)
	2011-2013	2019	Change	Change Relative to Non-Increasers
Young Adult Hours Worked				
Usual Hours Worked	9.83	11.49	1.66	
Indexers	9.36	11.69	2.34	0.68
Increase < $1	9.93	12.12	2.18	0.52
Increase >= $1	7.36	8.75	1.39	-0.27
Low-Skilled Hours Worked				
Non-Increasers	5.96	6.47	0.50	
Indexers	5.34	6.12	0.78	0.28
Increase < $1	4.81	6.87	2.06	1.55
Increase >= $1	4.94	4.42	-0.52	-1.02
Prime Age Hours Worked				
Non-Increasers	30.68	32.77	2.08	
Indexers	30.18	32.81	2.63	0.54
Increase < $1	31.25	33.24	1.99	-0.10
Increase >= $1	29.49	31.90	2.40	0.32
Prime-Age Employment				
Non-Increasers	0.761	0.800	0.039	
Indexers	0.757	0.808	0.051	0.022
Increase < $1	0.774	0.819	0.045	-0.005
Increase >= $1	0.745	0.794	0.049	-0.009
House Price Index				
Non-Increasers	279.6	376.7	97.1	
Indexers	291.2	469.1	177.9	80.8
Increase < $1	303.8	396.1	92.3	-4.8
Increase >= $1	465.6	675.6	210.0	112.9
Income Per Capita ($1000s)				
Non-Increasers	41.20	51.54	10.34	
Indexers	41.01	53.17	12.16	1.82
Increase < $1	45.54	57.05	11.51	1.17
Increase >= $1	51.07	68.77	17.70	7.36

Notes: This table reports usual weekly hours worked for each our of our four policy groups (non-increasers, indexers, increase < $1, and increase >= $1) broken out across three types of individuals: young adults, low-skilled, and prime age. Young adults are defined as individuals ages 16 to 21. Low-skilled adults are those ages 16 to 25 without a completed high school education. Prime age adults are defined as individuals between the ages of 26 and 54. This table also reports mean values of economic control variables (house price index and income per capita) for each of our four policy groups calculated using our sample of young adults. The income per capita variable uses BEA data, and the house price index variable uses FHFA data. Column 1 reports the average value between 2011 and 2013 for each row, column 2 reports the average value in 2019, and column 3 reports the difference between the two. Column 4 reports the change in the average value for each row relative to the relevant non-increaser value. Averages are weighted by state population.

Table A5. Unadjusted Differences in Usual Hours Worked Across Policy Regimes Using ACS Data, 2015-2019 Post Period, and $1 Cutoff

	(1) 2011-2013	(2) 2015-2019	(3) Change	(4) Change Relative to Non-Increasers
Young Adult Hours Worked				
Usual Hours Worked	14.38	15.64	1.26	
Indexers	13.95	15.58	1.63	0.37
Increase < $1	14.86	15.97	1.11	-0.16
Increase >= $1	11.64	12.70	1.05	-0.21
Low-Skilled Hours Worked				
Non-Increasers	8.62	9.03	0.42	
Indexers	7.84	8.92	1.08	0.66
Increase < $1	8.16	8.86	0.69	0.28
Increase >= $1	6.90	6.69	-0.21	-0.63
Prime Age Hours Worked				
Non-Increasers	33.07	33.98	0.91	
Indexers	32.42	33.67	1.25	0.34
Increase < $1	33.44	34.36	0.92	0.01
Increase >= $1	32.17	33.30	1.13	0.23
Prime Age Employment				
Non-Increasers	0.75	0.78	0.028	
Indexers	0.75	0.78	0.037	0.009
Increase < $1	0.77	0.80	0.032	0.004
Increase >= $1	0.75	0.79	0.038	0.010
House Price Index				
Non-Increasers	279.8	339.9	60.1	
Indexers	291.1	407.5	116.4	56.3
Increase < $1	303.6	363.0	59.4	-0.7
Increase >= $1	465.6	612.3	146.7	86.6
Income per Capita ($1000s)				
Non-Increasers	41.21	47.85	6.64	
Indexers	40.96	49.06	8.10	1.46
Increase < $1	45.44	53.18	7.74	1.10
Increase >= $1	51.04	63.00	11.96	5.32

Notes: This table reports usual weekly hours worked for each our of our four policy groups (non-increasers, indexers, increase < $1, and increase >= $1) broken out across three types of individuals: young adults, low-skilled, and prime-age. Young adults are defined as individuals ages 16 to 21. Low-skilled adults are those ages 16 to 25 without a completed high school education. Prime age adults are defined as individuals between the ages of 26 and 54. This table also reports mean values of economic control variables (house price index and income per capita) for each of our four policy groups calculated using our sample of young adults. Column 1 reports the average value between 2011 and 2013 for each row, column 2 reports the average value between 2015 and 2019, and column 3 reports the difference between the two. Column 4 reports the change in the average value for each row relative to the relevant non-increaser value. Averages are weighted by state population.

Table A6. Unadjusted Differences in Usual Hours Worked Across Policy Regimes Using CPS Data, 2015-2019 Post Period and $1 Cutoff

	(1)	(2)	(3)	(4)
	2011-2013	2015-2019	Change	Change Relative to Non-Increasers
Young Adult Hours Worked				
Usual Hours Worked	9.83	11.13	1.30	
Indexers	9.36	11.14	1.78	0.49
Increase < $1	9.93	11.38	1.45	0.15
Increase >= $1	7.36	8.57	1.21	-0.09
Low-Skilled Hours Worked				
Non-Increasers	5.96	6.43	0.47	
Indexers	5.34	6.15	0.82	0.35
Increase < $1	4.81	6.23	1.41	0.95
Increase >= $1	4.94	4.66	-0.28	-0.74
Prime Age Hours Worked				
Non-Increasers	30.68	32.17	1.49	
Indexers	30.18	32.05	1.86	0.37
Increase < $1	31.25	32.68	1.43	-0.06
Increase >= $1	29.49	31.20	1.71	0.22
Prime-Age Employment				
Non-Increasers	0.761	0.788	0.027	
Indexers	0.757	0.792	0.035	0.008
Increase < $1	0.774	0.805	0.031	0.004
Increase >= $1	0.745	0.779	0.034	0.007
House Price Index				
Non-Increasers	279.6	339.9	60.3	
Indexers	291.2	407.4	116.2	55.9
Increase < $1	303.8	364.2	60.4	0.1
Increase >= $1	465.6	608.5	142.9	82.6
Income Per Capita ($1000s)				
Non-Increasers	41.20	47.96	6.76	
Indexers	41.01	49.06	8.05	1.29
Increase < $1	45.54	53.20	7.66	0.90
Increase >= $1	51.07	62.86	11.79	5.03

Notes: This table reports usual weekly hours worked for each our of our four policy groups (non-increasers, indexers, increase < $1, and increase >= $1) broken out across three types of individuals: young adults, low-skilled, and prime-age. Young adults are defined as individuals ages 16 to 21. Low-skilled adults are those ages 16 to 25 without a completed high school education. Prime age adults are defined as individuals between the ages of 26 and 54. This table also reports mean values of economic control variables (house price index and income per capita) for each of our four policy groups calculated using our sample of young adults. The income per capita variable uses BEA data, and the house price index variable uses FHFA data. Column 1 reports the average value between 2011 and 2013 for each row, column 2 reports the average value between 2015 and 2019, and column 3 reports the difference between the two. Column 4 reports the change in the average value for each row relative to the relevant non-increaser value. Averages are weighted by state population.

