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Minimum Wage Effects in Low-Wage Areas

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Abstract

A proposal to raise the federal minimum wage to $15 by 2024 would increase the *relative* minimum wage – the ratio to the national median wage-- to about .68. In Alabama and Mississippi, our two lowest-wage states, the relative minimum wage would rise to .77 and .85, respectively. Yet research on state-level minimum wage policies does not extend beyond $10; the highest studied state-level relative minimum wage is .59. To close this gap we study minimum wage effects in counties and PUMAs where relative minimum wage ratios already reach as high as .82. Using ACS data since 2005 and 51 events, we sort counties and PUMAs according to their relative minimum wages and bites. We report average results for all the events in our sample, and separately for those with lower and higher impacts. We find positive wage effects but do not detect adverse effects on employment, weekly hours or annual weeks worked. We do not find negative employment effects among women, blacks and/or Hispanics. We do find substantial declines in household and child poverty.

JEL Classification: J20, J31, J48, J80

Keywords: minimum wage, employment, median wage, low-wage areas, poverty

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1. Introduction

In recent years, U.S. minimum wage policy has moved into new territory. Over forty cities and seven states are phasing in $15 standards, while the *Raise the Wage Act of 2019* (HR 582) proposes to raise the federal minimum wage gradually—in six steps-- from $7.25 today to $15 by 2024. Since $15 in 2024 is equivalent to about $13 today, HR 582 would raise the minimum wage above its previous real minimum wage peak of about $11.80-- achieved in 1968. A $15 national floor would also mark a new high of the federal minimum wage relative to the national median wage.

Economists distinguish among at least three ways of measuring minimum wage increases: a) the percent increase in the real (inflation-corrected) dollar value of the minimum wage; b) the percent increase in the *relative* level of the minimum wage—defined as the ratio of the minimum wage to the median wage; and c) the bite of the minimum wage—defined as the proportion of workers who receive a pay increase if the minimum wage increases. Each of these measures provides an indicator of the intensity of the policy, but the relative minimum wage and the bite are more sensitive to labor market conditions in lower-wage areas. The relative minimum wage is also correlated with area living costs; this measure therefore indicates how far a given minimum wage goes to covering local expenses.[1]

In this paper we address the effects of minimum wage increases on low-wage areas within states. Unlike most minimum wage studies, we use all three of the above measures in our analysis. Notably, and also unlike most minimum wage studies, our approach makes use of the variation in these measures among counties and metro areas within the lowest-wage states.

The national U.S. relative minimum wage today is about .36, among the lowest of any industrialized country. In contrast, a $15 federal minimum wage in 2024 would increase the relative minimum wage to about .68, higher than that of any other nation today. In our two

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[1] The relative minimum wage provides only an approximate metric for policy purposes, for a number of reasons. First, it does not take into account variation in the proportion of an economy's tradable goods sector, which is more subject than are non-tradable services to adverse effects when minimum wages rise. Second, it does not take into account the level of entry level wages in low-paid jobs, which might be imperfectly correlated with the minimum or the median wage. And it is only imperfectly correlated with living cost indices. And third, it can vary when the median wage varies, even if the minimum wage does not change. Nonetheless, the relative minimum wage is intuitive and transparent and is widely used to compare minimum wages around the world (OECD 2019)

lowest-wage states-- Alabama and Mississippi, the relative minimum wage would rise by 2024 to .77 and .85, respectively (BLS 2019).

What do we know about the effects of high minimum wages? Research on recent state-level minimum wage policies does not extend beyond the $10 level; the highest studied state-level relative minimum wage is .59. Studies of local minimum wages extend to higher levels—as much as $13 in 2016; but these areas have relatively high median wages, so they have low relative minimum wages and low minimum wage bites. Clearly, minimum wage policy proposals and campaigns are moving well beyond the terrain studied by researchers.

To close the gap between policy and research, we drill down here below the state level and use sub-state variation in wages that have mainly been ignored in minimum wage research. More specifically, we study the effects of high relative minimum wages and high minimum wage bites at the county level. In every state, counties vary considerably in their median wages. As a result, the ratio of minimum wages to county-level median wages varies much more than state-level ratios; the ratios are much higher in lower-wage areas. In a substantial number of counties, relative minimum wages have already exceeded .68, and reached as high as .82. Many, but not all, of the high relative minimum wage counties are in the 21 states that have remained at the federal minimum of $7.25 since 2009. County-level variation thus provides an under-utilized laboratory for studying the effects of high minimum wages in low-wage areas.

We use data from the American Community Survey (ACS) for our analysis. ACS data are available beginning in 2005. Unlike the Current Population Survey, the ACS has a sufficient sample size at the county level. However, the ACS reports county-level data only for the more populous counties, covering about 60 percent of the U.S. population. To be able to include data on all counties, including those in rural areas, we also use local areas based on census-defined Public Use Microdata Areas (Pumas) — areas of about 100,000 people.

We sort counties and Pumas according to their relative minimum wage and the bite of the minimum wage. We then use event study methods and generalized difference-in-difference models to examine minimum wage effects in areas with low and high relative minimum wages and low and high bites.

Following standard causal methods, our analysis examines wage, employment and poverty outcomes in samples of those who are most exposed to minimum wages: those with a high school education or less, and teens. We report average results for all the areas in our sample, and separately for those with higher relative minimum wages or higher bites. We show that positive wage effects are greater in areas with higher relative minimum wages and bites, validating our approach to studying high impact areas. To check that our methods identify causal effects, we conduct tests for common pre-trends as well as robustness and placebo tests.

Our results generally suggest the presence of positive wage effects. We do not detect adverse effects on employment hours or weeks worked, but we do find reduced household and child poverty in counties with high relative minimum wages, up to .82, and as well in areas with especially high bites. We also do not find negative effects among blacks, Hispanics and women. These findings considerably extend the policy terrain of studies that use state-of-the-art causal identification methods. The results have self-evident policy implications.

We review in Section 2 the current minimum wage policy and research context. Section 3 discusses expectations from economic theory. In Section 4 we discuss our research design, including our data and empirical methods and descriptive statistics. We present our main results in Section 5 and summarize and conclude in Section 6. Appendix A provides additional results using our preferred specification; Appendix B shows results with alternative specifications.

2. The policy and research context

2.1 The current policy terrain

Over 40 local governments have already enacted local minimum wages, many of them at the $15 level. Seven populous states--California, Connecticut, Illinois, Maryland, Massachusetts, New York, New Jersey-- and the District of Columbia have enacted $15 standards; Arizona, Oregon and Washington have enacted standards between $13 and $15. A number of prominent large retailers (Amazon, Costco, Target and Walmart) have already enacted minimum wages in the $11 to $15 range. Numerous others entities have enacted or implemented minimum wages in the $10 to $13 range. These local and state minimum wage levels reach higher than those studied in the research literature.[2]

The policy activity for a $15 standard is continuing, despite limited guidance from academic research. At the federal level, the *Raise the Wage Act of 2019* (HR 582), which would gradually increase the minimum wage to $15 by 2024, is close (at this writing) to passage in the House of Representatives. A competing measure, sponsored by Rep. Teresa Sewell (D, Alabama), would phase in a five-tier minimum wage, with tiers based on local living cost indices.

Meanwhile, a number of additional state legislatures, such as in Hawaii and Vermont, are likely soon to enact $15 standards. Other states have passed legislation pre-empting localities from raising their wage standards. Minimum wage ballot initiatives are also expected in a number of electoral "battleground" states, including Florida, in 2020. It seems clear that the $15 minimum wage issue will remain a prominent national policy issue through 2020 and beyond.

In states that already enacted policies, relative minimum wages have been increasing. As Table 1 shows, by 2021 the sixteen highest state-level relative minimum wages will range between .523 and .669. Interestingly, these states include a mix of high, middle and low wage states.

2.2 The state of empirical research on employment effects

The long-standing academic debate on minimum wages has progressed toward a reasonable consensus in recent years. The most important and comprehensive minimum wage paper in several decades, by Cengiz, Dube, Lindner and Zipperer, examines the effects on jobs of 138 prominent federal and state minimum wage events between 1984 and 2016. This study has been published online by the Quarterly Journal of Economics (QJE). The authors do not detect

[2] Two notable exceptions are Bailey, DiNardo and Stewart 2018 and Derenencourt and Montialoux 2019. Both of these papers study the effects of the major coverage extensions and subsequent minimum wage increases in the 1966 amendments to the Fair Labor Standards Act. These changes ushered in the highest real federal minimum wage to date. Both are similar to this paper in using variation among areas in the bite of minimum wage increases to identify effects on wages and employment.

significant negative effects on the number of low-wage jobs.[3] Cengiz et al. conduct numerous stress tests on their findings, including possible lags and leads, effects by subsample period, heterogeneity for higher minimum wages, placebo tests, robustness to including possible confounding variables, effects on individual demographic groups, and tests of substitution of educated workers for less-educated workers.

Cengiz et al. resolve a major issue in the literature: the appropriate controls to include in difference-in-difference specifications (Neumark, Salas and Wascher 2014; Allegretto et al. 2017). Cengiz et al. document that parsimonious and saturated specifications both provide similar results for the period since 2002. As a result, and although disagreements continue, the minimum wage literature has reached a working consensus, exemplified by the Cengiz et al. findings, and acknowledged by economists when they explicitly dissent from the consensus view.[4]

2.3 Policy has outpaced research

Despite the abundance of minimum wage studies and the recent advances in the research literature, studies such as Cengiz et al. are only partly germane to the current policy debate. Their highest state minimum wage is $10; their state-level relative minimum wages ranges between .37 and .59. Since current and proposed policies considerably exceed each of those benchmarks, extant research is not sufficiently informative for policy. Moreover, higher local minimum wage levels have often been adopted in areas with higher living costs and higher median wages, raising questions about their generalizability to other areas.

On the other hand, if a federal $15 minimum wage was enacted, actual pay increases in low-wage states would be much smaller than the nominal increase from $7.25 to $15. Moreover, pay increases in $7.25 states would not be much greater than in higher minimum wage states (Reich 2019). In other words, differences across states in pay for low wage jobs are smaller than

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[3] The editors of the QJE conducted especially extensive reviews of this article before accepting it for publication. The QJE has the highest ranking of any scholarly economics journal; less than four percent of its submissions are accepted for publication.

[4] Cengiz et al. also identify methodological flaws in recent studies that find negative employment effects, such as Meer and West (2016). Dube (2019) provides a readable nontechnical summary of recent minimum wage research. Clemens (2019) and Strain (2019) acknowledge the formation of a new minimum wage consensus, while presenting dissident perspectives on recent studies.

differences in pay for median pay jobs. Figure 1 shows entry-level wage rates for recent high school graduates since 2005 for three groups of states: those in which the state minimum wage exceeded the federal minimum in every year (gray), those in which the state minimum wage only sometimes exceeded the federal level (red), and those for which the state and federal minimum wage were always the same (blue). These groupings correspond respectively to differences in median wages. In contrast, entry-level wages among these three groups of states vary by a quite small amount, about 50 cents, throughout this period.

Nonetheless, additional research focused on lower-wage areas would be very informative for policy makers. Fortunately, it is possible to extend our knowledge of the likely effects of the newer and proposed high minimum wages. We present the results of such research here; we plan to issue updates as more areas reach higher standards and more data become available.

3. Theoretical considerations: what to expect

What do academic studies tell us about how minimum wages have been absorbed? And what might be the lessons of such studies for a $15 standard?

Economic theory is ambiguous about the general equilibrium effects of minimum wages on employment. Indeed, a substantial body of recent credible evidence explains why past minimum wage increases have not caused employment declines, even in the face of downwardly sloping labor demand curves. Credible causal studies have found that minimum wages are absorbed partly by small price increases in the most affected industries, namely restaurants and retail (Allegretto and Reich 2018; Brummund 2018; Cooper, Luengo-Prado and Parker 2019); partly by reduced employee turnover costs (Dube, Lester and Reich 2016); partly by increased employment in more concentrated (monopsonistic) local labor markets (Azar et al. 2019); partly by increased worker productivity (Coviello, Deserranno and Persico 2019); partly by increased labor supply of some groups (Godoey, Reich and Allegretto 2019); and partly by economic stimulus effects generated by increased worker purchasing power (Cooper, Luengo-Prado and Parker 2019).

Automation is also a factor, but it is not as decisive as is often stated (Aaronson and Phelan 2019). The importance of tradables—goods or services that can be exported or imported—turns out to be of minimal importance, especially in the current period, as low-wage manufacturing jobs have diminished in number (Cengiz et al. 2019; Reich 2019). Indeed, a focus on tradables alone ignores how minimum wage increases reallocate employment to non-tradable sectors (Dustmann et al. 2018).

Although these studies identify the principal absorption channels, they cannot tell us whether minimum wages at $15 will be absorbed in a similar manner. For example, restaurant price increases are limited by the elasticity of demand, effects on tradables could be greater at higher wages, automation possibilities could become more pertinent and stimulus effects could be greater with higher wage increases. A simulation model incorporating all these effects found that the positive and negative effects on employment were about the same (Reich et al. 2019). Moreover, negative effects occur gradually, without cliffs. Continual monitoring of the effects of phase-in minimum wages, with course corrections as necessary, could minimize the risk of negative employment effects.

