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IZA DP No. 12000

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ABSTRACT

Where Does the Minimum Wage Bite Hardest in California?*

This study uses employment data on California county-industry pairs (CIPs) between 1990 and 2016 to test whether minimum wage increases caused employment growth to slow most in the CIPS with a large share of low wage workers. Evidence supports the hypothesis, and we use the estimates to simulate the effect of a 10 percent increase in the minimum wage. The simulations suggest that a 10 percent increase could cause a 3.4 percent employment loss in the average CIP in California. The job loss is projected to be concentrated in two industries: accommodation and food services, and retail. While the most populated counties of California are expected to incur the largest employment loss in terms of the number of workers, the smaller counties generally experience a larger percentage point loss in employment due to the lower wages and the greater number of workers that would be affected by the minimum wage hike. Moreover, there is substantial variation across counties in terms of the percentage of jobs lost within a given industry.

JEL Classification: J23, J30, J38

Keywords: minimum wage, employment, California, labor demand

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Introduction

This study examines the effect of California's state minimum wage increases since 1990 on employment. While numerous empirical studies examine the effect of minimum wage hikes on employment, our study adds to the literature by using data from a single state to illustrate how much the effect of a state minimum wage can vary across regions within the state. While it is well known that the effects of minimum wage hikes are larger in low-wage industries like restaurants and retail, there is relatively little information about how much the effects can vary across counties within an industry.

California provides a desirable setting for such a study for three reasons. First, it has 17 million workers in 2018 and has a bigger labor force than any other state. This large labor force makes it possible to obtain accurate estimates of county-level employment and wages for a large number of industries. Second, the minimum wage in California has risen significantly over time and reached $11.00 in 2018. This is the second highest minimum wage among the 50 states. This large change in the minimum wage provides the type of identifying information necessary for the analysis. Finally, as we show later, there is significant cross-county variation in the fraction of workers in a given industry who are likely to be affected by a minimum wage hike.

Using a variety of empirical approaches, we find that the increases in California minimum wages led to slower employment growth in low-wage counties and low-wage industries. Our study simulates the effect of a 10 percent increase in the minimum wage. The simulations suggest that a 10 percent increase would cause a 3.4 percent employment loss in California[1]. The percentage of jobs lost would be greatest in the accommodation and food

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[1] This estimate does not include the job loss in rural areas not included in our analysis.

services, and retail trade industries. While the most populated counties of California are expected to incur the largest employment loss regarding the number of workers, the smaller counties experience a larger percentage point loss in employment due to the lower wages and the greater share of workers affected by the minimum wage hike. The estimates reveal considerable heterogeneity in response to a minimum wage hike. In percentage terms, the job loss estimate in a rural county with relatively low wages is approximately 2.5 times greater than in the urban counties with relatively high wages.

While our methodology could be applied to all 50 states, we choose to focus only on the CIPs in California for two reasons. First, by restricting attention to a single state, we can remove any of the heterogeneity in the minimum wage effect that might be caused by differences in the details of the state's minimum wage laws. For example, unlike most states, California does not offer a tip credit which allows firms to pay workers less than the minimum wage if their tips make up the difference between their wage and the minimum wage. California's lack of a tip credit could make employment at full-service restaurants more sensitive to a minimum wage hike than in a state where a tip credit is allowed. Second, given that California has both a large urban and rural population with a high variance in wage levels and the cost of living, we can show the high degree of heterogeneity in the effects of a minimum wage hike across counties within a state. While a $15 minimum wage may have modest effects on employment in a city like San Francisco, it could be much more disruptive in a rural California county.