Table A7. Unadjusted Differences in Usual Hours Worked Across Policy Regimes Using ACS Data, 2019 Post Period, and $2.5 Cutoff

	(1)	(2)	(3)	(4)
	2011-2013	2019	Change	Change Relative to Non-Increasers
Young Adult Hours Worked				
Non-Increasers	14.35	16.09	1.74	
Indexers	13.60	15.58	1.98	0.24
Increase < $2.5	14.67	16.01	1.34	-0.40
Increase >= $2.5	11.65	13.15	1.50	-0.24
Low-Skilled Hours Worked				
Non-Increasers	8.62	9.34	0.72	
Indexers	7.62	9.02	1.40	0.68
Increase < $2.5	8.36	9.09	0.73	0.00
Increase >= $2.5	6.74	6.64	-0.10	-0.82
Prime-Age Hours Worked				
Non-Increasers	33.07	34.31	1.24	
Indexers	32.29	33.94	1.65	0.41
Increase < $2.5	33.38	34.70	1.32	0.08
Increase >= $2.5	31.90	33.57	1.66	0.43
Prime-Age Employment				
Non-Increasers	0.751	0.791	0.040	
Indexers	0.743	0.795	0.052	0.012
Increase < $2.5	0.767	0.813	0.046	0.006
Increase >= $2.5	0.743	0.797	0.054	0.014
House Price Index				
Non-Increasers	278.3	375.8	97.5	
Indexers	265.2	406.1	140.9	43.4
Increase < $2.5	341.3	476.4	135.1	37.6
Increase >= $2.5	451.5	675.6	224.1	126.6
Income per Capita ($1000s)				
Non-Increasers	41.22	51.50	10.28	
Indexers	40.31	51.06	10.75	0.47
Increase < $2.5	46.67	60.05	13.38	3.10
Increase >= $2.5	49.13	66.36	17.23	6.95

Notes: This table reports usual weekly hours worked for each our of our four policy groups (non-increasers, indexers, increase < $1, and increase >= $1) broken out across three types of individuals: young adults, low-skilled, prime-age. Young adults are defined as individuals ages 16 to 21. Low-skilled adults are those ages 16 to 25 without a completed high school education. Prime age adults are defined as individuals between the ages of 26 and 54. This table also reports mean values of economic control variables (house price index and income per capita) for each of our four policy groups calculated using our sample of young adults. The income per capita variable uses BEA data, and the house price index variable uses FHFA data. Column 1 reports the average value between 2011 and 2013 for each row, column 2 reports the average value in 2019, and column 3 reports the difference between the two. Column 4 reports the change in the average value for each row relative to the relevant non-increaser value. Averages are weighted by state population.

Table A8. Unadjusted Differences in Usual Hours Worked Across Policy Regimes Using CPS Data, 2019 Post Period, and $2.5 Cutoff

	(1) 2011-2013	(2) 2019	(3) Change	(4) Change Relative to Non-Increasers
Young Adult Hours Worked				
Non-Increasers	9.83	11.47	1.65	
Indexers	9.56	11.56	2.00	0.36
Increase < $2.5	9.45	11.35	1.90	0.25
Increase >= $2.5	7.39	9.30	1.90	0.26
Low-Skilled Hours Worked				
Non-Increasers	5.96	6.47	0.50	
Indexers	5.36	5.85	0.49	-0.01
Increase < $2.5	5.03	6.34	1.31	0.81
Increase >= $2.5	4.94	4.71	-0.23	-0.73
Prime-Age Hours Worked				
Non-Increasers	30.68	32.76	2.08	
Indexers	30.04	32.68	2.63	0.55
Increase < $2.5	31.08	33.32	2.25	0.17
Increase >= $2.5	29.30	31.72	2.43	0.35
Prime-Age Employment				
Non-Increasers	0.761	0.800	0.039	
Indexers	0.755	0.804	0.049	0.010
Increase < $2.5	0.773	0.822	0.049	0.010
Increase >= $2.5	0.740	0.789	0.049	0.010
House Price Index				
Non-Increasers	278.1	375.1	97.0	
Indexers	263.9	407.6	143.7	46.7
Increase < $2.5	342.6	477.2	134.6	37.6
Increase >= $2.5	452.3	670.6	218.3	121.3
Income Per Capita ($1000s)				
Non-Increasers	41.21	51.54	10.33	
Indexers	40.31	51.10	10.79	0.46
Increase < $2.5	46.86	60.05	13.19	2.86
Increase >= $2.5	49.15	65.96	16.81	6.48

Notes: This table reports usual weekly hours worked for each our of our four policy groups (non-increasers, indexers, increase < $1, and increase >= $1) broken out across three types of individuals: young adults, low-skilled, prime-age. Young adults are defined as individuals ages 16 to 21. Low-skilled adults are those ages 16 to 25 without a completed high school education. Prime age adults are defined as individuals between the ages of 26 and 54. This table also reports mean values of economic control variables (house price index and income per capita) for each of our four policy groups calculated using our sample of young adults. The income per capita variable uses BEA data, and the house price index variable uses FHFA data. Column 1 reports the average value between 2011 and 2013 for each row, column 2 reports the average value between in 2019, and column 3 reports the difference between the two. Column 4 reports the change in the average value for each row relative to the relevant non-increaser value. Averages are weighted by state population.