4. Research design

Our research design focuses on effects of minimum wages across counties and other small areas with different relative minimum wages, using the wider variation in relative minimum wages that exists between localities within each state. We are not the first to use county-level variation to study minimum wage employment effects (see Card 1992) or to use the relative minimum wage metric. However, Card, Katz and Krueger (1993) showed that relative minimum wages vary more with the median wage than with the minimum wage, confounding whether the relative minimum wage measures policy variation. If unobserved shocks to the economy shift both median wages and employment rates in the same direction, relative minimum wages will be negatively correlated with employment rates even when there is no variation in actual minimum wage policy. This critique led minimum wage researchers to drop the use of the relative minimum wage in statistical analysis.

Similarly, researchers sometimes use variation in the bite of the minimum wage to identify effects of minimum wages in the absence of state-level variation in policy (Card 1992, Bailey, DiNardo and Stuart 2019). In Appendix B, we discuss these methods in more detail, together with a discussion of how the results from these methods differ from our preferred specifications.

In this paper, we do not use the relative minimum wage as a measure of minimum wage policy. Rather, we follow Cengiz et al. (2019) in using the local relative minimum wage as a proxy for the expected impact of minimum wage changes on local wage levels. We then estimate a set of event study and generalized difference-in-difference regressions, estimating effects of the minimum wage on wages and employment in high and low impact regions.

In the following, we first present the data used for the analysis. Then, we present the empirical models, followed by descriptive statistics on the geography and characteristics of high impact areas.

4.1 Data

Our main data source is the 1-year estimates from the American Community Survey (ACS), which is available for the years 2005 through 2017. The primary advantage of the ACS for our purposes is its large sample size – the ACS samples approximately 3 million addresses a year, compared to around 100,000 for the Current Population Survey – as well as its much higher response rate. The larger sample size allows us to credibly estimate local median wages as well as wages and employment rates for various demographic groups for smaller localities by calendar year.

The 1-year ACS files directly identify only a subset of counties; the identity of counties with a population below 65,000 is suppressed. In addition, we do not observe counties whose borders do not line up with those of the census-designated public use microdata areas (PUMAs).[5] As a result, only about 60 percent of the U.S. population resides in counties that are directly identified in the ACS. To overcome this problem, our empirical analysis instead uses "coumas" -- geographic areas defined by Case and Deaton (2017) in their work on deaths of despair. For every county and consistent PUMA, a couma corresponds to whichever has the *larger* population

[5] PUMAs consist of areas with at least 100,000 residents. The ACS provides PUMA information on all respondents. In less-populated areas, PUMAs typically consist of two adjacent counties. In more-populated areas, counties contain multiple PUMAs. Los Angeles County, for example, has over 30 PUMAs. In such areas, workers' relevant labor markets are better defined by their county than by their PUMA.

-- the county or the PUMA.[6] The larger unit better captures the relevant labor market.[7] Coumas then cover the entire U. S. population, including rural as well as urban areas. In 2017, there were 708 coumas; the median couma had 223,133 inhabitants.

The ACS contains a rich set of background variables as well as information on employment and earnings. For our key variable of interest -- the hourly wage – the ACS contains two disadvantages relative to the CPS. First, data on hourly earnings are not reported directly in the survey, but must be estimated by dividing the previous year's annual earnings by the product of weekly hours worked and yearly weeks worked. Each of these steps introduces measurement error, especially for part-year workers, as the number of weeks worked is reported in bins rather than as an exact number. This data issue adds noise to the hourly earnings variable, but not bias. Second, since respondents are surveyed throughout the year, the reference period varies by the month of the survey. To keep the analysis tractable, all responses are assigned the same reference period (the calendar year before the survey).[8]

We use this hourly wage measure to estimate the median wage across all workers in the couma, as well as average wages for a number of demographic groups. We identify three groups of workers that might have high exposure to minimum wage work: people who have not completed high school, people with high school degrees or less and teens (age 16-19). As a placebo group, we use people with a bachelor's degree or higher; this population is unlikely to work minimum wage jobs. For each of these groups, we calculate couma annual average wages as well as employment rates. All dollar amounts are adjusted for inflation to 2016 dollars, unless otherwise noted.

For employment, our main outcome variable is the employment to population ratio among people aged 16-70. When constructing this variable, we count as employed every individual who worked at some time during the reference year. We also include measures of

[6] Consistent PUMAs (CPUMAS) are defined by IPUMS; they are aggregations of one or more PUMAs: https://usa.ipums.org/usa/volii/cpuma0010.shtml. PUMA boundary definitions change after each decennial each census; in the ACS, the new definitions were implemented starting in 2012. CPUMAS represent the smallest geographic units that are consistent across all the years in our sample.

[7] We do not examine commuting patterns. For densely-populated areas, the relevant labor market could span more than one couma.

[8] If wages are growing faster than inflation, this procedure may cause us to overestimate median wages, in turn underestimating the relative minimum wage and the minimum wage bite.

weeks worked, full-year work (50-52 weeks worked in the reference year), usual weekly hours and a binary indicator for full time work (usual weekly hours of 35 hours or more). For these variables, we calculate the couma average over the full sample in each population of interest, as well as average values conditional on working (excluding people with zero wage income). Finally, in order to capture effects of minimum wages on households at the lower end of the earnings distribution, we include measures of household and child poverty rates.[9]

These variables are then collapsed by couma and year, yielding a couma-by-year dataset of median wages, average wages and employment rate for various demographics, as well as household and child poverty rates. We merge the sample with data on state population, state unemployment rates and state GDP from the University of Kentucky Center for Poverty Research (UKCPR) database. Our main source of minimum wage data is the Vaghul and Zipperer (2016) minimum wage database: the effective minimum wage is the highest of the state and federal minimum wage. Importantly, we ignore sub-state (city and county) minimum wages.

4.2 Empirical models

The period we study contains substantial variation in state and federal minimum wage policies. Our empirical analysis leverages this variation, estimating a set of regressions of couma level wages and employment, controlling for area and year fixed effects, as well a parsimonious set of couma and state-level control variables. In order for the regressions to estimate the causal effects of the minimum wage, we require the parallel trends assumption to hold. That is, conditional on the covariates in the regression model, the residual variation in minimum wages within states should be uncorrelated with underlying trends in employment and earnings. The models control fully for couma-specific factors that are constant over time, as well as aggregate changes to the economy. However, the models could still yield biased estimates if the timing of minimum wage changes is correlated with unobserved trends in outcomes. Such bias could be present, if, for example, states are more likely to pass minimum wage legislation when the economy is doing well.

[9] In future work, we will use the QCEW data to examine minimum wage effects on wages and employment in the most exposed detailed industries: food services and retail.

We first estimate a set of scaled event-study models (Finkelstein et al. 2016), estimating how average wages and employment rates change in the years before and after minimum wage increases. The intuition behind these models is simple: Increases in the minimum wage should not have any effects on earnings or employment in the years leading up to the policy change. Put differently, if wages and employment rates rise in the years leading up to minimum wage increases, the estimates from the generalized differences risk being biased upwards, reflecting unobserved state trends rather than the policies we study.

To define events, we first include all year-on-year increase in the applicable minimum wage (higher of state and federal) of 25 cents or more. Next, we require that the minimum wage did not change for at least two years leading up to the event – this requirement ensures that we are able to assess pre-trends. We do allow for additional changes to the minimum wage in the years following the initial increase –minimum wage policies are typically phased in over several years. To ensure we have enough post-periods to adequately capture effects of policy changes, we exclude events occurring after 2014. For each event, we include up to four years of data before and after the event year, though we do not require the sample to be balanced in event time.

These criteria yield a total of 51 events: 46 states experience at least one qualifying event, and 5 states experience two events during the sample period (see Appendix table A for a full list). The differential timing of these policy changes will be the primary source of variation in our empirical models. Crucially, the federal minimum wage increase in 2007-2009 will be a qualifying event for most of the states; the exceptions are a handful of states that were already above the new federal minimum. This pattern allows us to estimate effects of minimum wage increases in regions with relatively low minimum wages (and low state median wages).

For each event, we define δ_c as the change in log min wage over the event window.

$$\delta_c = logmw_c^{max} - logmw_c^{min}$$

We can write the augmented event study specification as

$$y_{cst} = \theta_s + \theta_t + X_{ct}\beta + \sum_{k=-3,k\neq 1}^{4} \left(\pi_{k(c,t)} \times \delta_c\right)\rho^k + \varepsilon_{ct} \tag{1}$$

These models control for state-event and year specific intercepts as well as a vector of state and couma characteristics: the models control for the state unemployment rate, state GDP per capita, and log couma population.[10] The primary coefficients of interest is the parameter vector ρ, which captures the expected change in outcomes around the time of the policy change. As these coefficients are only identified relative to each other, we follow convention and set the last pre-increase period as the reference category, i.e. $\rho^{-1} = 0$. Moreover, we bin event time at the earliest pre-period, that is, we set $\rho^{-4} = \rho^{-3}$.

If our empirical strategy is valid, there should be no systematic differential trends in wages and employment in the years leading up to minimum wage increases. That is, for $k = 0$, the estimated event time coefficients should be small and close to zero for all years leading up to the minimum wage increase.

Meanwhile, for $k \geq 0$, any positive (negative) effects of the minimum wage should show up as a discontinuous jump (drop) in the estimated event time coefficients. Qualitatively, we expect effects to show up as a discontinuous shift at time 0 (the year of the initial increase), potentially increasing in magnitude over the post-period reflecting gradual phase-ins of minimum wage policies. In this regression model, the event time indicators π_k are interacted with our measure of the aggregate change in the log minimum wage over the event window. The estimated sizes of the jump therefore indicate the (semi-) elasticities of employment and wages with respect to the minimum wage.

Following the standard approach in the literature, we also estimate generalized difference-in-differences models on the form

$$y_{cst} = \theta_s + \theta_t + X_{ct}\beta + logmw_{ct}\gamma + \varepsilon_{ct} \tag{2}$$

The econometric models presented in equations (1) and (2) form the basis of our empirical analysis. However, the key focus of this brief is not the average wage and employment impacts of higher minimum wages. Rather, we wish to estimate how impacts vary across localities with

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[10] For states with two events, we include a separate intercept for each of the two events. Similar models with couma-event fixed effects rather than state-event fixed effects yield nearly identical results, which is as expected given that minimum wage policies studied vary only at the state level (our analysis ignores county and city minimum wage ordinances).

different expected impacts. For each of the events in the sample, we calculate two couma-specific measures of expected impact. First, we follow Cengiz et al and define the event-specific Kaitz index as the ratio of the minimum wage at the end of the event window to the couma median wage in the last pre-increase year.[11] Second, we calculate the bite as the share of workers in the final pre-increase year whose hourly wage is below the new minimum wage. These two metrics will then be used to classify the localities in the events sample into subsamples; models (1) and (2) are then estimated separately on each group.

4.3 Descriptive statistics

Relative minimum wages and minimum wage bites vary considerably more among coumas than they do among states. We demonstrate this point in Figure 2, which uses federal and state minimum and median wage data to plot the distribution of relative minimum wages and minimum wage bites across coumas. The relative minimum wages and minimum wage bites are displayed at the state (grey bars) and couma levels (white bars), respectively.

As Figure 2a shows, the distribution of couma-level relative minimum wages following minimum wage increases is considerably wider than the distribution across states. While state-level relative minimum wages vary between .35 and 61, couma-level relative minimum wages vary between .26 and .82. Importantly, the maximum couma-level relative minimum wage is 35 percent higher than the maximum state-level relative minimum wage, and more than one-third higher than in Cengiz et al. While the state-level relative minimum wage after minimum wage increases exceeds 0.50 for less than 33 percent of Americans, a significantly larger share – 56 percent -- live in areas where the couma relative minimum wage reaches 0.50 or higher. Our empirical analysis leverages this variation to analyze how employment responds to minimum wage changes at these higher indices of minimum to median wages.

Figure 2b shows comparable histograms for the share of workers below the new minimum wage when a minimum wage is increased—the minimum wage's bite. Once again, the

[11] Hyman Kaitz, a statistician at the Bureau of Labor Statistics, is credited with introducing this ratio into the minimum wage literature.

variation in the minimum wage bite associated with the minimum wage events is substantially greater across coumas than among states.

One of our key metrics of the expected impact of minimum wage increases is the couma relative minimum wage, defined as the ratio of the new minimum wage to the pre-increase median. Figure 3 explores the relative importance of variations in the minimum wage and the median wage in determining the ratio of the two measures across decile bins (labeled KR deciles in the figure, for Kaitz ratios). Minimum wage levels are essentially the same in all the Kaitz ratio deciles, while median wages fall monotonically with increases in the Kaitz ratio decile. The variation in relative minimum wages between high and low Kaitz ratio coumas appears to come almost entirely from variation in median wages, and not from minimum wage policy.

Figures 4a and 4b provide maps of relative minimum wages and average bites for each of the minimum wage events in our sample.[12] Figure 4a presents couma-level relative minimum wages for each minimum wage event in the sample period. Figure 4b shows the bite, the share below the new minimum wage, for each of the minimum wage events in the sample period. For both metrics, the highest impact areas have the darkest colors. A comparison of figures 4a and 4b indicates that the relative minimum wage and the minimum wage bite are highly correlated. The figures also show that coumas with the highest relative minimum wages and bites are not limited to one geographic area. Relative minimum wages are high in much of Arkansas, Florida, Kansas, Louisiana, Maine, Nebraska and Oklahoma, in much of western and southern Texas, and in much of the Pacific Northwest, including areas of California near the Oregon border. They are not as high in Alabama, Mississippi and Missouri.