The Minimum Wage History for the State of California

Figure 1 provides a comparison of the federal and California minimum wage from 1990 through 2022. For 2018 through 2022, the minimum wages are based on legislation passed as of

July 2017. The figure shows that beginning in 2001, California began a practice of increasing its minimum wage at a faster rate than mandated by federal law. In 2001, the California minimum exceeded the federal minimum by $1.10 ($6.25 versus $5.15). The gap between the California and federal minimum wage fluctuated since 2000 as both the state and federal minimum wages increased. As of 2018, California's $11.00 minimum is second only to the $11.50 minimum in Washington state. Moreover, under current law, California's minimum wage will increase to $15.00 by 2022 while the federal minimum is scheduled to remain at $7.25. If current laws remain in effect, this will make California the first state to have a minimum of $15 and will lead to the largest gap between a state and federal minimum wage in the United States.[2, 3]

This study uses the California experience between 1990 and 2016 as a way to illustrate how much the effect of a minimum wage can vary across counties and industries within a state. While numerous studies have examined the effect of minimum wage hikes on employment [see Neumark and Washer (2008); Congressional Budget Office (2014); and Neumark (2015) for a review of such studies], our study is unique in two ways. First, we focus entirely on the employment experience in California. The labor market in California differs from many other states because of the mixture of rural and urban counties, the mixture of industries, and the large differences in the cost of living and wages across counties. Second, while much of the recent research that estimates the effect of minimum wage hikes by comparing employment trends in a

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[2] This statement is based on analysis of historical federal and state minimum wages provided by the Department of Labor at https://www.dol.gov/whd/state/stateMinWageHis.htm. The data goes back to 1968 and there is no point at which a state had a minimum wage that exceeded the federal minimum by $7.75 or more. While data prior to 1968 wasn't available, we are confident that the no state had a minimum wage that exceeded the minimum by that amount in earlier years. In fact, Alaska had the highest state minimum wage in 1968 ($2.10) when the federal minimum wage was $1.60.

[3] Several cities will have a $15 minimum wage by 2022, including Los Angeles, Minneapolis, New York City, San Francisco, Seattle, and Washington D.C.

given industry (e.g., restaurants) or a given demographic group (e.g., teenagers) across states, our comparison groups are "county-industry pairs" (CIPs) within California. For example, the restaurant industry in Orange County is one CIP and that in San Francisco County would be another CIP. Our empirical analysis tests whether the employment effects of minimum wage hikes systematically vary with the CIP's share of workers that earn low wages.

The Data

To test for differences in employment growth across CIPs, we use data from the Quarterly Census of Employment and Wages (QCEW) between 1990 and the second quarter of 2016. The QCEW data provides a quarterly count of employment and payroll reported by employers and covers 98 percent of U.S. jobs. The quarterly counts are available at the county, state, and national levels by industry. The data provide a complete tabulation of employment and total payroll for workers covered by either state or federal unemployment insurance programs. We restrict our analysis to private-sector employers. The QCEW does not include self-employed workers.

Our analysis of employment trends uses employment by county for each two-digit North American Industry Classification System (NAICS) industry. We convert to annual employment measures by averaging across the quarterly employment counts to remove seasonality in the data. For our analysis, we need a measure of how much the minimum wage binds in each CIP. While the QCEW reports total payroll and the number of workers, this level of aggregation and the lack of information on hours worked makes it unsuitable for estimating the share of workers earning a wage close to the minimum. To obtain an estimate, we use the 1990 5% Census Public Use

Micro Data Sample (PUMS).[4] We estimate the percentage of workers in each CIP that are "low wage workers" – which we define as anyone earning a wage no less than $.25 below and no more than $1.00 above the 1989 state minimum of $4.25.[5] Unfortunately, the Census identifies only 34 of the 58 California counties and our analysis is thus restricted to this subset. To improve the accuracy of the estimate of the percentage of workers with low wages for a CIP, we drop any county that contains a city minimum wage law causing the minimum wage to vary across jurisdictions within the county.[6] While San Francisco had a minimum wage above the state minimum since 2004, we include it since it is a county-wide minimum wage.

To assure that our wage estimates for a CIP are reasonably accurate, we exclude any CIP with less than 200 observations on wages in the Census sample.[7] The sample also excludes any CIP without at least one-quarter of employment data in each year of the sample period. These tend to be relatively small CIPs because the QCEW masks employment counts when there is a concern that disclosing the CIP employment count could reveal too much information about a specific establishment. We also exclude Kern county where the total employment for the included industries covered less than 40 percent of private sector employment in the county in 2016. Finally, we eliminate any CIP that shows more than a 25 percent change in employment

[4] We also had to map census codes for industry to match NAICS codes in the QCEW and account for the fact that NAICS codes changed in the QCEW over time.