Table A9. Summary of Wage Regression Results

Panel A: Low-Skilled Workers	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome	OW	OW	OW	OW	MW	MW	MW	MW
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
$1 Cutoff; Post Period 2015-2019	0.85	1.21	0.75	0.60	1.46	2.02	1.50	0.85
	[0.62,1.03]	[0.85,1.46]	[0.40,0.96]	[0.33,0.87]	[1.25,1.63]	[1.65,2.30]	[1.31,1.69]	[0.54,1.22]
$1 Cutoff; Post Period 2015	0.72	1.30	0.35	0.51	0.79	1.18	0.71	0.49
	[0.24,1.26]	[0.07,2.84]	[-0.07,0.64]	[0.22,0.85]	[0.72,0.88]	[1.01,1.43]	[0.58,0.78]	[0.44,0.55]
$1 Cutoff; Post Period 2019	1.19	1.76	0.94	0.86	2.33	3.28	2.10	1.60
	[0.62,1.61]	[0.78,2.27]	[0.40,1.39]	[0.20,1.62]	[1.88,2.71]	[2.21,3.76]	[1.77,2.50]	[0.94,2.38]
$1 Cutoff; No Switchers; Post Period 2015-2019	0.81	1.27	0.77	0.39	1.37	2.09	1.51	0.52
	[0.55,0.95]	[0.92,1.47]	[0.40,0.97]	[0.15,0.54]	[1.22,1.50]	[1.63,2.37]	[1.34,1.74]	[0.37,0.64]
$1 Cutoff; No Switchers; Post Period 2019	1.03	1.91	0.97	0.20	2.12	3.42	2.13	0.81
	[0.38,1.34]	[0.71,2.37]	[0.31,1.36]	[-0.22,0.50]	[1.73,2.37]	[2.12,3.88]	[1.85,2.51]	[0.62,0.96]
$2.5 Cutoff; Post Period 2019	1.17	2.05	1.17	0.28	2.30	3.74	2.24	0.92
	[0.72,1.53]	[1.49,2.43]	[0.70,1.63]	[-0.17,0.73]	[2.16,2.47]	[3.51,3.91]	[1.91,2.71]	[0.74,1.31]
Overall Average Effects	1.01	1.64	0.92	0.47	1.92	2.91	1.90	0.94
	[0.57,1.50]	[0.86,2.33]	[0.40,1.49]	[-0.13,1.24]	[1.26,2.55]	[1.76,3.85]	[1.36,2.53]	[0.43,2.07]
Panel B: Young Workers	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome	OW	OW	OW	OW	MW	MW	MW	MW
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
$1 Cutoff; Post Period 2015-2019	0.61	0.91	0.51	0.39	1.46	2.02	1.51	0.85
	[0.36,0.76]	[0.56,1.05]	[0.24,0.78]	[0.12,0.64]	[1.26,1.63]	[1.65,2.31]	[1.31,1.70]	[0.54,1.23]
$1 Cutoff; Post Period 2015	0.41	0.77	0.14	0.33	0.79	1.18	0.71	0.49
	[0.18,0.64]	[0.39,1.21]	[-0.29,0.57]	[0.10,0.49]	[0.72,0.88]	[1.01,1.43]	[0.58,0.78]	[0.44,0.55]
$1 Cutoff; Post Period 2019	0.96	1.48	0.77	0.64	2.33	3.28	2.13	1.58
	[0.51,1.29]	[0.63,1.88]	[0.33,1.19]	[0.14,1.20]	[1.88,2.71]	[2.24,3.76]	[1.77,2.52]	[0.93,2.36]
$1 Cutoff; No Switchers; Post Period 2015-2019	0.57	0.95	0.52	0.22	1.37	2.09	1.52	0.51
	[0.37,0.73]	[0.55,1.12]	[0.29,0.77]	[-0.13,0.52]	[1.21,1.50]	[1.63,2.38]	[1.34,1.75]	[0.36,0.65]
$1 Cutoff; No Switchers; Post Period 2019	0.84	1.59	0.79	0.14	2.13	3.43	2.16	0.81
	[0.49,1.14]	[0.58,1.96]	[0.32,1.28]	[-0.31,0.83]	[1.74,2.38]	[2.12,3.89]	[1.86,2.54]	[0.62,0.96]
$2.5 Cutoff; Post Period 2019	0.97	1.76	0.89	0.24	2.31	3.75	2.25	0.92
	[0.70,1.24]	[1.41,2.04]	[0.44,1.30]	[-0.07,0.71]	[2.17,2.48]	[3.52,3.91]	[1.92,2.72]	[0.74,1.31]
Overall Average Effects	0.79	1.34	0.70	0.33	1.92	2.92	1.91	0.94
	[0.39,1.20]	[0.59,1.95]	[0.29,1.22]	[-0.14,0.94]	[1.26,2.55]	[1.75,3.86]	[1.36,2.55]	[0.42,2.05]

Notes: This table presents averages across estimates from the regression analyses in our pre-analysis plan. The underlying estimates are, in each case, estimates of β_(g(s)) from equation (1). They are thus estimates of the change in the hourly wage or minimum wage among individuals in our analysis samples from states that increased their minimum wages relative to individuals in states that did not increase their minimum wages. The key dimensions along which we average the estimates (e.g., contrasting time periods, contrasting the "Low-Skill" and "Young" samples, or contrasting the effects of "Large" increases, "Small" increases, and the inflation-indexed minimum wage changes enacted by the "Indexer" group) are clearly labeled in the body of the table. For estimated effects on hourly wages, we use data from the CPS ORG and for estimated effects on minimum wages we use data from the basic monthly CPS. The grouping of states we describe as "$1 Cutoff" corresponds with the grouping in Table 1, which is the grouping from our original pre-analysis plan. The grouping of states we describe as "$2.5 Cutoff" corresponds with the grouping in Table 2, which reflects minimum wage changes enacted after we developed our pre-analysis plan. (Note that the inclusion of estimates involving updated groupings was, itself, specified in our pre-analysis plan.) The "$1 Cutoff Post Period 2015" results were not part of the pre-analysis plan and are thus not included in the "Overall Average Effects" calculations. Panel A includes individuals 16 to 25 with less than a completed high school education and Panel B includes all individuals ages 16 to 21.

Table A10. Summary of Wage Regression Results Using Specifications from Clemens and Strain (2017)