To see this more clearly, Figure 5 ranks states according to their population in localities that are in the top quartile of relative minimum wages (upper panel, labeled Kaitz ratio in the figure) and bite (lower panel). While the highest shares of high relative minimum wage areas are found in two relatively low-wage, rural states (Montana and West Virginia), the overall picture is more mixed. For instance, California, a state with high average wages that is implementing a $15

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[12] For the five states that have two events over the sample period, the map shows the first event only. States that have no qualifying event are colored white. The map boundaries correspond to IPUMS-defined CPUMAs (consistent pumas): coumas that represent a single county with several cpumas are all assigned the same value.

minimum wage by 2022, has a higher share of the population living in high relative minimum wage localities than do both Mississippi and Alabama, two of the nation's poorest states.[13]

In Appendix A, we show similar graphs with the population share of each state that lives in areas with bites above 0.15 and 0.2, and the share that live in areas with relative minimum wages above 0.5 and 0.6, respectively. These figures show that for moderately high thresholds – 15 percent bite, 0.5 relative minimum wage – most states have at least some observations in the high impact sample. At the higher thresholds, the remaining sample includes a substantial but smaller number of states – 32 states have one or more couma-events where the bite is above 20 percent, while 25 states have one or more couma-events with a relative minimum wage higher than 0.6.

Appendix Figure A2 shows the distribution of blacks, Hispanics and college graduates by Kaitz ratio. High impact coumas have lower proportions of black workers. In contrast, the proportion of blacks is higher in low-wage states, especially those in the South. Our high sample of high-impact coumas includes many areas of California that are more populated by Hispanics than by blacks.

Meanwhile, the proportion of college graduates in the workforce varies inversely with the relative median wage. This result is not surprising, since median wages and education levels are positively correlated. Nonetheless, the pattern is reassuring and supports using low impact coumas for our counterfactuals.

5. Main results

We present first results using event study models and then our results using generalized difference-in-difference methods.

5.1 Event- study models

Figure 6a presents estimated event study models of employment and earnings for individuals with high school education or less. The panels on the left represent the effects of the minimum

[13] Note that the two measures do not always line up. The most extreme case is South Dakota, which consists of a single couma, where 100 percent of the population resides in high KR localities, while 0 percent of the population resides in high bite localities.

wage in localities with final relative minimum wages in the lowest quartile of the event sample.[14] In this sample, the inflation-adjusted indices of the minimum wage at the end of the event window to the median wage in the year before the minimum wage range between 0.26 and 0.46. The panels on the right present the effects in localities with relative minimum wages in the highest quartile; here the relative minimum wages range from 0.56 to 0.82. The two upper panels present results for wages. The two lower panels present results for employment.

Higher minimum wages tend to have the largest effects on wages of less-educated workers in areas where the relative minimum wage is higher. In the low relative minimum wage coumas, the wage increase at the time of the minimum wage change is small; while point estimates tend to be positive following the increase, these are indistinguishable from the slight pretrend in wages for this sample. In the high impact regions, estimated event time coefficients tend to be close to zero in the years before minimum wage increases for both wages and employment. These results indicate the absence of pre-trends in wages and employment in high impact areas. In these localities, we estimate a significant jump in event time coefficients for wages at time 0, when the new, higher minimum wage is implemented.

Employment effects meanwhile do not appear to differ between the high and low impact areas. The two lower panels show the effects on employment to population ratios, for individuals between 16 and 70. The absence of a jump at time 0 indicates that effects on employment are small to negligible in both samples.

To summarize to this point, the couma-level relative minimum wages appear to be informative on the impact of the minimum wage: In the population of adults with high school or less education, we find the largest wage effects in localities where the relative minimum wage is high. However, this wage effect does not translate to job loss, even in the highest quartile event subsample.

To assess the robustness of these findings, we estimate additional models that split the sample by the bite of the minimum wage rather than by the relative minimum wage itself. These

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[14] Specifically, we define the event-specific relative median wages as the ratio of the highest minimum wage observed in the event window to the median wage in the final pre-event year.

models, which we present in Figure 6b, yield broadly similar conclusions. Wage effects are clearly larger in high bite localities. Employment effects are small overall; in the high bite subsamples they are close to zero.[15]

As Appendix Table A1 indicates, many of our events are generated by the federal minimum wage increases from 2007 to 2009. Since this timing coincides with the onset of the Great Recession, our analysis might be affected by the sharp declines in employment that began during the Great Recession and extended into the first years of the economic recovery. Indeed, Clemens and Wither (2019) find that minimum wage effects during this period did generate negative employment effects. However, Zipperer (2016) presents evidence indicating that Clemens and Wither do not sufficiently control for differential effects of the Great Recession across industries and regions. We do not control for industrial and regional differences in our analysis and yet we do not detect negative employment effects.

Thus far, our results indicate that higher minimum wages tend to increase wage rates in low-wage coumas, without reducing employment rates. These results suggest we should expect to see a corresponding increase in incomes at low levels. Figure 7, which plots the estimated event study models of poverty, indicates that this is indeed the case. In high relative minimum wage coumas, poverty falls significantly after the minimum wage increase is implemented. In the low relative minimum wage coumas, there is no significant effect on poverty rates, consistent with the lack of statistically significant wage effects in these areas.

5.2 Generalized difference-in-difference estimates

We also estimate a generalized differences-in-differences regression model on the event sample, replacing the event time coefficients with the contemporaneous values of the log minimum wage. To define high and low exposure localities, we again use two event-specific metrics: the relative minimum wage defined using the pre-increase median wage, and the bite—

[15] In the high bite subsamples, the coefficients on employment tend to be negative, though not statistically significant, in the post-period. However, there is a negative pre-trend in employment in this sample, indicating that this result represents a differential trend rather than a causal impact of policy change.

the share of workers with pre-increase wages below the new minimum. Specifically, we consider localities where the relative minimum wage is above and below .5, respectively, as well as a subsample of localities where the relative minimum wage is .6 or higher.[16] We also examine coumas with shares above and below 15 percent of below-minimum wage workers, as well as coumas where 20 percent or more of the workers were paid below the new minimum wage.

Table 2 shows the results from this exercise. Overall, these results are consistent with the findings from the event study models. For both metrics, higher minimum wages raise wages of less-educated people more in areas where exposure is higher. This pattern holds for both people without a high school degree as well as for people with high school or less. The wages of teens tend to increase in all localities, though the size of the increase is larger in high impact coumas. Overall, this pattern indicates that the two metrics – the Kaitz ratio and the bite – capture variation in the impact of minimum wage policies.

Meanwhile, the model fails to find significant effects on employment for either of the noncollege-educated samples or for teens. This result holds both in the pooled sample of all localities (column 1) as well as across coumas. If high impact localities were less able to absorb the higher wage costs, we might expect employment effects to be more negative in high Kaitz ratio/high bite coumas; however, this does not appear to be the case. In fact, comparing point estimates across columns (2) – (7) reveals a somewhat puzzling pattern: although not statistically significant, employment point estimates tend to be larger and more positive in the high impact coumas. We interpret this pattern as indicating possible differential employment trends in high couma areas. As we will show below, this pattern is consistent with the pattern found in the placebo sample.

To further compare these results with those in the literature, we calculate employment elasticities with respect to the minimum wage and own-wage elasticities, using the estimates from Table 1 as well as average employment rates in each subgroup. These estimates appear in Table A2. In the pooled sample of all localities, our estimated own-wage elasticities for the three

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[16] That is, higher than the highest state-level relative minimum wage analyzed by Cengiz et al.

high impact groups range from -0.159 to 0.176. These are well within the range of estimates reported in the literature (see Harasztosi and Lindner 2019 for a review).

For the college-educated sample, the models find no effects on wages or employment in the pooled sample. This result accords with what we would expect, given the low exposure of this group to minimum wage work. Looking across coumas yields overall similar results for wages, with the exception of a marginally significant and small negative wage effect in the lowest Kaitz ratio subsample.

The placebo regressions find no significant effects on employment for college graduates in the full sample of high Kaitz ratio and high bite coumas (defined as above 0.5/0.15 respectively) or for high bite coumas. For the sample with the highest bites (above 0.2), the model finds a statistically significant positive effect on employment; in the sample with Kaitz ratios above 0.6 employment effects are marginally significant. [17] This finding suggests some possible misspecification in our models. Misspecification could result if changes in minimum wages are correlated with unobserved employment growth in the highest Kaitz ratio coumas. However, the sample of coumas with Kaitz ratios over 0.5 includes almost all the states, while the sample with Kaitz ratios over 0.6 includes about half the states. The employment result for the more limited sample may therefore reflect some selection effects. Such selection effects could also account for the pattern of point estimates of employment effects for less educated workers becoming larger and more positive in high impact samples, as the estimated employment effects in the high bite samples are very similar across education levels. The lack of pre-trends for this sample, shown in the previous section, also strengthens our confidence in the overall results.

Finally, the last two rows show the effects on the poverty rate in the full population, as well as on child poverty: a higher minimum wage significantly reduces these measures in high exposure areas.

[17] The statistical significance of these results should be interpreted with some caution. We cluster standard errors on state; in the highest bite subsamples, we have only 25 clusters. With few clusters, we are likely to underestimate standard errors, as a result, the statistical significance of effects in this sample may be overstated.

So far, the estimated models find no evidence of negative employment effects. However, these results could be misleading if employers respond to higher wages by cutting back on hours rather than by reducing head count. To address this possibility, we estimate effects of the minimum wage on hours and weeks worked; these models are estimated on the full sample of all people with high school or less as well as on the subsample of workers (that is, excluding non-workers). The results, presented in Table 3, indicate no significant negative effects on hours or weeks worked.[18]

We also estimate wage and employment outcomes for blacks, Hispanics and women. The results, shown in Table A3, do not detect negative employment effects.

To summarize, the generalized differences-in-differences models indicate that while higher minimum wages raise wages more in high-exposure areas, we do not see a corresponding reduction in employment or hours. Importantly, this result holds even in areas where the exposure rates are very high, including localities where more than one in five workers are directly affected by the minimum wage.

6. Summary and conclusions

We use sub-state variation in median wages to array local areas according to the likely effects of minimum wages. Doing so substantially expands the range of relative minimum wages and minimum wage bites beyond the levels observed with state-level data. Our sample of relative minimum wages in low-wage areas encompasses relative minimum wages as high as .82. This ratio is comparable to the highest state-level relative minimum wages that would obtain if the federal minimum wage was gradually increased to $15 by 2024. It lies well above the .59 ceiling in previous minimum wage research.

Using American Community Survey data from 2005 to 2017, we estimate both event study and generalized difference-in-difference models to analyze the effects of minimum wages on wages, employment and poverty in areas with low and high relative minimum wages (low

[18] In fact, the results suggest possible positive intensive margin effects in the lowest bite coumas: conditional on working, hours and weeks worked both increase in this subsample.

median wages) and with low and high minimum wage bites. We conduct these analyses among a range of high-exposure groups (those with high school education or less, and teens). The results are similar across all these groups. We find that minimum wages increase wages more in the high impact areas, validating our methodological approach. We do not detect that minimum wages decrease employment or hours in low or high impact areas. Minimum wage increases do, however, reduce poverty rates among households and children. Overall, these results close the gap between current minimum wage policy and evidence-based research.