[5] In the early stages of this project, we attempted to do the analysis using employment measured at the three-digit level. We abandoned that approach and switched to two-digit analysis because the narrower definition of industries results in missing data for a large share of the CIPs since the QCEW masks employment counts when there are a small number of employers due to concerns with confidentiality of firm level data. Also, the sample sizes for the wage estimates drawn from the Census become too small to be reliable for many of the CIPs.

[6] This restriction results in Alameda, Contra Costa, and Santa Clara counties being dropped from the sample. The largest cities in these counties are Oakland, Concord, and San Jose, respectively.

[7] We also experimented with using the average weekly wage measure available in the QCEW for each CIP. The advantage of this measure is that it is available for all CIPs. The disadvantage is that it is a noisier measure of how much the minimum wage would bind since it is a measure of weekly (not hourly) earnings and does not directly translate into the percentage of workers who are close to the minimum wage. While the qualitative effects of a minimum wage hike were similar with either measure of earnings, the share of workers with low wages fit the employment data better (i.e., adjusted R-squared was higher).

between years. Such changes are clear outliers in the data and may reflect changes in reporting behavior by a firm that has multiple establishments.[8]

Table 1 lists the 29 counties that fit our requirements for inclusion along with the employment level in each county. In total, there are 11.6 million private sector wage and salary workers in the 29 included counties. The CIPs included in our sample represent 90 percent of the private sector employment for the 29 counties, and 74 percent of statewide private sector wage and salary employment. While a large share of employment is included in our sample, the exclusion restrictions result in small rural counties being underrepresented since data is more likely to be suppressed when employment counts are low, and the necessary wage data from the Census are less likely to be available for small counties.

Table 2 lists the industries that we include in the sample, the number of counties with adequate employment data for each industry, and the share of state-wide employment covered in our sample. The industries that are included in our sample employed 13.8 million workers in California in 2016. Our sample includes 73.5% of statewide employment in these industries.

Figure 2 describes the variation in the share of workers earning low wages across CIPs. For each industry, the figure shows the minimum, maximum, and average share of workers with low wages across counties. The two industries with the largest share of low wage workers are agriculture, forestry, fishing and hunting (20 percent low wage) and accommodation and food services (19 percent). At the other extreme, the two industries with the lowest share of workers earning low wages are utilities, and finance and insurance (1 and 4 percent).

[8] The Bureau of Labor Statistics points out that, in the QCEW, large month-to-month changes in employment could reflect changes in employer reporting practices at the beginning of a new calendar year. For example, an employer with multiple locations in the state may report as a single corporation. In a subsequent reporting period, the company may change their method of reporting leading to a large change in employment. This issue is discussed on the BLS website at https://www.bls.gov/cew/cewfaq.htm#Q11

Within a given industry, there is substantial variation in the share of workers earning low wages across counties. For example, in accommodation and food services, the share ranges from 10 to 28 percent; in agriculture, the range is from 15 to 27 percent. As a result, the extent to which a minimum wage increase binds varies substantially across both counties and industries.

Empirical Approach

Our empirical approach for determining the effect of the California minimum wage hikes uses regression analysis to determine whether minimum wage increases cause employment to rise more slowly in CIPs where the minimum wage binds more and affects more workers.

To provide some context for the analysis, Figure 3 provides an illustration of employment trends for low, medium, and high wage CIPs. The split between the three wage levels is based on the percentage of workers earning low wages. The CIPs in the bottom quartile in terms of the fraction of workers earning low wages (i.e., less than 7% earning low wages) are classified as high wage CIPs. Those in the top quartile of the distribution -- with more than 14% of workers earning low wages --are classified as low wage CIPs. The CIPs that are neither in the top or bottom quartile (i.e., between 7 and 14% earning low wages) are classified as medium wage industries.