Panel A: Low-Skilled Workers	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Elasticity	OW	OW	OW	OW	MW	MW	MW	MW
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
Original Categories								
Post Period 2015-2019	0.80	1.10	0.77	0.54	1.37	1.85	1.52	0.73
	[0.50,1.01]	[0.71,1.45]	[0.40,0.98]	[0.25,0.78]	[1.12,1.57]	[1.41,2.25]	[1.30,1.73]	[0.31,1.08]
Post Period 2015	0.82	1.48	0.37	0.60	0.80	1.20	0.71	0.50
	[0.26,1.33]	[0.10,2.85]	[-0.09,0.67]	[0.24,1.08]	[0.72,0.88]	[1.01,1.42]	[0.58,0.78]	[0.40,0.58]
Post Period 2019	1.12	1.64	0.97	0.76	2.22	3.09	2.13	1.45
	[0.52,1.58]	[0.70,2.17]	[0.38,1.46]	[0.12,1.54]	[1.71,2.63]	[2.16,3.69]	[1.78,2.52]	[0.74,2.25]
Overall Average Effects	0.96	1.37	0.87	0.65	1.79	2.47	1.82	1.09
	[0.51,1.50]	[0.71,2.12]	[0.39,1.35]	[0.18,1.39]	[1.17,2.55]	[1.48,3.64]	[1.35,2.45]	[0.38,2.05]
Panel B: Young Workers	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Elasticity	OW	OW	OW	OW	MW	MW	MW	MW
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
Original Categories								
Post Period 2015-2019	0.55	0.81	0.52	0.33	1.37	1.86	1.52	0.72
	[0.32,0.71]	[0.49,1.02]	[0.26,0.78]	[0.02,0.58]	[1.12,1.58]	[1.40,2.26]	[1.30,1.74]	[0.30,1.08]
Post Period 2015	0.45	0.84	0.15	0.35	0.80	1.20	0.71	0.50
	[0.21,0.65]	[0.36,1.21]	[-0.27,0.57]	[0.10,0.51]	[0.72,0.88]	[1.01,1.42]	[0.58,0.78]	[0.40,0.58]
Post Period 2019	0.91	1.38	0.79	0.56	2.22	3.10	2.15	1.42
	[0.44,1.23]	[0.59,1.87]	[0.32,1.23]	[0.01,1.09]	[1.71,2.63]	[2.18,3.70]	[1.77,2.55]	[0.73,2.22]
Overall Average Effects	0.73	1.09	0.66	0.45	1.80	2.48	1.84	1.07
	[0.35,1.20]	[0.52,1.77]	[0.28,1.17]	[0.01,1.02]	[1.17,2.55]	[1.48,3.65]	[1.34,2.47]	[0.37,2.05]

Notes: This table presents averages across estimates from the regression analyses in our pre-analysis plan. The underlying estimates are calculated from regression equation (3) from Clemens and Strain (2017). They are thus estimates of the change in either the hourly wage or in the applicable minimum wage among individuals in our analysis samples from states that increased their minimum wages relative to individuals in states that did not increase their minimum wages. The numbers in brackets below each average are the lower and upper bound of the 95 percent confidence interval generated by bootstrapping the estimated average. The key dimensions along which we average the estimates (e.g., contrasting time periods, contrasting the “Low-Skilled” and “Young” samples, or contrasting the effects of “Large” increases, “Small” increases, and the inflation-indexed minimum wage changes enacted by the “Indexer” group) are clearly labeled in the body of the table. For estimated effects on hourly wages, we use data from the CPS ORG and for estimated effects on minimum wages we use data from the basic monthly CPS. The grouping of states we describe as “Original” corresponds with the grouping in Table 1, which is the grouping from our original pre-analysis plan. The "Post Period 2015" results were not part of the pre-analysis plan and are thus not included in the "Overall Average Effects" calculations. Panel A includes employed individuals 16 to 25 with less than a completed high school education and Panel B includes employed individuals ages 16 to 21.

Table A11. Summary of Elasticities Using Regression Specifications from Clemens and Strain (2017)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Group	Low-Skilled	Low-Skilled	Low-Skilled	Low-Skilled	Young	Young	Young	Young
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
Panel A: Usual Weekly Hours Worked								
Overall Average Effects	-0.01	-0.83	0.55	0.27	-0.11	-0.52	0.04	0.15
Mean in 2011-2013 Baseline	7.49	6.90	8.16	7.84	13.10	11.64	14.86	13.95
Change from Baseline (%)	-0.08	-12.09	6.68	3.47	-0.84	-4.51	0.27	1.11
Panel B: Minimum Wages								
Overall Average Effects	1.79	2.47	1.82	1.09	1.80	2.48	1.84	1.07
Mean in 2011-2013 Baseline	7.69	7.72	7.41	7.80	7.68	7.71	7.41	7.81
Change from Baseline (%)	23.33	32.02	24.59	13.93	23.37	32.11	24.79	13.75
Panel C: Hourly Wages								
Overall Average Effects	0.96	1.37	0.87	0.65	0.73	1.09	0.66	0.45
Mean in 2011-2013 Baseline	8.77	9.19	8.45	8.55	9.20	9.54	8.96	8.98
Change from Baseline (%)	10.97	14.88	10.29	7.58	7.96	11.46	7.31	4.98
Elasticity of Hourly Wage w.r.t Minimum Wage	0.47	0.46	0.42	0.54	0.34	0.36	0.29	0.36
Panel D Elasticities								
Own Wage	-0.01	-0.81	0.65	0.46	-0.11	-0.39	0.04	0.22
	[-0.96,0.52]	[-2.12,-0.06]	[-0.67,1.55]	[-1.31,1.22]	[-0.86,0.21]	[-1.39,-0.02]	[-0.87,0.56]	[-1.68,1.44]
Minimum Wage	0.00	-0.38	0.27	0.25	-0.04	-0.14	0.01	0.08
	[-0.35,0.29]	[-0.82,-0.02]	[-0.15,0.73]	[-0.41,0.97]	[-0.20,0.07]	[-0.34,-0.01]	[-0.18,0.15]	[-0.28,0.38]

Notes: This table reports average usual weekly hours and wage effects for each minimum wage policy group and skill group along with own-wage and minimum wage elasticities using the regression specifications from Clemens and Strain (2017). The numbers in brackets below each elasticity are 95 percent confidence intervals generated by bootstrapping the estimated elasticity. The baseline mean for the usual weekly hours panel comes from the ACS and the overall average effects on usual weekly hours are calculated from regression estimates on data from the ACS and CPS. The baseline mean and estimated overall average effects on hourly wages come from the basic monthly CPS. The baseline mean and estimated overall average effects on hourly wages come from the CPS ORG. Averages in the "mean in 2011-2013 baseline" rows are calculated using our original policy categories, while those in the "overall average effects rows" use results generated on both the original and new policy categories. Low-Skilled individuals are ages 16 to 25 with less than a completed high school education and young individuals are ages 16 to 21. Average effects for usual weekly hours (panel A), minimum wages (panel B), and hourly wages (panel C) are taken from Tables 4 and A10. The hourly wage elasticity with respect to the minimum wage is the percentage change in average hourly wages from the baseline period of 2011-2013 divided by the percentage change in minimum wages from 2011-2013. The own-wage elasticity for each policy-skill group is the estimated usual weekly hours effect divided by the percentage change in average hourly wages from the baseline period of 2011-2013 and the minimum wage elasticity is the estimated usual weekly hours effect divided by the percentage change in the minimum wage from 2011-2013.