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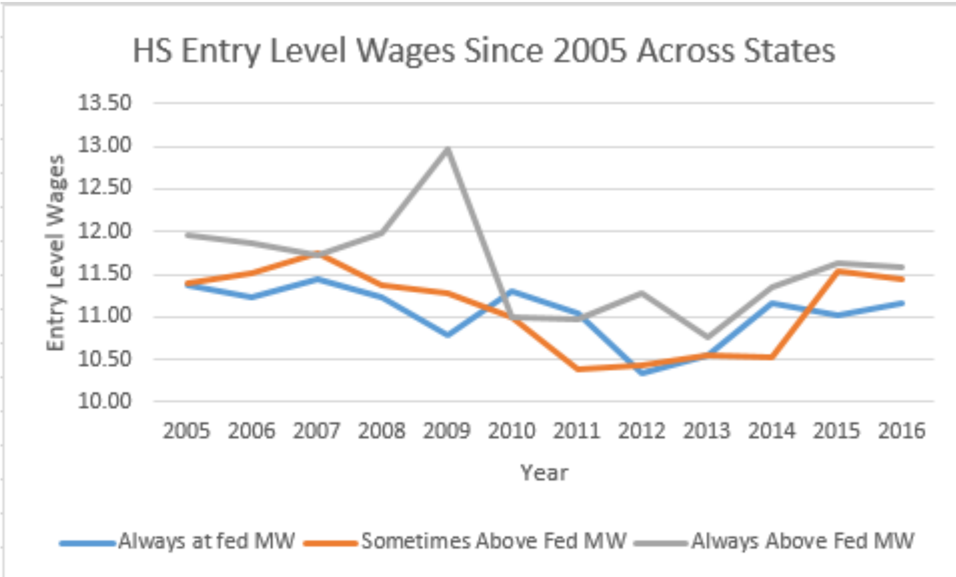
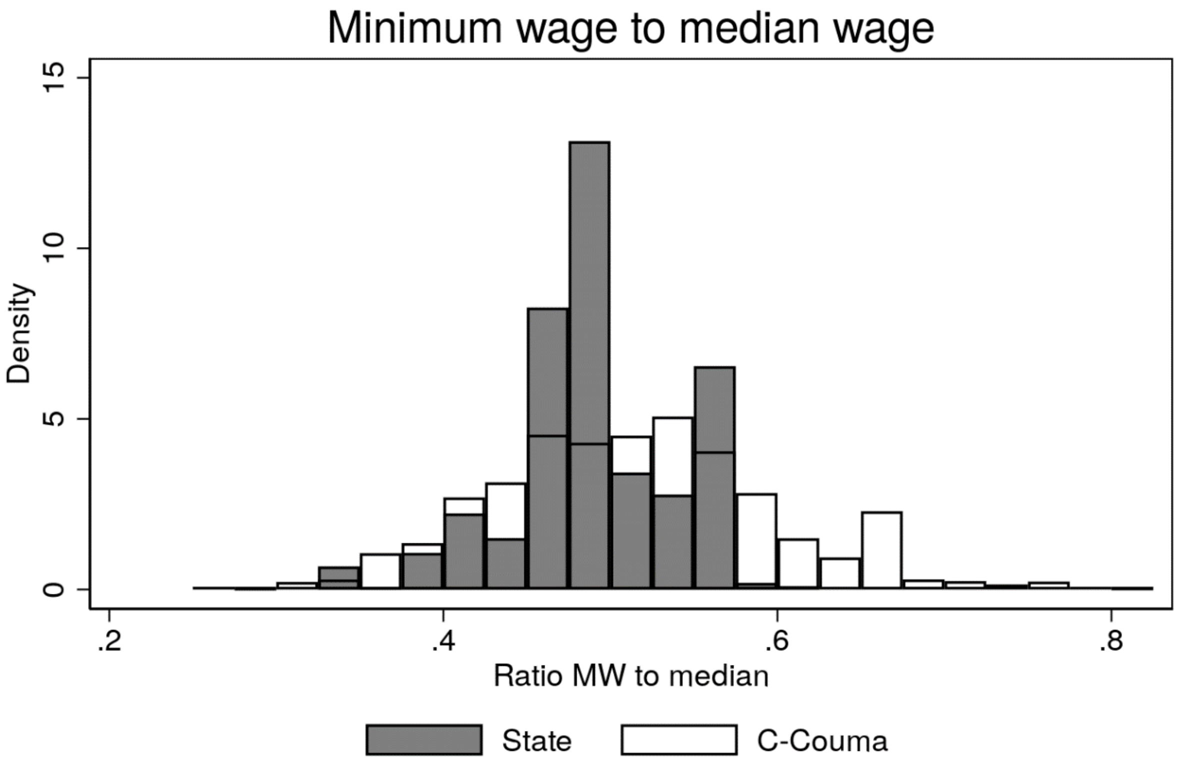
Figure 1 Entry-level wages for high school graduates since 2005



Source: Economic Policy Institute, *State of Working America Data Library*, “Entry level wages.”

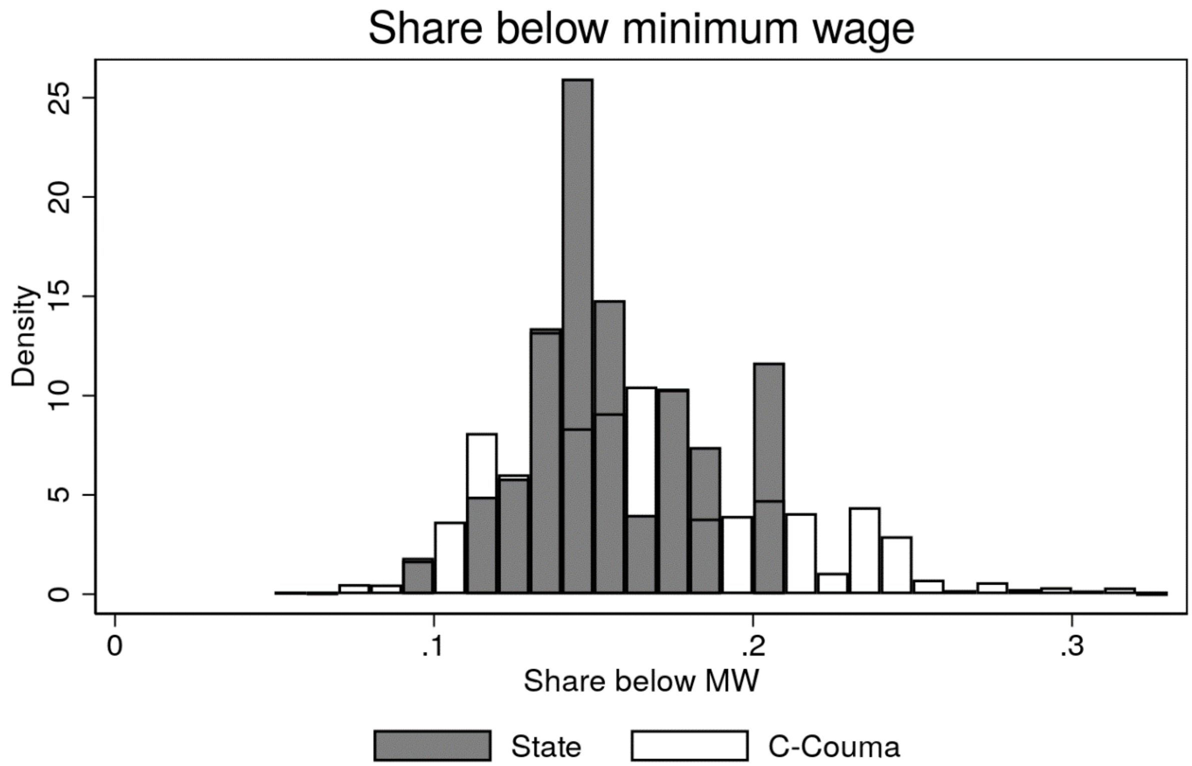
Note: CPS average hourly wages for high school graduates age 17 to 20 and not enrolled in school.

Figure 2a Histograms of ratio of state minimum wage to state and couma median wages



Figures plots the ratio of state minimum wage to couma and state median wage.
Source:ACS (2005-2017) and Vaghul and Zipperer (2016)

Figure 2b Histograms of share below new minimum wage, for states and coumas



Figures plots the estimated population share with hourly wages below the (new) minimum.
Source:ACS (2005-2017) and Vaghul and Zipperer (2016)

Figure 3 Source of variation in the relative minimum wage by decile

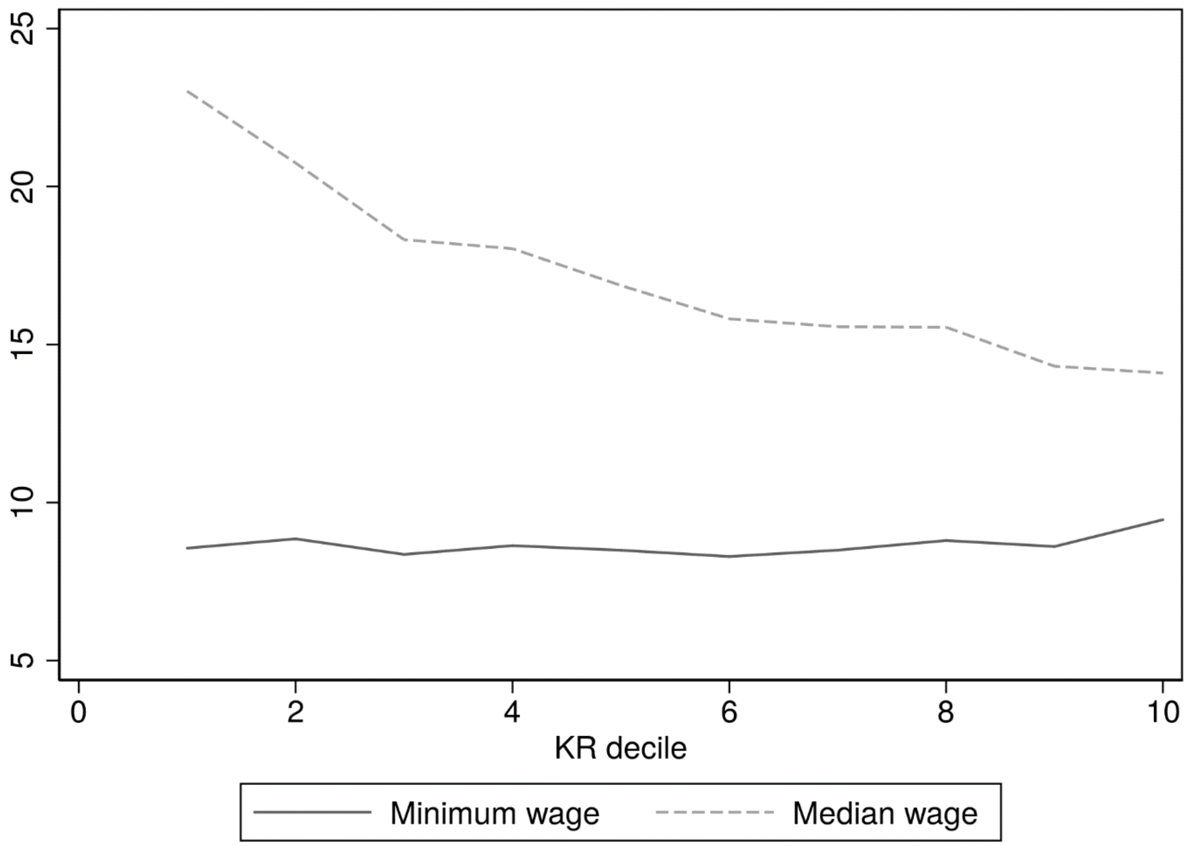
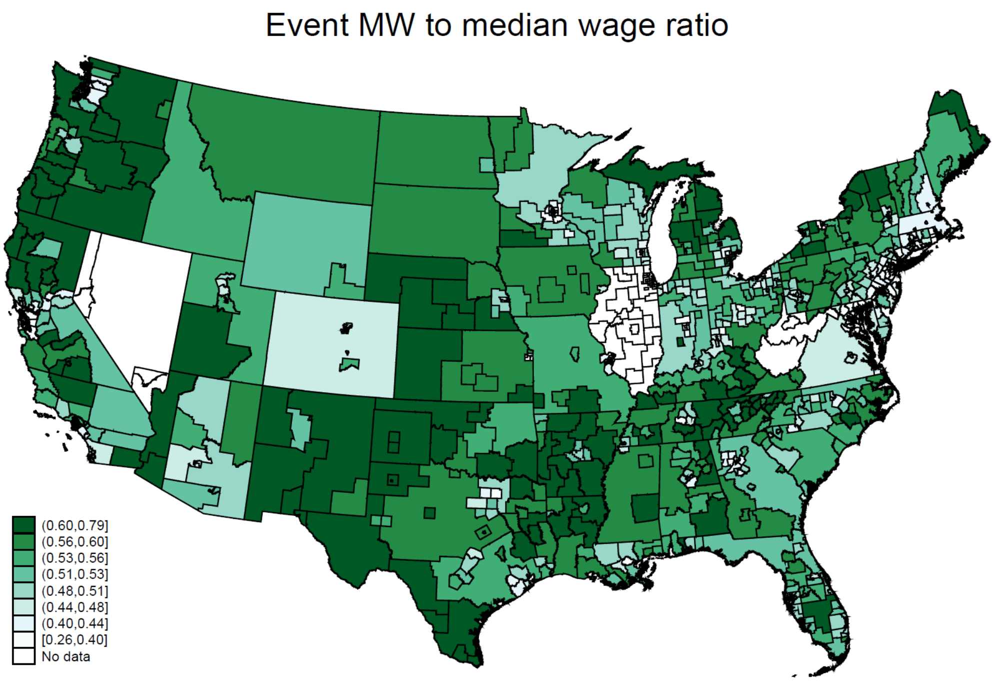