The employment measure is an index set to 100 in 1990. Since 1990, the rate of employment growth has been highest in the low wage CIPs (47 percent) and lowest in the high wage CIPs (9 percent). This evidence alone might lead one to erroneously conclude that California's minimum wage increases have not slowed (and perhaps increased) employment in low wage industries. Such a conclusion would be inappropriate since other economic factors may have caused the employment trends to differ across high, medium and low wage CIPs. For example, there may be economic forces at work (such as import competition, technical change [Baily and Bosworth (2014); Autor and Dorn (2013)] that cause industries to grow at different rates. For example, increased import competition and technological change have led to declines in U.S. manufacturing employment [Autor et al. (2013, 2015); Pierce and Schott (2016)]. In our data, manufacturing is always either a high or medium wage industry in all counties. In no county is manufacturing a low wage industry. Consequently, import competition and/or technological change may have caused employment growth to slow in high and medium wage industries. A failure to account for such industry-specific trends would lead to a misinterpretation of the data.

Another important factor that needs to be considered in comparing employment growth across CIPs is that some counties are growing at a faster rate than others. More rapid growth in low-wage counties (e.g., rural counties) could lead to a higher rate of employment growth in the low-wage CIPs.

Given that many factors other than the minimum wage can cause employment growth to differ across CIPs, we use regression methods to isolate the effect of minimum wage increases on employment.

In our first empirical specification, we assume that a change in the minimum wage will lead to a change in the level of employment at the time of passage and control for other factors that would influence employment such as county-specific unemployment rates, time trends, and fixed effects. The identifying assumption for each model is that, holding the controls constant, employment growth would be similar across CIPs in the absence of a minimum wage hike. The models differ in terms of the number of controls that are introduced to capture the effects of unobservable factors that might impact employment across CIPs. In the first specification, we estimate

$$(1)\ lemp_{ijt} = \beta_0 + \beta_1(\mathrm{lmin}_{\mathrm{it}} * \mathrm{low\_wage}_{\mathrm{ij}}) + \beta_{2j}(\mathrm{urate}_{\mathrm{it}}) + \gamma_t + \lambda_i t + \theta_j t + \alpha_{ij} + u_{ijt}$$

The subscript i indexes county, j indexes industry, and t is year.

The coefficient of interest (β_1) measures whether the effect of the minimum wage ($\mathrm{lmin}_{\mathrm{it}}$) varies across CIPs based on the fraction of workers earning low wages. The expectation is that minimum wages have a larger negative employment effect in industries with a larger share of low wage workers – and thus, we expect β_1 to be negative.

The validity of the estimates of the minimum wage effect hinges on the model's ability to control for other factors that influence employment in each CIP that might also be correlated with the timing of minimum wage hikes. This specification controls for several different types of variables that might have an employment effect. First, cyclical effects are controlled for by the county-specific unemployment rate ($\mathrm{urate}_{\mathrm{it}}$). Note also that the model allows the cyclicality of employment (β_{2j}) to differ across industries. For example, the model allows manufacturing employment to be more cyclical than health services. The year-specific fixed effects (γ_t) capture the effect of any year-specific shock that has a common effect across all CIPs. The model also includes county-specific time trends (λ_i), and industry-specific time trends (θ_j) . County-specific time trends capture the effect of, for example, differential population growth across counties. Industry-specific time trends capture the effect of factors that are causing employment in a given industry to share a common trend across all counties. For example, increased import competition may cause employment in manufacturing to gradually fall across all counties.

The CIP-specific fixed effects (α_{ij}) capture the effect of variables that are fixed over time in a CIP that might affect employment. For example, differences in population, geography, or natural resources could cause a CIP to have unusually high or low employment in a county over time.

While the model described in (1) contains only two observable variables as controls, it controls for unobserved factors that lead to county-specific time trends, industry-specific time trends, and CIP-specific fixed effects. In total, this model includes 84 control variables (including the CIP fixed effects).

We also consider models that allow for more flexibility regarding controlling for unobservables. While these models are less restrictive and less likely to result in biased estimates of the minimum wage effect, they come at the expense of introducing more collinearity between the control variables and the variable of interest (lmin * low_wage) which may reduce the precision of our estimated coefficient of interest. In the extreme, if we add a year-specific fixed effect for each CIP, there would be perfect collinearity between our variable of interest (lmin * low_wage) and the fixed effects – and it would be impossible to identify any effect of the minimum wage on employment.