Table A12. Summary of Hours Worked Regression Results for Separate ACS and CPS Samples

Panel A: Low-Skilled	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	ACS	ACS	ACS	ACS	CPS	CPS	CPS	CPS
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
$1 Cutoff; Post Period 2015-2019	-0.07	-0.75	0.11	0.43	0.05	-0.78	0.75	0.17
	[-0.60,0.39]	[-1.25,0.03]	[-0.72,0.74]	[-0.16,0.91]	[-0.36,0.46]	[-1.25,-0.14]	[0.08,1.27]	[-0.29,0.66]
$1 Cutoff; Post Period 2015	0.20	-0.28	0.34	0.53	-0.07	-0.48	-0.17	0.43
	[-0.37,0.63]	[-0.71,0.48]	[-0.77,1.05]	[-0.21,1.04]	[-0.46,0.38]	[-0.83,0.19]	[-0.77,0.59]	[-0.10,0.97]
$1 Cutoff; Post Period 2019	-0.35	-1.24	-0.15	0.33	0.10	-1.08	1.32	0.06
	[-0.99,0.14]	[-1.93,-0.61]	[-1.34,0.54]	[-0.33,0.87]	[-0.55,0.68]	[-1.86,-0.12]	[-0.05,2.31]	[-0.60,0.70]
$1 Cutoff; No Switchers; Post Period 2015-2019	-0.06	-0.75	0.12	0.44	0.00	-0.77	0.75	0.03
	[-0.63,0.44]	[-1.25,0.02]	[-0.79,0.70]	[-0.32,1.18]	[-0.39,0.39]	[-1.27,-0.12]	[0.03,1.23]	[-0.37,0.85]
$1 Cutoff; No Switchers; Post Period 2019	-0.33	-1.26	-0.14	0.40	0.04	-1.06	1.32	-0.15
	[-0.95,0.19]	[-1.94,-0.63]	[-1.43,0.60]	[-0.36,1.21]	[-0.60,0.64]	[-1.85,-0.25]	[-0.04,2.33]	[-0.67,0.59]
$2.5 Cutoff; Post Period 2019	-0.28	-1.02	-0.23	0.39	-0.08	-0.67	0.59	-0.18
	[-0.86,0.31]	[-1.87,0.13]	[-1.15,0.45]	[-0.29,1.08]	[-0.79,0.57]	[-1.53,0.41]	[-0.60,1.60]	[-0.79,0.30]
Overall Average Effects	-0.22	-1.00	-0.06	0.40	0.02	-0.87	0.95	-0.01
	[-0.88,0.37]	[-1.86,-0.11]	[-1.17,0.64]	[-0.30,1.14]	[-0.59,0.61]	[-1.70,0.20]	[-0.27,2.14]	[-0.66,0.63]

Panel B: Young	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	ACS	ACS	ACS	ACS	CPS	CPS	CPS	CPS
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
$1 Cutoff; Post Period 2015-2019	-0.20	-0.52	-0.23	0.15	0.07	-0.32	0.16	0.36
	[-0.65,0.11]	[-1.04,-0.17]	[-0.99,0.33]	[-0.23,0.50]	[-0.45,0.41]	[-1.21,0.19]	[-0.45,0.57]	[-0.18,0.87]
$1 Cutoff; Post Period 2015	-0.04	-0.26	-0.04	0.18	-0.11	-0.26	-0.28	0.20
	[-0.46,0.26]	[-0.75,0.17]	[-0.85,0.55]	[-0.24,0.50]	[-0.59,0.40]	[-0.98,0.54]	[-0.93,0.37]	[-0.46,0.94]
$1 Cutoff; Post Period 2019	-0.43	-0.84	-0.40	-0.06	0.14	-0.49	0.50	0.40
	[-0.96,-0.10]	[-1.44,-0.51]	[-1.32,0.34]	[-0.63,0.38]	[-0.66,0.64]	[-1.56,0.17]	[-0.20,0.98]	[-0.51,1.27]
$1 Cutoff; No Switchers; Post Period 2015-2019	-0.17	-0.54	-0.23	0.26	-0.09	-0.34	0.16	-0.10
	[-0.62,0.18]	[-1.04,-0.14]	[-0.97,0.33]	[-0.25,0.68]	[-0.51,0.32]	[-1.10,0.22]	[-0.37,0.62]	[-0.38,1.05]
$1 Cutoff; No Switchers; Post Period 2019	-0.35	-0.88	-0.41	0.24	-0.10	-0.53	0.51	-0.28
	[-0.85,0.04]	[-1.51,-0.58]	[-1.27,0.29]	[-0.34,0.89]	[-0.65,0.46]	[-1.52,0.18]	[-0.13,0.97]	[-0.79,1.28]
$2.5 Cutoff; Post Period 2019	-0.40	-0.68	-0.53	0.01	0.11	0.02	0.17	0.15
	[-0.87,-0.06]	[-1.04,-0.29]	[-1.22,-0.07]	[-1.07,0.60]	[-0.58,0.90]	[-0.72,1.20]	[-0.70,0.81]	[-0.72,2.22]
Overall Average Effects	-0.31	-0.69	-0.36	0.12	0.03	-0.33	0.30	0.10
	[-0.82,0.08]	[-1.35,-0.23]	[-1.19,0.30]	[-0.55,0.73]	[-0.59,0.64]	[-1.31,0.57]	[-0.47,0.91]	[-0.68,1.29]

Notes: This table presents averages across estimates from the regression analyses in our pre-analysis plan. The underlying estimates are estimates of β (g(s)) from either equation (1) or equation (2). They are thus estimates of the change in usual weekly hours worked among individuals in our analysis samples from states that increased their minimum wages relative to individuals in states that did not increase their minimum wages. The key dimensions along which we average the estimates (e.g., contrasting time periods, contrasting analyses using ACS vs. CPS data, contrasting the "Low-Skill" and "Young" samples, or contrasting the effects of "Large" increases, "Small" increases, and the inflation-indexed minimum wage changes enacted by the "Indexer" group) are clearly labeled in the body of the table. The grouping of states we describe as "$1 Cutoff" corresponds with the grouping in Panel A of Figure 1, which is the grouping from our original pre-analysis plan. The grouping of states we describe as "$2.5 Cutoff" corresponds with the grouping in Panel B of Figure 1, which reflects minimum wage changes enacted after we developed our pre-analysis plan. (Note that the inclusion of estimates involving updated groupings was, itself, specified in our pre-analysis plan.) The "$1 Cutoff Post Period 2015" results were not part of the pre-analysis plan and are thus not included in the "Overall Average Effects" calculations. Panel A includes individuals 16 to 25 with less than a completed high school education and Panel B includes all individuals ages 16 to 21.