Figure 4 Relative minimum wage and minimum wage bite maps

a. Event relative minimum wages



b. Share below new minimum wage

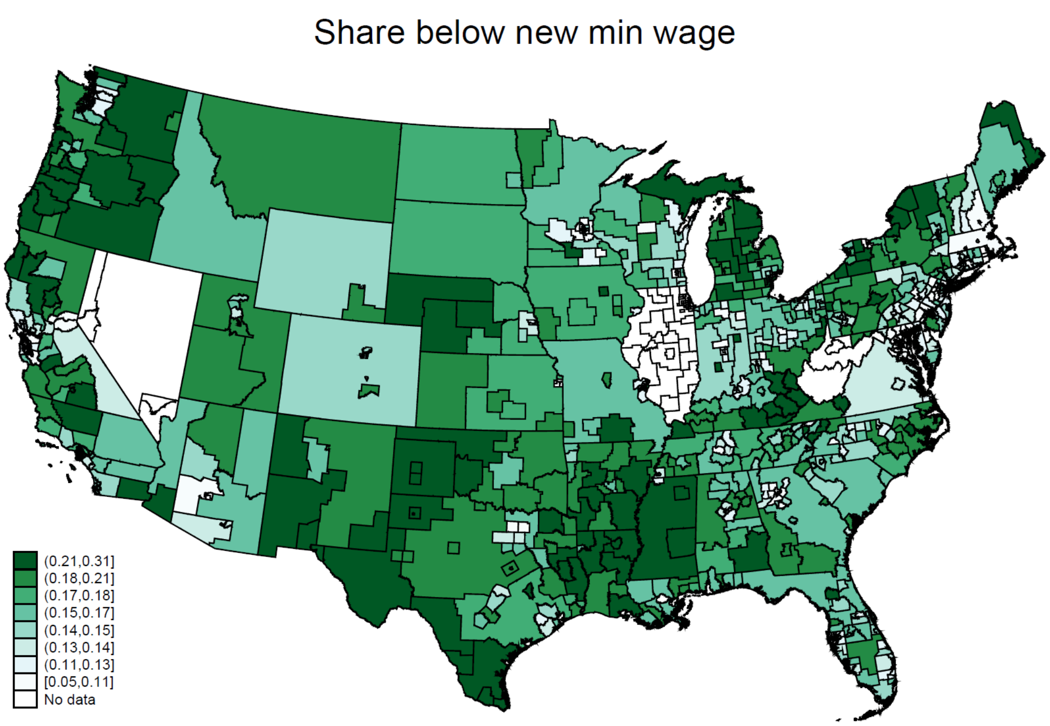
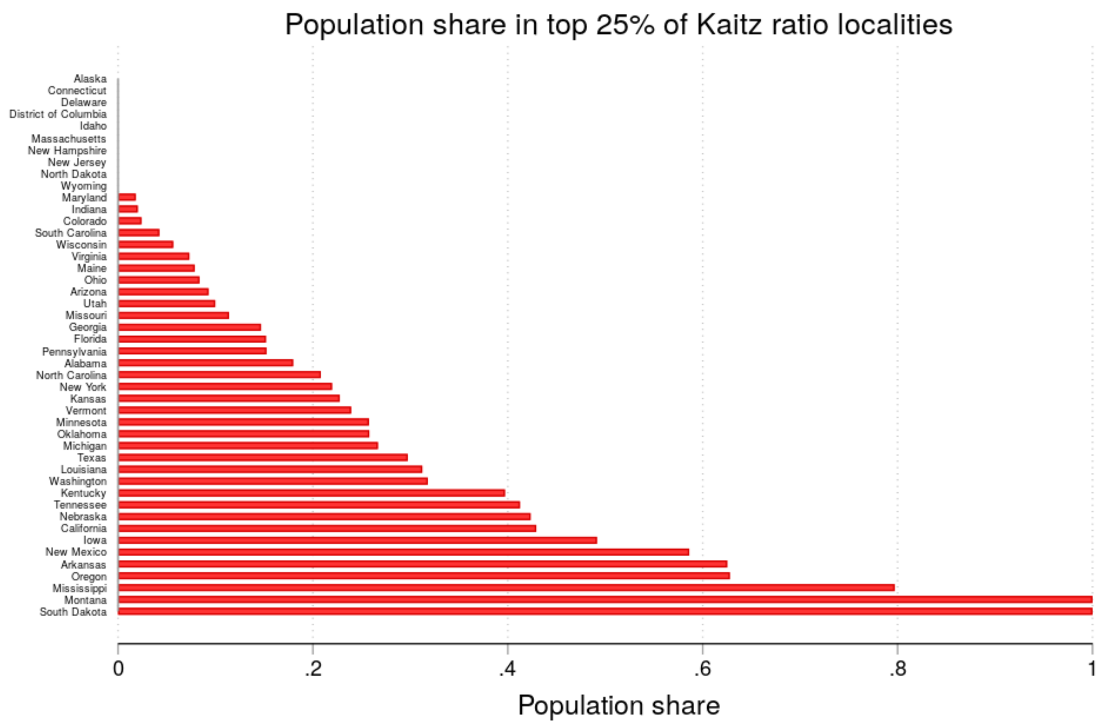


Figure 5 Population share in top quartile impact coumas



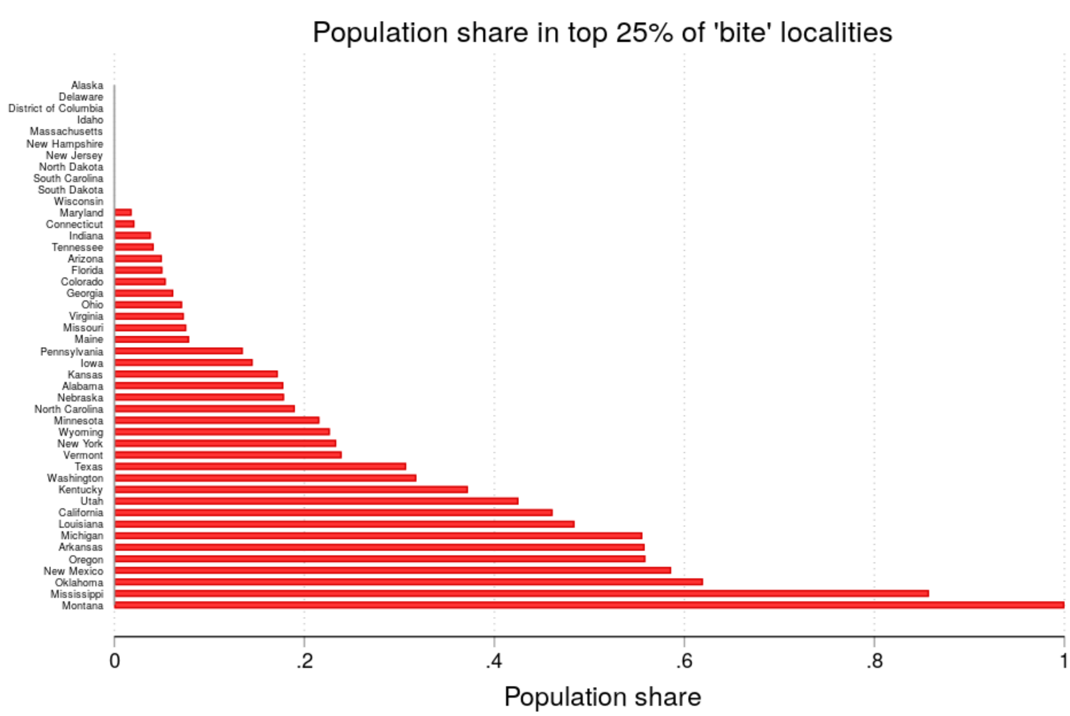
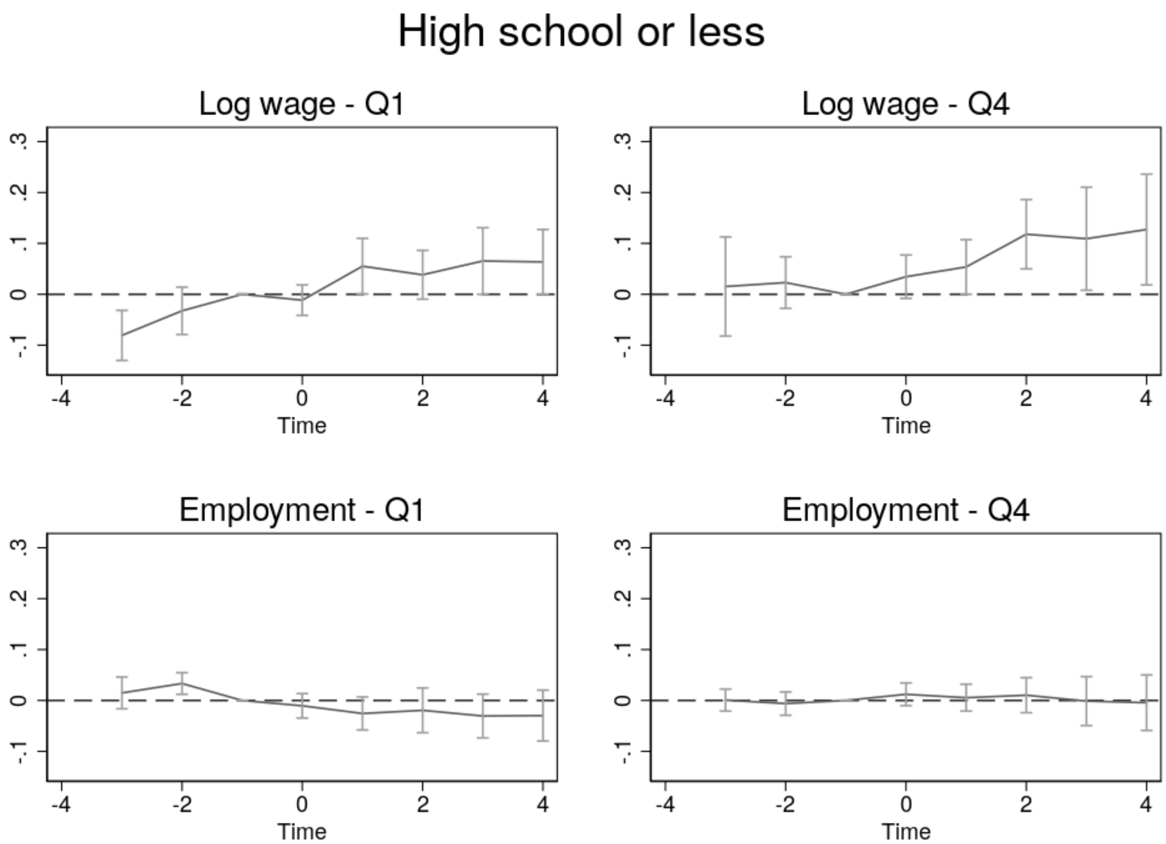
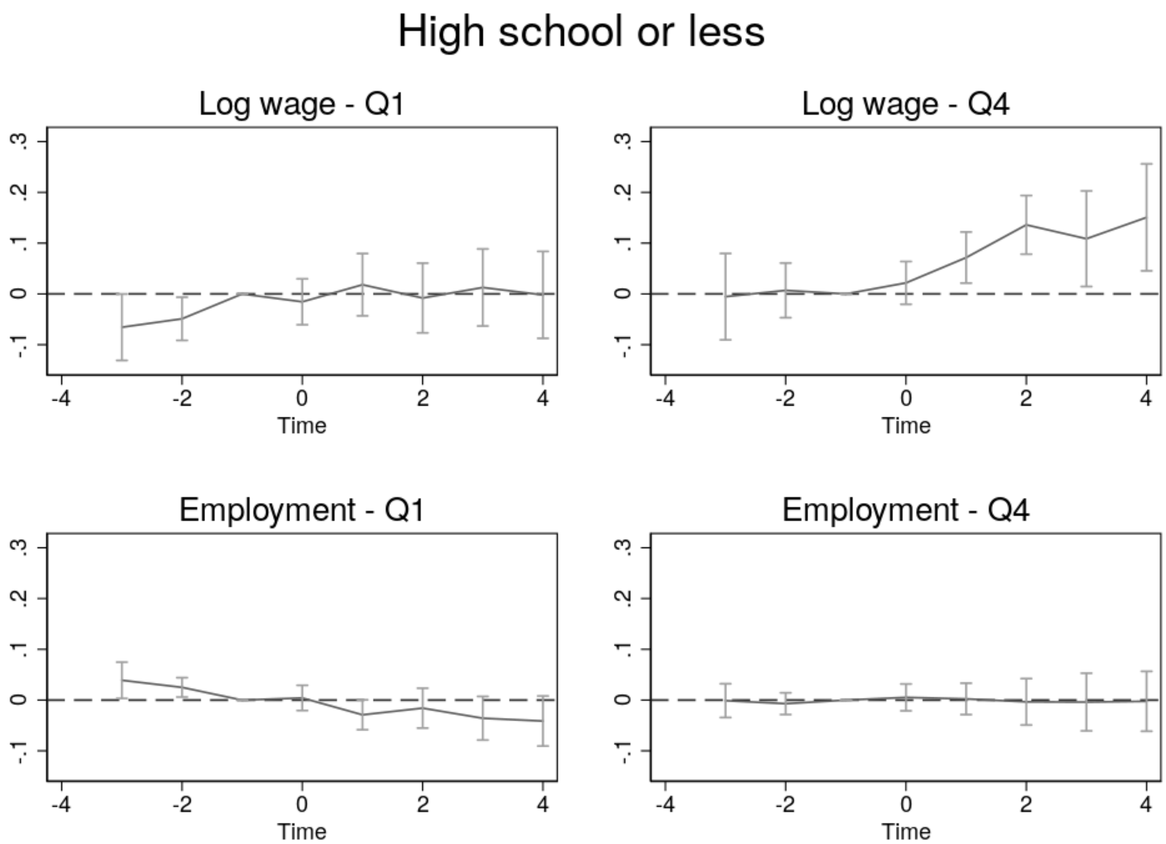


Figure 6a Event Study Models by Relative Minimum Wage



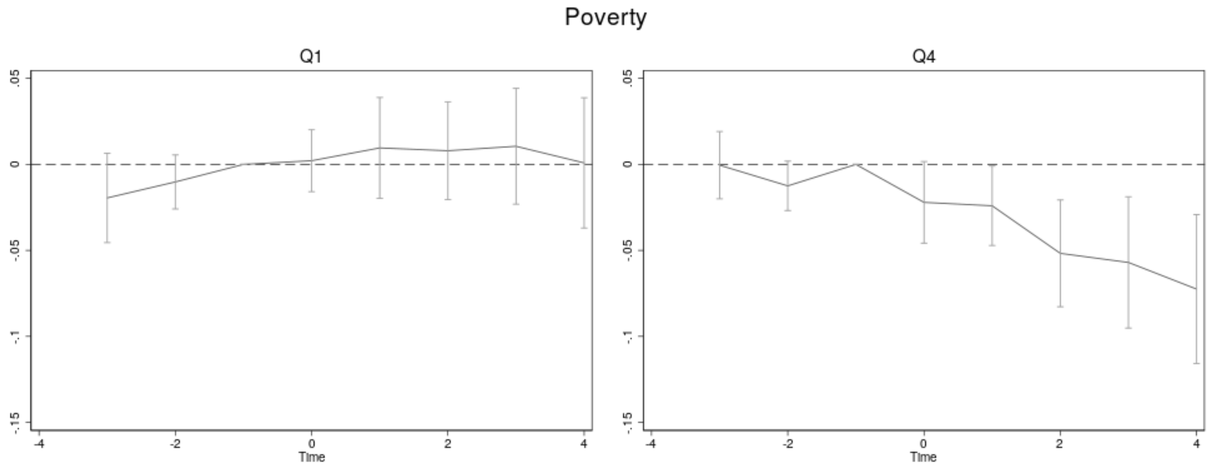
Note: Figure shows event study models of log wage and employment, estimated on the sample of people age 16-70 with high school or less, by quartile of the couma relative minimum wage distribution.