In the second model, we replace county-specific time trends with county-specific year effects. County-specific year effects capture the effect of any year-specific shock to a county that affects employment in all industries. This model provides more flexibility than the county-specific time trends in our first specification, but also increases the number of control variables from 84 to 783.

In the third model, we adjust the second model by replacing industry-specific time trends with CIP-specific time trends. This model allows, for example, a different time trend for manufacturing in each county. In the final model, we adjust the third model by dropping CIP specific time trends and allowing both industry-specific and county-specific year effects. This model controls for any factors that would impact all industries or all counties in a given year.

In each of the above specifications, the effect of minimum wage hikes is identified by comparing the employment growth of CIPs with high versus low shares of workers earning near the minimum wage. The differences between the models turns on how much flexibility is allowed regarding unobserved shocks that might influence employment growth in a given CIP. Moving from specification one to four, more flexibility is introduced for the impact of unobserved factors, but there is also an increase in the number of control variables and the degree of multi-collinearity which can inflate standard errors. Table 3 presents estimates of the four specifications of the empirical model. The standard errors are corrected for clustering by CIP. The models are estimated with weighting by CIP employment levels. In all four specifications, there is a statistically significant (at the .01 level) negative effect of minimum wages that is greatest in low wage industries. The range of estimated effects of lmin* low_wage across the four specifications is from -2.4 to -5.4. The standard error of the estimated coefficient is largest in the final model, but this is also the model where the estimated effect of the minimum is greatest.

An important concern with any empirical model is its robustness. We tested the model's robustness to several changes. First, we examined whether the model's results are being driven by outliers in the data. To find outliers, we computed the change in the coefficient of interest (lmin*low_wage) from excluding each of the 244 CIPs. We discovered that the exclusion of the manufacturing industry in Los Angeles County (LA) had an especially large effect. In fact, in three of the four specifications, excluding the LA manufacturing CIP caused the coefficient of interest to change by more than twice as much as any other CIP. The bottom panel of table 3 reveals how sensitive the coefficient of interest is to the exclusion of this CIP. In three of the four specifications, the coefficient on lmin*low_wage is reduced by more than 1.0 (in absolute value). The exception is the third specification where it drops only slightly. This is unsurprising since the third specification allows for CIP-specific time trends that would allow for a long downward trend in LA manufacturing.

More careful examination of the data reveals that among manufacturing industries, LA County had a more rapid downward trend than any other county in the state. LA is also the county with the highest share of low-wage workers in manufacturing, and the county with the highest level of manufacturing employment. The combination of these facts causes the estimated effect of the minimum wage to be amplified when LA manufacturing is included in the data.

Another concern with the LA manufacturing CIP is that its inclusion generates evidence of pre-trends in the data.[9] As noted by Angrist and Pischke (2009) and Malani and Reif (2013), pre-trends could be evidence of either an endogeneity problem, or agents anticipating and adjusting behavior before the treatment going into effect. While there is some evidence of pre-trends when all CIPs are used, as we show later, the pre-trends disappear when LA manufacturing is dropped from the data.

Since we are uncomfortable with LA manufacturing having such a large effect on the estimates and the evidence of pre-trends when it is included, the remainder of our analysis

[9] In the context of the analysis here, pre-trends exist when leading values of the minimum wage have explanatory power for the current level of employment.

focuses on models that exclude the CIP from the data. This results in a more conservative estimate of the disemployment effects of the minimum wage increases, but also removes a CIP that is problematic in that employment declines appear to precede increases in the minimum wage.