Table A13. Summary of Hours Worked Regression Results Using Specifications from Clemens and Strain (2017) for Separate ACS and CPS Samples

Panel A: Low-Skilled	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	ACS	ACS	ACS	ACS	CPS	CPS	CPS	CPS
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
Original Categories								
Post Period 2015-2019	0.01	-0.58	0.14	0.47	0.09	-0.69	0.78	0.19
	[-0.57,0.51]	[-1.13,0.12]	[-0.70,0.78]	[-0.20,1.02]	[-0.35,0.54]	[-1.20,-0.08]	[0.13,1.31]	[-0.31,0.71]
Post Period 2015	0.22	-0.24	0.35	0.54	-0.06	-0.45	-0.16	0.43
	[-0.37,0.66]	[-0.70,0.54]	[-0.76,1.04]	[-0.25,1.05]	[-0.45,0.38]	[-0.84,0.19]	[-0.76,0.61]	[-0.12,0.98]
Post Period 2019	-0.27	-1.06	-0.11	0.35	0.15	-1.00	1.36	0.07
	[-0.97,0.24]	[-1.88,-0.37]	[-1.27,0.57]	[-0.45,0.98]	[-0.52,0.78]	[-1.91,-0.06]	[-0.05,2.40]	[-0.67,0.79]
Overall Average Effects	-0.13	-0.82	0.02	0.41	0.12	-0.84	1.07	0.13
	[-0.93,0.39]	[-1.76,0.01]	[-1.10,0.70]	[-0.31,1.00]	[-0.46,0.71]	[-1.72,-0.08]	[0.07,2.33]	[-0.56,0.72]
Panel B: Young	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	ACS	ACS	ACS	ACS	CPS	CPS	CPS	CPS
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
Original Categories								
Post Period 2015-2019	-0.18	-0.45	-0.20	0.12	0.06	-0.31	0.18	0.32
	[-0.66,0.15]	[-1.01,-0.06]	[-0.95,0.38]	[-0.32,0.51]	[-0.43,0.41]	[-1.12,0.25]	[-0.42,0.57]	[-0.21,0.88]
Post Period 2015	-0.06	-0.28	-0.04	0.15	-0.16	-0.33	-0.28	0.13
	[-0.47,0.24]	[-0.74,0.17]	[-0.82,0.53]	[-0.31,0.48]	[-0.66,0.36]	[-1.03,0.52]	[-0.92,0.36]	[-0.53,0.87]
Post Period 2019	-0.43	-0.79	-0.36	-0.12	0.10	-0.55	0.54	0.31
	[-0.99,-0.04]	[-1.51,-0.40]	[-1.26,0.32]	[-0.73,0.36]	[-0.65,0.59]	[-1.52,0.14]	[-0.19,1.03]	[-0.63,1.19]
Overall Average Effects	-0.30	-0.62	-0.28	-0.00	0.08	-0.43	0.36	0.31
	[-0.88,0.10]	[-1.37,-0.12]	[-1.11,0.34]	[-0.66,0.44]	[-0.58,0.57]	[-1.38,0.17]	[-0.31,0.95]	[-0.47,1.03]

Notes: This table presents averages across estimates from the regression analyses in our pre-analysis plan. The underlying estimates are calculated from regression equation (3) from Clemens and Strain (2017). They are thus estimates of the change in usual weekly hours worked among individuals in our analysis samples from states that increased their minimum wages relative to individuals in states that did not increase their minimum wages. The key dimensions along which we average the estimates (e.g., contrasting time periods, contrasting analyses using ACS vs. CPS data, contrasting the "Low-Skilled" and "Young" samples, or contrasting the effects of "Large" increases, "Small" increases, and the inflation-indexed minimum wage changes enacted by the "Indexer" group) are clearly labeled in the body of the table. The grouping of states we describe as "Original" corresponds with the grouping in Panel A of Figure 1, which is the grouping from our original pre-analysis plan. The "Post Period 2015" results were not part of the pre-analysis plan and are thus not included in the "Overall Average Effects" calculations. Panel A includes individuals 16 to 25 with less than a completed high school education and Panel B includes all individuals ages 16 to 21.

Table A14. Summary of Hours Worked Regression Results With No Time-Varying Covariates

Panel A: Low-Skilled Workers	(1)	(2)	(3)	(4)
Sample	All	All	All	All
Policy Group	All Change	Large	Small	Indexer
$1 Cutoff; Post Period 2015-2019	-0.04	-0.74	0.41	0.22
	[-0.41,0.36]	[-1.15,-0.01]	[-0.24,0.86]	[-0.16,0.65]
$1 Cutoff; Post Period 2015	0.04	-0.37	0.08	0.42
	[-0.29,0.39]	[-0.66,0.34]	[-0.59,0.62]	[0.05,0.72]
$1 Cutoff; Post Period 2019	-0.15	-1.11	0.54	0.12
	[-0.63,0.39]	[-1.76,-0.25]	[-0.41,1.25]	[-0.33,0.58]
$1 Cutoff; No Switchers; Post Period 2015-2019	-0.07	-0.73	0.41	0.13
	[-0.45,0.34]	[-1.14,-0.03]	[-0.26,0.88]	[-0.22,0.56]
$1 Cutoff; No Switchers; Post Period 2019	-0.19	-1.11	0.54	-0.00
	[-0.72,0.30]	[-1.66,-0.32]	[-0.43,1.25]	[-0.43,0.58]
$2.5 Cutoff; Post Period 2019	-0.25	-0.86	0.13	-0.03
	[-0.77,0.33]	[-1.53,0.28]	[-0.77,0.90]	[-0.41,0.44]
Overall Average Effects	-0.14	-0.91	0.41	0.08
	[-0.63,0.35]	[-1.61,0.02]	[-0.54,1.12]	[-0.36,0.58]
Panel B: Young Workers	(1)	(2)	(3)	(4)
Sample	All	All	All	All
Policy Group	All Change	Large	Small	Indexer
$1 Cutoff; Post Period 2015-2019	0.00	-0.29	0.00	0.29
	[-0.43,0.25]	[-1.00,0.08]	[-0.63,0.46]	[-0.09,0.61]
$1 Cutoff; Post Period 2015	-0.02	-0.17	-0.13	0.24
	[-0.44,0.33]	[-0.79,0.39]	[-0.72,0.36]	[-0.11,0.60]
$1 Cutoff; Post Period 2019	-0.09	-0.51	0.07	0.18
	[-0.58,0.21]	[-1.32,-0.19]	[-0.62,0.55]	[-0.26,0.54]
$1 Cutoff; No Switchers; Post Period 2015-2019	-0.07	-0.29	0.00	0.07
	[-0.41,0.17]	[-0.93,0.09]	[-0.56,0.44]	[-0.18,0.44]
$1 Cutoff; No Switchers; Post Period 2019	-0.18	-0.51	0.07	-0.09
	[-0.59,0.18]	[-1.45,-0.18]	[-0.51,0.56]	[-0.38,0.98]
$2.5 Cutoff; Post Period 2019	-0.12	-0.22	-0.13	-0.02
	[-0.55,0.25]	[-0.61,0.38]	[-0.77,0.38]	[-0.36,0.59]
Overall Average Effects	-0.09	-0.36	0.00	0.09
	[-0.53,0.22]	[-1.12,0.12]	[-0.63,0.51]	[-0.32,0.59]