Figure 6b Event Study Models by Bite

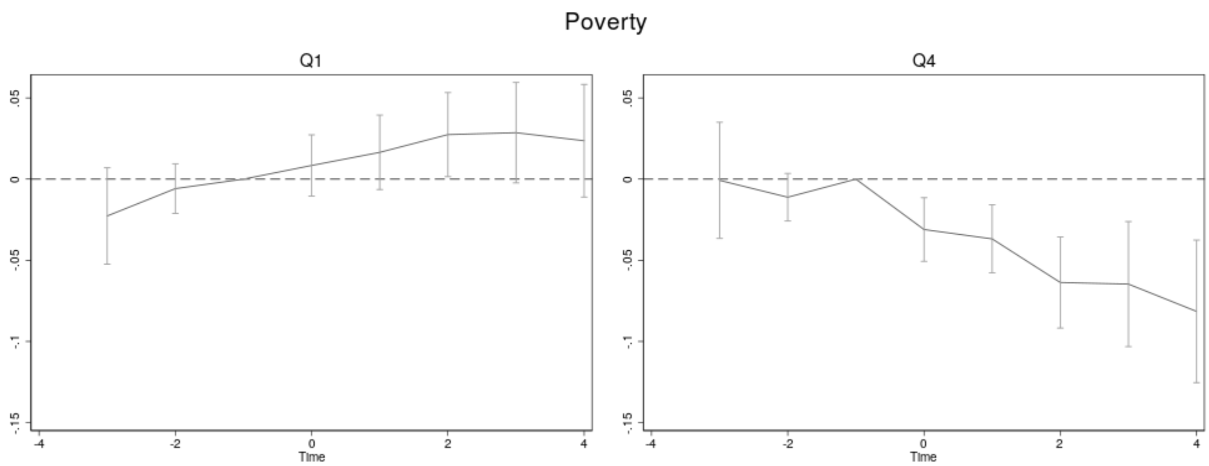


Note: Figure shows event study models of log wage and employment, estimated on the sample of people age 16-70 with high school or less, by quartile of the distribution of share below new minimum wage

Figure 7 Event Study results, poverty



(a) KR quartiles



(b) Bite quartiles

Note: Figure plots estimated event study coefficients from equation (1) estimated on coumas in the top and bottom quartiles of the relative minimum wage (Kaitz ratio) distribution. The dependent variable is an indicator variable equal to one for people in households with incomes below the federal poverty line.

Table 1 State-level relative minimum wages in 2021

Rank	State	Minimum wage (1)	Median wage (2)	Relative minimum wage (3) = (1) / (2)
1	Arkansas	$ 11.00	$ 16.69	0.659
2	California	14.00	22.03	0.635
3	Arizona	12.24	19.40	0.631
4	Maine	12.24	19.46	0.629
5	Oregon	12.75	20.74	0.615
6	New Mexico	10.50	17.88	0.587
7	Washington	13.77	24.17	0.570
8	Colorado	12.24	22.17	0.552
9	Missouri	10.30	18.89	0.545
10	South Dakota	9.46	17.53	0.540
11	Vermont	11.20	20.82	0.538
12	New York	12.75	23.69	0.538
13	Massachusetts	13.50	25.51	0.529
14	Connecticut	13.00	24.59	0.529
15	Illinois	11.00	20.94	0.525
16	Nevada	9.75	18.63	0.523
U.S.		7.25	20.25	0.358
Under HR 582		$ 11.15	20.25	0.551

Notes: New York and Oregon have regional minimum wages; table shows base state rate. State data refer to enacted policies. Future minimum wage increases for cost of living are computed assuming continued 2 percent growth per year. 2021 median hourly wage projected from 2018 median hourly wage for all occupations, assuming continued nominal wage growth of 3 percent per year.
Sources: EPI Minimum Wage Tracker; U.S. Bureau of Labor Statistics, May 2018 Occupational Employment Survey.

Table 2 Wage and employment effects: generalized difference-in-differences estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Localities:	All	KR<50%	KR>50%	KR>60%	LTMW<15%	LTMW>15%	LTMW>20%
Sample: Less than high school							
Log wage	0.114***	0.0818	0.132***	0.175**	0.0601	0.156***	0.180**
	(0.0370)	(0.0489)	(0.0371)	(0.0809)	(0.0504)	(0.0332)	(0.0676)
Employment	0.0109	-0.00864	0.0239	0.0413	0.00102	0.0145	0.0436
	(0.0270)	(0.0253)	(0.0381)	(0.0596)	(0.0291)	(0.0399)	(0.0629)
Sample: High school or less							
Log wage	0.0610**	0.00162	0.108***	0.179***	0.0203	0.0865***	0.146**
	(0.0271)	(0.0224)	(0.0333)	(0.0601)	(0.0259)	(0.0312)	(0.0662)
Employment	-0.000074	-0.0185	0.0185	0.0375	-0.0152	0.0137	0.0303
	(0.0190)	(0.0178)	(0.0245)	(0.0400)	(0.0174)	(0.0252)	(0.0313)
Sample: Teens							
Log wage	0.161***	0.109*	0.209***	0.325**	0.109	0.210***	0.230*
	(0.0527)	(0.0599)	(0.0679)	(0.122)	(0.0645)	(0.0655)	(0.126)
Employment	-0.0262	-0.0731	0.0297	0.0139	-0.0270	-0.0186	0.00341
	(0.0358)	(0.0460)	(0.0344)	(0.0521)	(0.0489)	(0.0391)	(0.0587)
Sample: BA+							
Log wage	0.0143	-0.0319*	0.0450	-0.0359	-0.0232	0.0299	-0.0694
	(0.0211)	(0.0162)	(0.0366)	(0.0643)	(0.0192)	(0.0310)	(0.0552)
Employment	-0.00391	-0.0128	0.00918	0.0494*	-0.00724	0.00430	0.0521**
	(0.00993)	(0.00949)	(0.0157)	(0.0273)	(0.0119)	(0.0142)	(0.0232)
Sample: all							
Poverty	-0.00486	0.00309	-0.0162	-0.0878**	-0.00272	-0.0122	-0.0653**
	(0.0102)	(0.00852)	(0.0174)	(0.0364)	(0.0104)	(0.0153)	(0.0316)
Child poverty	-0.00632	0.00514	-0.0194	-0.131**	0.00733	-0.0256	-0.0754
	(0.0164)	(0.0172)	(0.0283)	(0.0579)	(0.0189)	(0.0236)	(0.0543)
Observations	5887	2213	3674	1225	2196	3691	1384
Couma-events	743	281	462	156	277	466	177

Note: All models control for state by event and year fixed effects, log couma population, log state unemployment rate and log state GDP. Observation weighted by population. * p<0.10 ** p<0.05 *** p<0.01

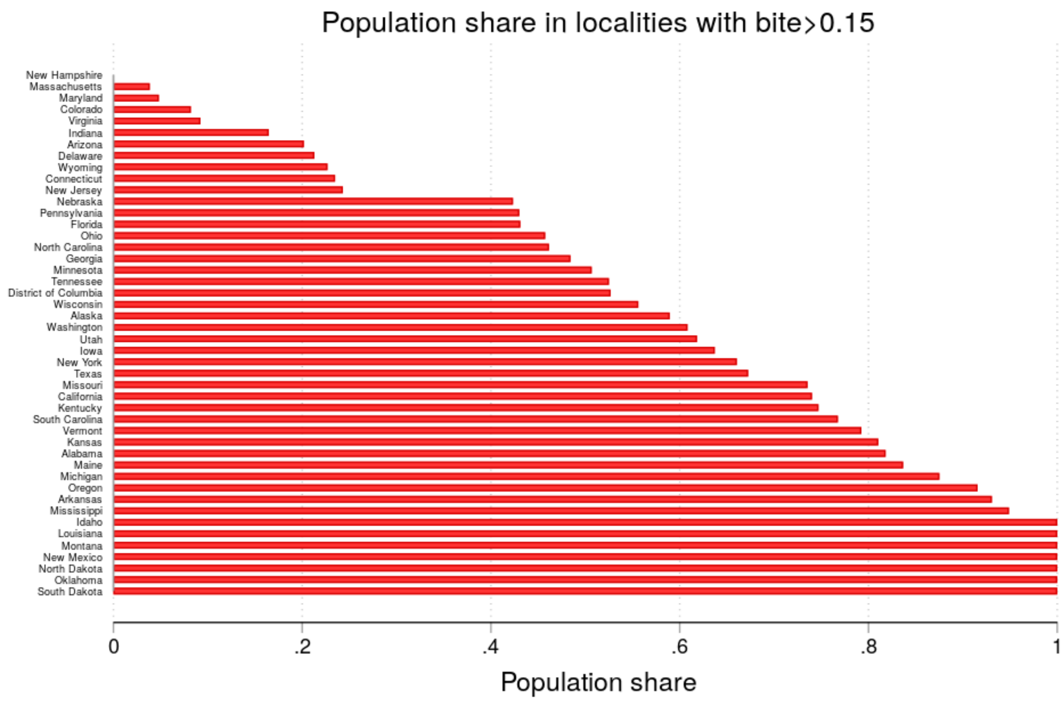
Table 3 Hours and weeks worked

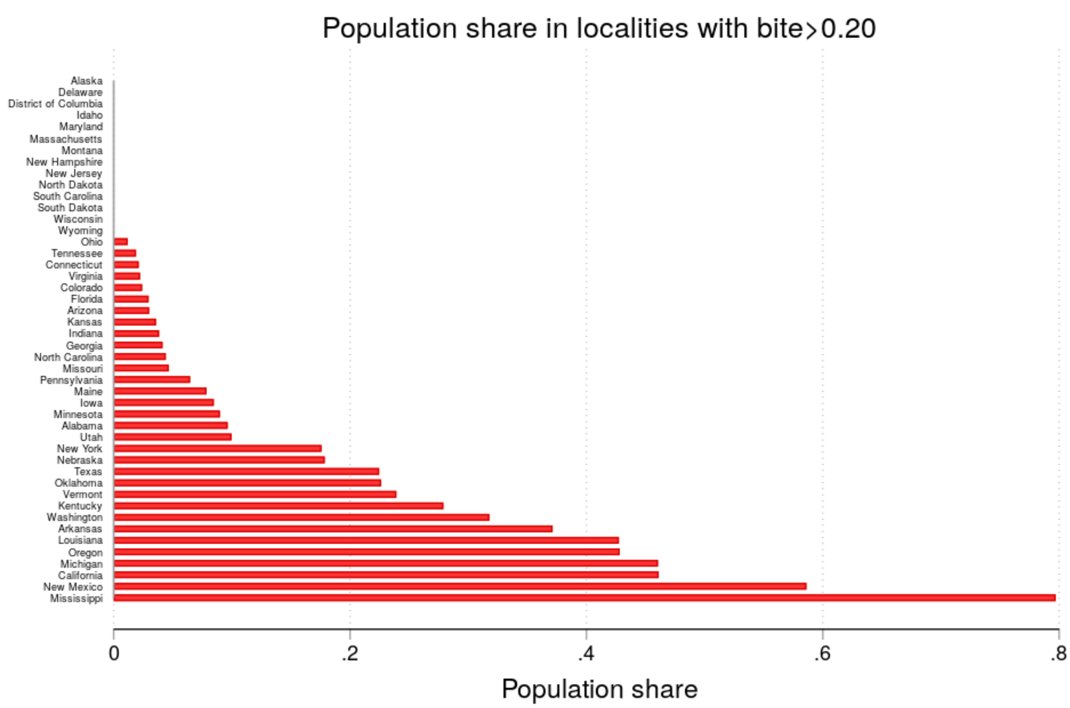
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Localities:	All	KR<50%	KR>50%	KR>60%	LTMW<15%	LTMW>15%	LTMW>20%
Sample: All HS or less							
Weeks worked	0.292	-0.401	0.979	2.646	0.0907	0.590	1.614
	(0.920)	(0.645)	(1.384)	(2.410)	(0.678)	(1.373)	(2.095)
Full year work	0.00753	0.00000640	0.0124	0.0367	0.0151	0.00162	0.0135
	(0.0180)	(0.0129)	(0.0274)	(0.0415)	(0.0143)	(0.0257)	(0.0409)
Weekly hours	0.109	-0.191	0.434	1.280	0.0826	0.193	-0.0457
	(0.836)	(0.743)	(1.178)	(2.376)	(0.740)	(1.183)	(1.949)
Full-time work	0.0107	0.00339	0.0162	0.0366	0.00991	0.0118	-0.000265
	(0.0220)	(0.0192)	(0.0314)	(0.0625)	(0.0196)	(0.0309)	(0.0488)
Sample: HS or less, excluding non-workers							
Weeks worked	0.612	0.546	0.678	2.576**	0.938**	0.500	1.704
	(0.494)	(0.377)	(0.892)	(1.089)	(0.423)	(0.823)	(1.281)
Full year work	0.0181	0.0221	0.0112	0.0539*	0.0375**	0.00320	0.0282
	(0.0188)	(0.0172)	(0.0269)	(0.0279)	(0.0182)	(0.0240)	(0.0371)
Weekly hours	0.543	0.863*	0.145	0.359	1.013**	0.104	-1.175
	(0.423)	(0.456)	(0.640)	(1.393)	(0.389)	(0.640)	(1.309)
Full-time work	0.0235	0.0295*	0.0130	0.0241	0.0333**	0.0135	-0.0251
	(0.0171)	(0.0154)	(0.0255)	(0.0548)	(0.0147)	(0.0255)	(0.0459)
Observations	5887	2213	3674	1225	2196	3691	1384
Couma-events	743	281	462	156	277	466	177