In another check for robustness, we considered different start dates for the estimation. As noted by Neumark et al. (2014a), the estimate of time trends can be sensitive to the endpoints in the data and can significantly alter the estimated effect of a minimum wage – particularly if the endpoints include a point where the economy is in recession and the sample period is short. In our case, we have 27 years of data and the economy is not in recession in 2016. Nevertheless, we considered the sensitivity of our results to alternative start dates. The results (available in appendix table A2) indicate that of the 12 different sets of estimates (four regression specifications times three different starting points), all 12 of the coefficient estimates are negative, and 11 of the 12 are statistically significant at the .05 level. The only statistically insignificant results occur when the start year is pushed to 2000. This is the shortest sample period considered and eliminates a large increase in the minimum wage that occurred in 1998.

We also estimated a model that included only the four industries with the largest average share of low-wage workers – agriculture; accommodation and food services; retail trade; and arts, entertainment, and recreation (available in appendix table A3). The advantage of this model is that it relies upon a comparison of industries that are more similar in terms of their heavy reliance on low wage workers. The disadvantage is that the data set is reduced from 244 to 72 CIPs and the amount of identifying information is reduced. With data for only these four industries, the estimated coefficients on lmin*low_wage range from -0.8 to -3.9 and are statistically significant at the .01 level for the first and third specifications, but are insignificant at the .10 level for specifications 2 and 4.[10] [11]

As yet another test of robustness, we use the methodology proposed by Meer and West (2016). Their method allows for the possibility that a change in the minimum wage affects the rate of growth in employment instead of a shift in the intercept. The Meer-West approach is to use "long-differences" to estimate the effect of minimum wage hikes. The specification is

$$(2)\ \Delta_{\mathrm{r}} lemp_{ijt} = \beta_0 + \beta_1 \Delta_{\mathrm{r}} \mathrm{lmin} *\ \mathrm{low\_wage_{ij}} + u_{ijt}$$

Where Δ_r is a difference operator. For example, $\Delta_{\mathrm{r}} lemp_{ijt}$ is the r-period change in log-employment that occurs between period (t-r) and t. We estimate this long difference corresponding to the four specifications in our earlier regression models, keeping in mind that when differencing across time, for example, CIP-specific fixed effects difference out of the model. Similarly, when differencing across time, an industry-specific time trend becomes an industry-specific fixed effect, and a county-specific time trend becomes a county-specific fixed effect.

The estimates of the Meer-West model, presented in table 4, correspond to the time-differenced versions of the four specifications in our earlier analysis of employment levels. The model that is presented is based on five-year differences, though the results are fairly robust to choosing shorter or longer differences.[12] In three of the four specifications, the coefficient

[10] The results for these models are available in appendix table A3.
[11] We also tested the robustness of our results to reducing the minimum sample size in the Census for a CIP wage estimate from 200 to 50. This added 63 additional CIPs to the data set, but increased total employment in the sample by only 2.6 percent. The estimated effects change only slightly.
[12] The coefficient on dlmin_low_wage is negative and statistically significant at the .01 level for the first 3 specifications for differences between 1 and 10 years. For the fourth specification, the effect is negative and

estimates imply a statistically significant (at .01 level) negative effect of minimum wage increases on employment growth. In the fourth specification, the coefficient is negative and statistically significant at the .10 level.

As a final check of our estimates, we test for pre-trends in the data. Pre-trends in the data exist when, for example, employment begins to fall more rapidly in the low-wage sector even before the minimum wage rises. Such pre-trends may be indicative of a spurious relationship between minimum wage increases and employment growth rather than a true causal effect. On the other hand, pre-trends could reflect causal effects if employers begin reducing employment in anticipation of a future increase in the minimum wage. To test for pre-trends, we include three years of leads of the minimum wage. We also add three lags of the minimum to allow for the possibility that employers take a few years to adjust employment after an increase in the minimum.

Table 5 presents estimates of the same four specifications presented in table 3 with the leads and lags added. In all four specifications, the leads are statistically insignificant at the .10 level. The contemporaneous effect of a minimum wage hike is reduced by inclusion of the leads and lags and is statistically significant at the .01 level in two of the four specifications. In all four specifications, the lags are jointly significant at the .01 level, and the sum of the lags are always negative. This suggests that the disemployment effects of an increase may take a few years to materialize fully and is consistent with the findings in, for example, Neumark et al. (2014b).