Notes: This table presents averages across estimates from the regression analyses with no time-varying covariates in our pre-analysis plan. The underlying estimates are estimates of β (g(s)) from either equation (1) or equation (2). They are thus estimates of the change in usual weekly hours worked among individuals in our analysis samples from states that increased their minimum wages relative to individuals in states that did not increase their minimum wages. The numbers in brackets below each average are the lower and upper bound of the 95 percent confidence interval generated by bootstrapping the estimated average. The key dimensions along which we average the estimates (e.g., contrasting time periods, contrasting the "Low-Skill" and "Young" samples, or contrasting the effects of "Large" increases, "Small" increases, and the inflation-indexed minimum wage changes enacted by the "Indexer" group) are clearly labeled in the body of the table. The grouping of states we describe as "$1 Cutoff" corresponds with the grouping in Panel A of Figure 1, which is the grouping from our original pre-analysis plan. The grouping of states we describe as "$2.5 Cutoff" corresponds with the grouping in Panel B of Figure 1 which reflects minimum wage changes enacted after we developed our pre-analysis plan. (Note that the inclusion of estimates involving updated groupings was, itself, specified in our pre-analysis plan.) The "$1 Cutoff Post Period 2015" results were not part of the pre-analysis plan and are thus not included in the "Overall Average Effects" calculations. Panel A includes individuals 16 to 25 with less than a completed high school education and Panel B includes all individuals ages 16 to 21.

Table A15. Summary of Wage Regression Results From Specifications With No Time-Varying Covariates

Panel A: Low-Skilled Workers	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome	OW	OW	OW	OW	MW	MW	MW	MW
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
$1 Cutoff; Post Period 2015-2019	0.96	1.43	0.75	0.70	1.62	2.32	1.51	1.03
	[0.64,1.22]	[0.95,1.63]	[0.39,0.98]	[0.39,1.14]	[1.41,1.83]	[1.68,2.49]	[1.36,1.70]	[0.62,1.46]
$1 Cutoff; Post Period 2015	0.65	1.17	0.33	0.44	0.78	1.15	0.70	0.48
	[0.25,1.32]	[0.29,2.95]	[-0.04,0.61]	[0.16,0.71]	[0.71,0.89]	[1.02,1.44]	[0.56,0.78]	[0.45,0.52]
$1 Cutoff; Post Period 2019	1.36	2.11	0.93	1.03	2.50	3.59	2.11	1.80
	[0.67,1.83]	[1.09,2.61]	[0.27,1.31]	[0.30,1.99]	[1.98,2.86]	[2.24,3.94]	[1.82,2.44]	[0.95,2.69]
$1 Cutoff; No Switchers; Post Period 2015-2019	0.87	1.44	0.76	0.41	1.49	2.33	1.52	0.60
	[0.61,1.01]	[0.99,1.60]	[0.28,0.96]	[0.19,0.56]	[1.23,1.58]	[1.48,2.51]	[1.38,1.73]	[0.58,0.62]
$1 Cutoff; No Switchers; Post Period 2019	1.10	2.14	0.95	0.22	2.21	3.62	2.13	0.89
	[0.47,1.40]	[0.83,2.55]	[0.26,1.27]	[-0.26,0.51]	[1.66,2.41]	[1.90,3.95]	[1.83,2.52]	[0.89,0.90]
$2.5 Cutoff; Post Period 2019	1.29	2.33	1.24	0.29	2.37	3.88	2.28	0.96
	[0.90,1.69]	[1.74,2.71]	[0.71,1.83]	[-0.18,0.71]	[2.21,2.59]	[3.58,3.98]	[2.00,2.82]	[0.89,1.29]
Overall Average Effects	1.12	1.89	0.93	0.53	2.04	3.15	1.91	1.06
	[0.61,1.65]	[0.98,2.61]	[0.35,1.61]	[-0.15,1.58]	[1.38,2.70]	[1.86,3.96]	[1.39,2.60]	[0.59,2.29]
Panel B: Young Workers	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome	OW	OW	OW	OW	MW	MW	MW	MW
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
$1 Cutoff; Post Period 2015-2019	0.72	1.12	0.53	0.50	1.63	2.33	1.52	1.03
	[0.44,0.90]	[0.68,1.30]	[0.30,0.83]	[0.20,0.88]	[1.42,1.84]	[1.68,2.50]	[1.36,1.71]	[0.62,1.48]
$1 Cutoff; Post Period 2015	0.39	0.71	0.13	0.31	0.78	1.15	0.71	0.48
	[0.19,0.64]	[0.41,1.25]	[-0.26,0.56]	[0.10,0.49]	[0.71,0.89]	[1.02,1.44]	[0.56,0.77]	[0.45,0.52]
$1 Cutoff; Post Period 2019	1.09	1.75	0.77	0.76	2.50	3.60	2.13	1.77
	[0.56,1.44]	[0.88,2.15]	[0.33,1.20]	[0.16,1.47]	[1.98,2.87]	[2.27,3.94]	[1.82,2.46]	[0.95,2.68]
$1 Cutoff; No Switchers; Post Period 2015-2019	0.64	1.12	0.54	0.26	1.49	2.34	1.54	0.60
	[0.44,0.79]	[0.55,1.30]	[0.28,0.82]	[0.01,0.51]	[1.22,1.59]	[1.47,2.52]	[1.38,1.73]	[0.58,0.62]
$1 Cutoff; No Switchers; Post Period 2019	0.91	1.78	0.79	0.17	2.23	3.63	2.16	0.89
	[0.52,1.19]	[0.59,2.10]	[0.26,1.30]	[-0.12,0.68]	[1.67,2.42]	[1.90,3.95]	[1.84,2.54]	[0.89,0.91]
$2.5 Cutoff; Post Period 2019	1.04	1.93	0.95	0.24	2.38	3.88	2.29	0.96
	[0.68,1.34]	[1.50,2.22]	[0.46,1.43]	[-0.02,0.66]	[2.22,2.59]	[3.60,3.98]	[2.00,2.83]	[0.89,1.30]
Overall Average Effects	0.88	1.54	0.72	0.39	2.04	3.16	1.93	1.05
	[0.46,1.30]	[0.69,2.14]	[0.30,1.28]	[-0.04,1.06]	[1.39,2.69]	[1.87,3.96]	[1.41,2.61]	[0.59,2.29]