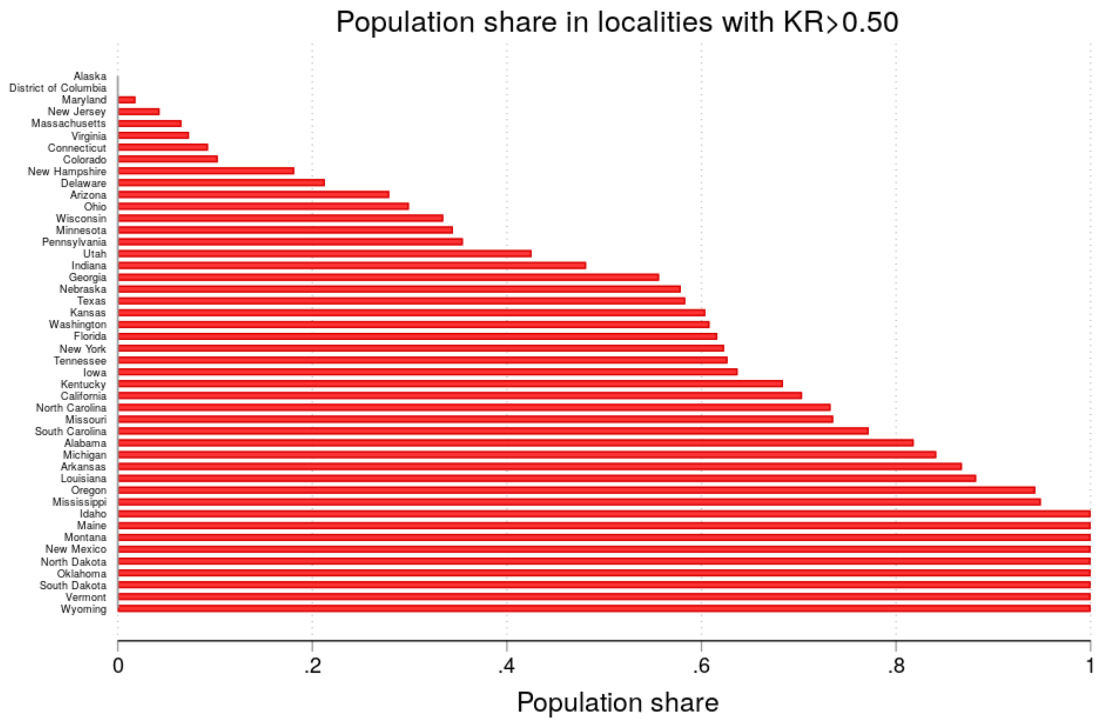
Note: Estimates for people age 16-70 with high school or less education. All models control for state by event and year fixed effects, log couma population, log state unemployment rate and log state GDP. Observation weighted by population. * p<0.10 ** p<0.05 *** p<0.01

7. Appendix A – Additional Exhibits

Figure A1 Population share by Kaitz ratio and bite






Population share in localities with KR>0.50
Alaska
District of Columbia
Maryland
New Jersey
Massachusetts
Virginia
Connecticut
Colorado
New Hampshire
Delaware
Arizona
Ohio
Wisconsin
Minnesota
Pennsylvania
Utah
Indiana
Georgia
Nebraska
Texas
Kansas
Washington
Florida
New York
Tennessee
Iowa
Kentucky
California
North Carolina
Missouri
South Carolina
Alabama
Michigan
Arkansas
Louisiana
Oregon
Mississippi
Idaho
Maine
Montana
New Mexico
North Dakota
Oklahoma
South Dakota
Vermont
Wyoming
0
.2
.4
.6
.8
1
Population share

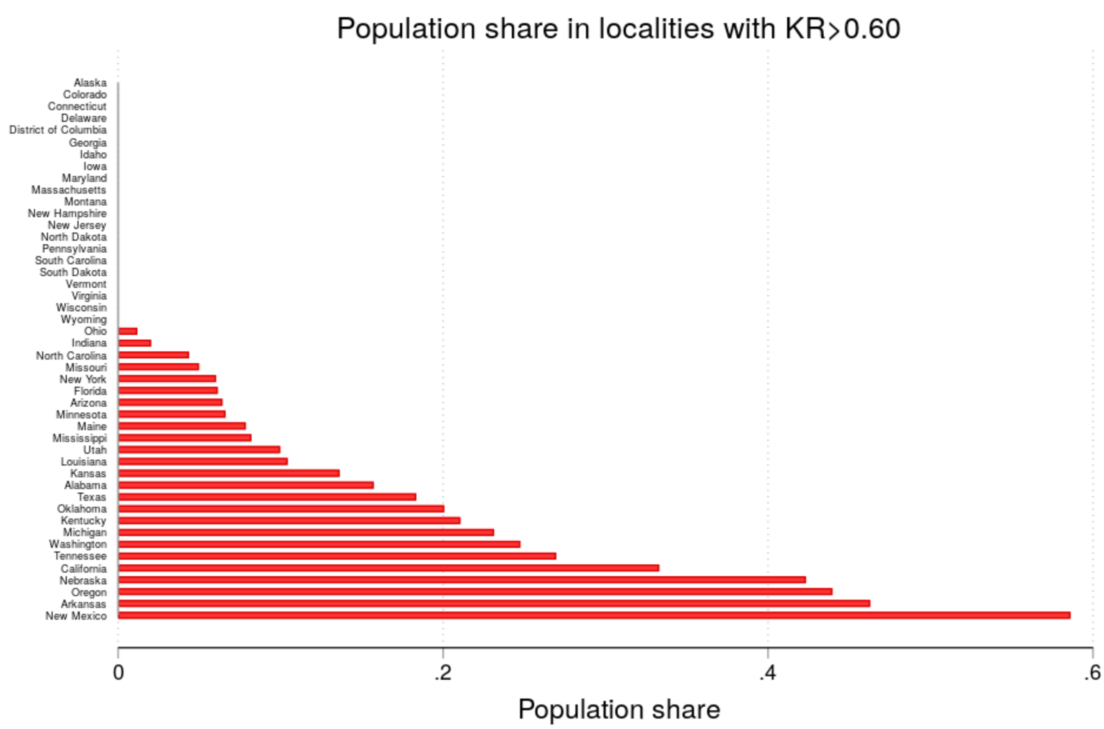
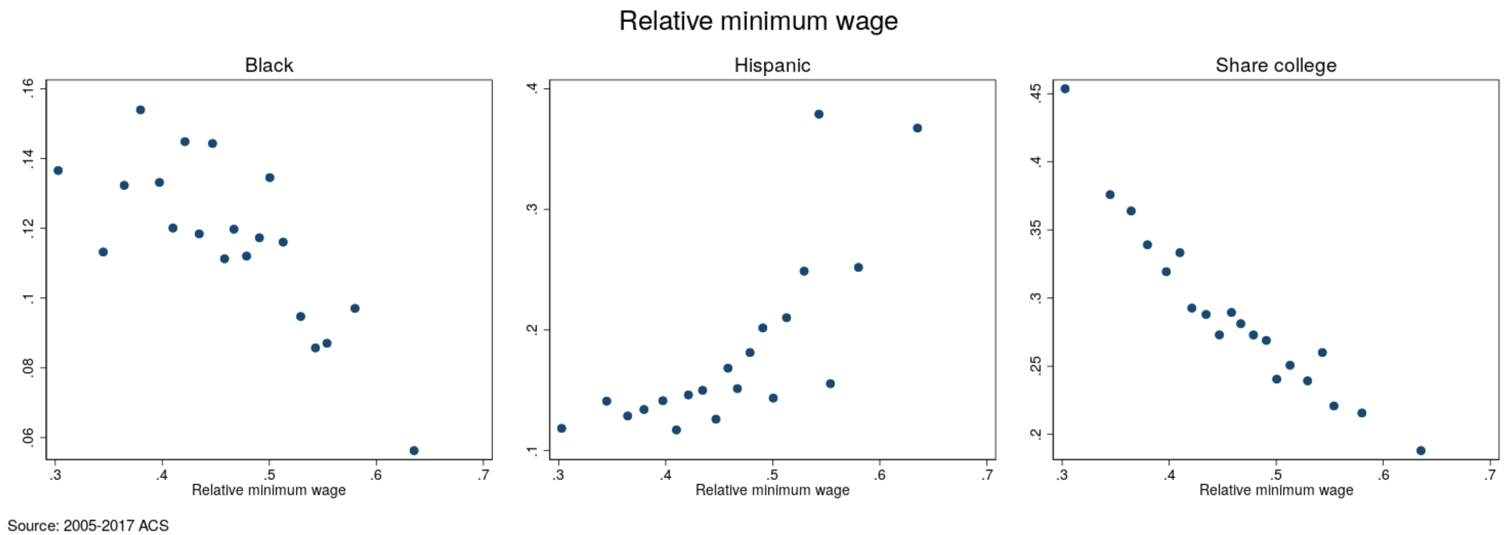

Population share in localities with KR>0.60
Alaska
Colorado
Connecticut
Delaware
District of Columbia
Georgia
Idaho
Iowa
Maryland
Massachusetts
Montana
New Hampshire
New Jersey
North Dakota
Pennsylvania
South Carolina
South Dakota
Vermont
Virginia
Wisconsin
Wyoming
Ohio
Indiana
North Carolina
Missouri
New York
Florida
Arizona
Minnesota
Maine
Mississippi
Utah
Louisiana
Kansas
Alabama
Texas
Oklahoma
Kentucky
Michigan
Washington
Tennessee
California
Nebraska
Oregon
Arkansas
New Mexico
0
.2
.4
.6
Population share

Figure A2 Share black, Hispanic and college graduates, by Kaitz ratio and bite



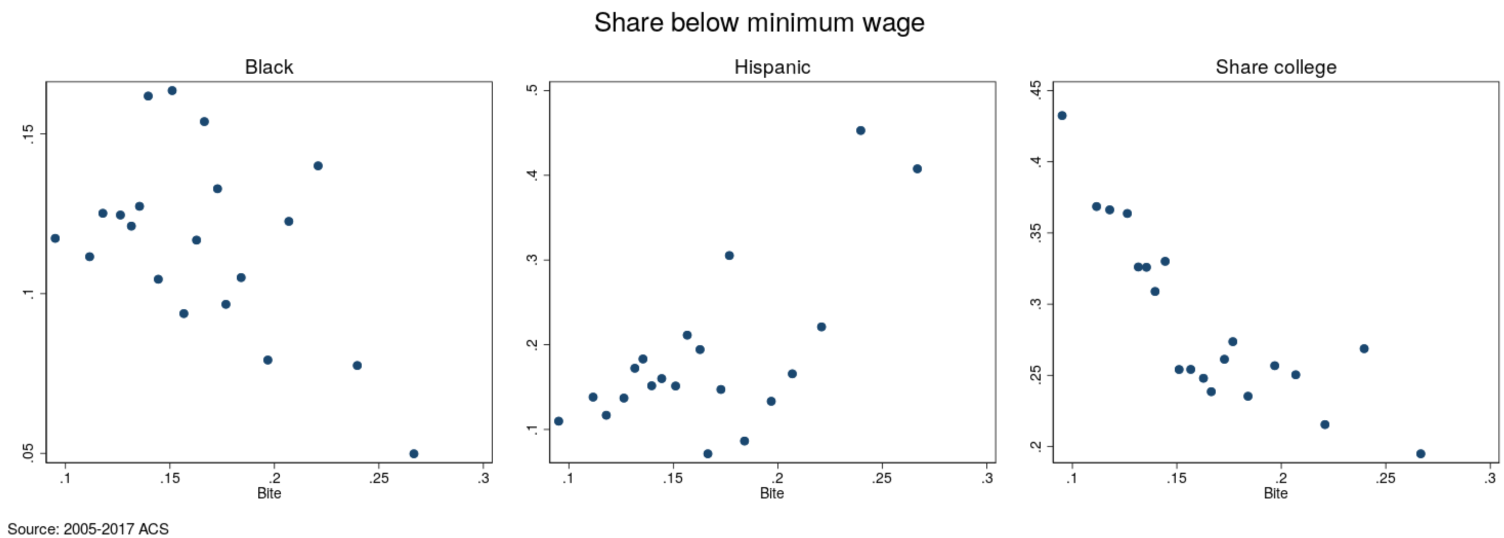


Table A1 Minimum wage events

	First event			Second event		
State	Year	First yr (%)	Total (%)	Year	First yr(%)	Total (%)
AK	2010	5%	9%			
AL	2007	10%	32%			
AR	2009	11%	12%			
AZ	2007	27%	32%			
CA	2007	8%	11%	2014	11%	21%
CO	2007	29%	33%			
CT	2009	5%	7%	2014	4%	13%
DC	2008	4%	14%	2014	13%	35%
DE	2007	5%	11%	2014	5%	12%
FL	2009	7%	7%			
GA	2007	10%	32%			
IA	2007	17%	32%			
ID	2007	10%	32%			
IN	2007	10%	32%			
KS	2007	10%	32%			
KY	2007	10%	32%			
LA	2007	10%	32%			
MA	2007	8%	11%			
MD	2007	16%	32%			
ME	2009	4%	9%			
MI	2014	8%	11%			
MN	2009	11%	14%	2014	9%	22%
MO	2007	23%	32%			
MS	2007	10%	32%			
MT	2007	16%	32%			
NC	2007	16%	32%			
ND	2007	10%	32%			
NE	2007	10%	32%			
NH	2007	23%	32%			
NJ	2014	12%	13%			
NM	2007	10%	37%			
NY	2013	9%	20%			
OH	2007	29%	33%			
OK	2007	10%	32%			
OR	2009	6%	6%			
PA	2007	35%	35%			
SC	2007	10%	32%			
SD	2007	10%	32%			
TN	2007	10%	32%			
TX	2007	10%	32%			
UT	2007	10%	32%			
VA	2007	10%	32%			
VT	2009	5%	5%			
WA	2009	6%	6%			
WI	2009	11%	11%			
WY	2007	10%	32%			

Note: table shows minimum wage events included in event study sample.

Table A2 Employment elasticities and elasticities of the poverty rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Localities:	All	KR<50%	KR>50%	KR>60%	LTMW<15%	LTMW>15%	LTMW>20%
Sample: Less than high school							
El wrt MW	0.020	-0.038	0.076	0.068	0.013	0.031	0.091
El wrt own wage	0.176	-	0.576	0.390	-	0.196	0.505
Sample: High school or less							
El wrt MW	0.008	-0.018	0.037	0.082	0.002	0.019	0.041
El wrt own wage	0.124	-	0.341	0.456	-	0.222	0.284
Sample: Teens							
El wrt MW	-0.026	-0.114	0.086	0.130	0.013	-0.052	-0.088
El wrt own wage	-0.159	-	0.413	0.400	-	-0.247	-0.383
Poverty - el wrt MW							
Poverty all	-0.029	0.023	-0.086	-0.406	-0.020	-0.065	-0.305
Child poverty	-0.030	0.031	-0.080	-0.470	0.044	-0.106	-0.278
Observations	5887	2213	3674	1225	2196	3691	1384
Coumas	743	281	462	156	277	466	177

Note: Own-wage employment elasticities reported only for subsamples where the wage elasticity of the wage with respect to the minimum wage was significant at the 5 percent level.

Table A3 Wage and employment outcomes, high school or less, by gender and race/ethnicity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Localities:	All	KR<50%	KR>50%	KR>60%	LTMW<15%	LTMW>15%	LTMW>20%
Sample: Women							
Log wage	0.0719***	0.0457*	0.0904***	0.120**	0.0423	0.0907***	0.124**
	(0.0266)	(0.0262)	(0.0321)	(0.0496)	(0.0307)	(0.0302)	(0.0485)
Employment	-0.00365	-0.0188	0.0112	0.0167	-0.0172	0.00944	0.0363
	(0.0190)	(0.0210)	(0.0212)	(0.0274)	(0.0199)	(0.0240)	(0.0243)
Sample: Men							
Log wage	0.0503	-0.0319	0.117***	0.210***	0.00633	0.0766**	0.156*
	(0.0313)	(0.0291)	(0.0372)	(0.0715)	(0.0310)	(0.0351)	(0.0790)
Employment	0.00299	-0.0176	0.0248	0.0498	-0.0104	0.0154	0.0195
	(0.0212)	(0.0181)	(0.0302)	(0.0558)	(0.0182)	(0.0284)	(0.0468)
Sample: Black/Hispanic							
Log wage	0.0676**	0.0730**	0.0432	0.226**	0.0914**	0.0187	0.206**
	(0.0301)	(0.0356)	(0.0462)	(0.0964)	(0.0344)	(0.0427)	(0.0949)
Employment	-0.0425	-0.0414	-0.0447	-0.0462	-0.0537	-0.0386	-0.0229
	(0.0299)	(0.0304)	(0.0441)	(0.0693)	(0.0325)	(0.0376)	(0.0630)
Sample: White non-Hispanic							
Outcome: Log wage	0.0510*	0.0165	0.0778**	-0.0476	0.0282	0.0711*	-0.0667
	(0.0290)	(0.0324)	(0.0368)	(0.0925)	(0.0368)	(0.0365)	(0.0868)
Outcome: Employment	0.00251	-0.0225	0.0270	0.0832**	-0.00996	0.0132	0.0455
	(0.0170)	(0.0156)	(0.0239)	(0.0365)	(0.0172)	(0.0230)	(0.0373)
Observations	5887	2213	3674	1225	2196	3691	1384
Couma-events	743	281	462	156	277	466	177

Note: Estimates for subsamples of people age 16-70 with high school or less. All models control for state by event and year fixed effects, log couma population, log state unemployment rate and log state GDP. Observation weighted by population.
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Appendix B: Relationship to other estimators

In this paper, we use the Kaitz ratio and the bite of the minimum wage to rank coumas by expected impact of minimum wage changes. Our variable of interest in the estimated models is the minimum wage itself, parametrized as its natural logarithm.

In the literature meanwhile, the Kaitz ratio and the minimum wage bite are frequently used as explanatory variables to estimate effects of minimum wages.[19] In this appendix, we discuss these methods in some detail and show how the results from these specifications compare with the findings of our preferred models.

Equation B1 shows the first of the two specifications. The model is similar to our preferred generalized difference-in-differences specification from equation (2). The key difference is that the relative minimum wage / Kaitz ratio is the variable of interest. Note that in these models we cannot replace the couma fixed effects with state fixed effects without changing the results, as within-state Kaitz ratios typically vary significantly at a given minimum wage.

$$y_{ct} = \theta_c + \theta_t + X_{it}\beta + KR_{ct}\gamma^{KR} + \varepsilon_{ct} \tag{B1}$$

In model (B1), the parameter of interest γ^{KR} is identified by within-couma variation in the ratio of the minimum to the median wage. As discussed in the paper, this measure will in turn be affected by changes to the median wage that result from local business cycle fluctuations, in addition to changes in minimum wage policies.

The second model follows Card (1992), who uses variation in the bite of the minimum wage to estimate effects on wages and employment. This model is frequently used to evaluate minimum wage changes for which there is no control group, such as a national minimum wage change that is binding for all localities. We have adapted the model somewhat to our setting--where we have multiple policy changes across states and years. Formally, we model outcomes in couma-event *c* in state-event *s* year *t*:

[19] For example, Wehby, Dave and Stewart (2018) use the relative minimum wage as their RHS variable; Card (1992) and Bailey, DiNardo and Stewart (2018) use the minimum wage bite.

$$y_{cst} = \theta_c + \theta_s \times post_{st} + \theta_t + X_{it}\beta + (ltmw_c \times post_{st})\gamma^{LTMW} + \varepsilon_{ct} \quad \text{(B2)}$$

where $post_{st}$ is an indicator variable that is equal to 1 in the year of the initial minimum change and later years and $ltmw_c$ is the "bite" of the minimum wage in couma *c*. As before, the bite is defined as the share of workers whose hourly wage is less than the minimum wage at the end of the four-year event window (to allow for phase-ins).[20]

Here, the parameter of interest γ^{LTMW} is identified from variation in the minimum wage bite across coumas (within each state). That is, the effects of the minimum wage are identified by comparing how outcomes change differentially following policy changes in localities where different shares of the population are expected to receive a wage increase.

We show the results from these specifications in tables B1 and B2. Equation (1) yields negative estimates of γ^{KR} for wages for all three education groups: less than high school, high school or less and bachelor's degree or higher. This finding is consistent with lower median wages correlating with lower wages across the board as well as higher *relative* minimum wages. In other words, the standard criticisms against using the relative minimum wage as a minimum wage metric appear to be validated. Meanwhile, employment effects are positive for less educated workers and negative for the more educated group. Similarly, higher Kaitz ratios are associated with significantly higher levels of poverty. Again, this result likely reflects changes in the denominator of the Kaitz ratio rather than the minimum wage itself.

Table B2 shows results from equation (B2). Overall, these results seem more intuitively plausible. Consistent with what we would expect if the models were correctly specified, these models find significant effects of the minimum wage on wages for less-educated workers, but not for the placebo samples of BA+ workers. Overall, the model fails to find significant employment losses for the affected demographic groups. Meanwhile, a negative effect on employment of more educated workers raises concerns about possible misspecifications.

To summarize, using the relative minimum wage as the RHS variable leads to implausible results, such as negative effects on wages, and is not recommended. These findings

[20] We follow Bailey et al. (2019) and use the share below the new minimum wage rather than the share between the old and the new because of the significant measurement error in hourly wages computed from the ACS (weeks worked is available only in bins).

are consistent with our observation that variation in the relative minimum wage mainly reflects variation in the median wage rather than in the minimum wage. Using the minimum wage bite as the RHS variable generates more plausible results, but some concerns about misspecification remain. Moreover, using the bite as the RHS variable assumes that minimum wage and employment effects are proportional to the bite. Our preferred specifications explicitly allow for wage and employment effects to vary across bites in a nonlinear manner; our results in the main part of this paper show that the wage effects are indeed heterogeneous across bites. It may still be the case that using the bite as a RHS variable is not problematic in some contexts. Nonetheless, our analysis here provides a basis for preferring the specifications that we use in the main part of this paper.

Table B1 Wage and employment effects with the relative minimum wage as the RHS variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Localities:	All	KR<50%	KR>50%	KR>60%	LTMW<15%	LTMW>15%	LTMW>20%
Sample: Less than high school							
Log wage	-0.308***	-0.143	-0.495***	-0.737***	-0.172	-0.453***	-0.658***
	(0.0967)	(0.114)	(0.108)	(0.198)	(0.118)	(0.111)	(0.173)
Employment	0.0939***	0.0501	0.121***	0.123***	0.105*	0.0801**	0.131***
	(0.0259)	(0.0478)	(0.0307)	(0.0366)	(0.0527)	(0.0363)	(0.0367)
Sample: High school or less							
Log wage	-0.398***	-0.338***	-0.514***	-0.613***	-0.332***	-0.498***	-0.591***
	(0.0505)	(0.0539)	(0.0593)	(0.117)	(0.0565)	(0.0585)	(0.0868)
Employment	0.0304*	-0.0126	0.0557**	0.0775**	0.0129	0.0374	0.0481*
	(0.0173)	(0.0227)	(0.0219)	(0.0288)	(0.0247)	(0.0240)	(0.0269)
Sample: Teens							
Log wage	-0.0489	0.0773	-0.210***	-0.265**	0.0876	-0.188**	-0.335***
	(0.0786)	(0.118)	(0.0683)	(0.0991)	(0.119)	(0.0702)	(0.0707)
Employment	0.0475	-0.0235	0.0896**	0.0696	0.0597	0.0369	0.0702
	(0.0320)	(0.0501)	(0.0395)	(0.0563)	(0.0592)	(0.0447)	(0.0504)
Sample: BA+							
Log wage	-0.326***	-0.356***	-0.340***	-0.503***	-0.351***	-0.342***	-0.525***
	(0.0492)	(0.0565)	(0.0504)	(0.0791)	(0.0598)	(0.0516)	(0.0583)
Employment	-0.0633***	-0.0526***	-0.0608**	-0.0601	-0.0619***	-0.0555**	-0.0500
	(0.0162)	(0.0181)	(0.0241)	(0.0445)	(0.0177)	(0.0236)	(0.0358)
Sample: all							
Poverty	0.0890***	0.0723***	0.113***	0.131***	0.0833***	0.0989***	0.130***
	(0.0119)	(0.0181)	(0.0181)	(0.0406)	(0.0225)	(0.0148)	(0.0351)
Child poverty	0.143***	0.115***	0.180***	0.198***	0.160***	0.144***	0.222***
	(0.0247)	(0.0401)	(0.0299)	(0.0517)	(0.0386)	(0.0287)	(0.0503)
Observations	5887	2213	3674	1225	2196	3691	1384
Coumas	743	281	462	156	277	466	177

Note: All models control for couma by event and year fixed effects, log state population, state unemployment rate and state GDP per capita. Observations weighted by population. * p<0.10 ** p<0.05 *** p<0.01

Table B2 Wage and employment effects with the share wage<MW as the RHS variable

	(1)	(2)	(3)	(4)
Sample:	LTHS	HS or less	Teens	BA+
Log wage	0.177	0.254***	0.302**	-0.0826
	(0.117)	(0.0693)	(0.136)	(0.0904)
Employment	0.0145	-0.0113	-0.00398	-0.0639**
	(0.0286)	(0.0239)	(0.0464)	(0.0304)
Observations	6394	6394	6394	6394
Coumas	743	743	743	743