Notes: This table presents averages across estimates from the regression analyses in our pre-analysis plan not including time-varying covariates. The underlying estimates are, in each case, estimates of β_(g(s)) from either equation (1) or equation (2). They are thus estimates of the change in the hourly wage or minimum wage rate among individuals in our analysis samples from states that increased their minimum wages relative to individuals in states that did not increase their minimum wages. The numbers in brackets below each coefficient are The numbers in brackets below each average are the lower and upper bound of the 95 percent confidence interval generated by bootstrapping the estimated average. generated by bootstrapping the estimated average. The key dimensions along which we average the estimates (e.g., contrasting time periods, contrasting the "Low-Skilled" and "Young" samples, or contrasting the effects of "Large" increases, "Small" increases, and the inflation-indexed minimum wage changes enacted by the "Indexer" group) are clearly labeled in the body of the table. For estimated effects on hourly wages, we use data from the CPS ORG, and for estimated effects on minimum wages we use data from the basic monthly CPS. The grouping of states we describe as "$1 Cutoff" corresponds with the grouping in Panel A of Figure 1, which is the grouping from our original pre-analysis plan. The grouping of states we describe as "$2.5 Cutoff" corresponds with the grouping in Panel B of Figure 1, which reflects minimum wage changes enacted after we developed our pre-analysis plan. (Note that the inclusion of estimates involving updated groupings was, itself, specified in our pre-analysis plan.) The "$1 Cutoff Post Period 2015" results were not part of the pre-analysis plan and are thus not included in the "Overall Average Effects" calculations. Panel A includes individuals ages 25 and younger with less than a completed high school education and Panel B includes all individuals ages 16 to 21.

Table A16. Summary of Elasticities From Regression Specifications with no Time-Varying Covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Group	Low-Skilled	Low-Skilled	Low-Skilled	Low-Skilled	Young	Young	Young	Young
Policy Group	All Change	Large	Small	Indexer	All Change	Large	Small	Indexer
Panel A: Usual Weekly Hours Worked								
Overall Average Effects	-0.14	-0.91	0.41	0.08	-0.09	-0.36	0.00	0.09
Mean in 2011-2013 Baseline	7.49	6.90	8.16	7.84	13.10	11.64	14.86	13.95
Change from Baseline (%)	-1.86	-13.17	4.97	1.08	-0.70	-3.13	0.02	0.62
Panel B: Minimum Wages								
Overall Average Effects	2.04	3.15	1.91	1.06	2.04	3.16	1.93	1.05
Mean in 2011-2013 Baseline	7.69	7.72	7.41	7.80	7.68	7.71	7.41	7.81
Change from Baseline (%)	26.51	40.76	25.81	13.53	26.61	40.93	25.99	13.47
Panel C: Hourly Wages								
Overall Average Effects	1.12	1.89	0.93	0.53	0.88	1.54	0.72	0.39
Mean in 2011-2013 Baseline	8.77	9.19	8.45	8.55	9.20	9.54	8.96	8.98
Change from Baseline (%)	12.73	20.58	10.97	6.20	9.59	16.14	8.00	4.32
Elasticity of Hourly Wage w.r.t Minimum Wage	0.48	0.50	0.42	0.46	0.36	0.39	0.31	0.32
Panel D Elasticities								
Own Wage	-0.15	-0.64	0.45	0.17	-0.07	-0.19	0.00	0.14
	[-0.80,0.35]	[-1.38,0.03]	[-0.89,1.18]	[-2.90,2.87]	[-0.61,0.17]	[-1.21,0.07]	[-0.92,0.43]	[-2.05,1.77]
Minimum Wage	-0.07	-0.32	0.19	0.08	-0.03	-0.08	0.00	0.05
	[-0.31,0.19]	[-0.60,0.01]	[-0.24,0.57]	[-0.40,0.72]	[-0.16,0.07]	[-0.32,0.03]	[-0.17,0.14]	[-0.20,0.30]

Notes: This table reports average usual weekly hours and wage effects for each minimum wage policy group and skill group along with own-wage and minimum wage elasticities. The numbers in brackets below each elasticity are the lower and upper bound of the 95 percent confidence interval generated by bootstrapping the estimated elasticity. The baseline mean for the usual weekly hours panel comes from the ACS and the overall average effects on usual weekly hours are calculated from regression estimates on data from the ACS and CPS. The baseline mean and estimated overall average effects on minimum wages come from the basic monthly CPS. The baseline mean and estimated overall average effects on hourly wages come from the CPS ORG. Averages in the “mean in 2011-2013 baseline” rows are calculated using our original policy categories, while those in the “overall average effects rows” use results generated on both the original and new policy categories. Low-Skilled individuals are ages 16 to 25 with less than a completed high school education and young individuals are ages 16 to 21. Average effects for usual weekly hours (panel A), minimum wages (panel B), and hourly wages (panel C) are taken from Tables A14 and A15. The hourly wage elasticity with respect to the minimum wage is the percentage change in average hourly wages from the baseline period of 2011-2013 divided by the percentage change in minimum wages from 2011-2013. The own-wage elasticity for each policy-skill group is the estimated usual weekly hours effect divided by the percentage change in average hourly wages from the baseline period of 2011-2013 and the minimum wage elasticity is the estimated usual weekly hours effect divided by the percentage change in the minimum wage from 2011-2013.

Table A17. List of States with Statutory Minimum Wage Changes and the Year of First Associated Increase 2013-2019

State	Year of First Statutory Increase
Alaska	2015
Arizona	2017
Arkansas	2015
California	2014
Colorado	2017
Connecticut	2014
Delaware	2014
District of Columbia	2014
Hawaii	2015
Maine	2017
Maryland	2015
Massachusetts	2015
Michigan	2014
Minnesota	2014
Missouri	2019
Nebraska	2015
New Jersey	2014
New York	2014
Oregon	2016
Rhode Island	2013
South Dakota	2015
Vermont	2015
Washington	2017
West Virginia	2015

Note: Data on minimum wage changes comes from the U.S. Department of Labor. States are counted as statutory increaser states if the minimum wage rate in force in that state increased between January 1, 2013 and January 1, 2019 as the result of a new piece of legislation passed between 2013 and 2018. The year of first statutory increase is the year in which the first minimum wage increase mandated by a new piece of legislation goes into effect. A slight tweak on this assignment rule involves the state of New York. New York passed legislation in March 2013 to increase its minimum wage on December 31, 2013. We assign the year of first statutory increase to 2014, reflecting that 2014 was the first year during which the increase was in effect.