In review, we have considered numerous regression models to estimate the effect of minimum wage increases on employment in California. Our results point to a statistically

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statistically significant at the .10 level for all differences of 5 or more years, but statistically insignificant for differences of four or fewer years.

significant disemployment effect of minimum wage increases that is robust to the set of controls, the sample period, and whether using conventional panel data analysis or long-differences in employment. While we consider the results robust to alternative specifications, we think it is important to note that, given the high degree of flexibility (and thus collinearity) in the models, the estimates can be fairly sensitive to changes in controls and/or time periods. Nevertheless, we believe that the bulk of the evidence points toward substantial negative effects of California minimum wage increases on employment – particularly in low wage CIPs. We now turn to the size of the disemployment effects.

Simulations of Employment Loss

To put our range of estimated minimum wage employment effects in perspective, a coefficient of -1 on lmin* low_wage implies that, in an industry where 20% of the workers are paid within $1 of the minimum wage (in 1989 dollars), a 10% increase in the minimum causes a 2% decrease in employment. For the average CIP in our sample, the proportion of workers with low wages is .10. In table 3, the coefficient on lmin*low_wage ranges from -2.4 to -3.8 which implies that, in a CIP with the average share of low wage workers, the reduction in employment associated with a 10% increase in the minimum wage would range between 2.4 and 3.8 percent implying a minimum wage elasticity of between -.24 and -.38.

Other studies find a wide range of estimated minimum wage elasticities. For example, the CBO (2014) reports a range of 0 to -0.20 for teenagers, and 0 to -0.07 for adults. Meer and West (2016) report a minimum wage elasticity of -.08 for all workers. More recently, Jardim et al. (2017) summarize a series of studies for the restaurant industry with elasticities ranging from

0.02 to -0.24, though they argue that most previous studies underestimate the elasticities and that the restaurant industry may have a lower elasticity than other industries. Their analysis of the 2016 Seattle Washington minimum wage increase estimates a minimum wage elasticity of -0.23 to -0.28 for all workers.[13] Overall, our estimated range of elasticities fits within the bounds of earlier studies. It is important to note, however, that these elasticities are not entirely comparable because the studies differ regarding the industries examined, the size of the minimum wage hike, and the fraction of workers impacted by the minimum wage increase.

While it is well known that the disemployment effects of increases in the minimum wage differ sharply across industries or demographic groups, our study is one of the first to examine how much the effect can differ across geographic areas within a state. To give some sense of the disparity in the effects of a minimum wage hike, we use the models in table 3 to simulate the effect of a 10 percent increase in the minimum wage on employment in each CIP. The simulation assumes a coefficient of -3.32 on lmin*low_wage which is the average coefficient in table 3 across the 4 specifications considered with L.A. manufacturing excluded. Using this elasticity, the percent change in employment in county i industry j that results from a 10 percent increase in the minimum wage is calculated as $-3.32*low\_wage\_share_{ij}*10$.

The results of the simulation, summarized in table 6, show that the minimum wage increase would lead to a 3.4 percent employment loss statewide. The loss in employment ranges from a low of 2.2 percent in Marin County (north and across the bay from San Francisco) to 5.2 percent in Butte County (a rural area about 160 miles northeast from San Francisco). To put this in context, in percentage terms, the job loss from a minimum wage hike is approximately 2.5 times greater in Butte than San Francisco County.

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[13] While the range of elasticities is -0.23 to -0.28 for all workers, this translates into an elasticity -2.7 to -3.5 for workers who are directly affected by the minimum wage.

Part of the reason that the job loss differs so much across counties is that there are substantial differences in the industrial composition across counties. In addition, there is substantial variation across counties in terms of the employment loss *within a given industry*. Table 6 shows the percentage of jobs lost in two of the largest low wage sectors – accommodation and food services; and retail. The predicted percentage point reduction in employment varies from 2.7 to 6.5 across counties in retail, and from 3.6 to 8.9 in accommodation and food services. Clearly, even within industry, a minimum wage hike will have very different employment effects across the counties of California. Given these facts, it would not be surprising if the political support for a minimum wage hike would vary sharply across counties within a state.

Summary and Conclusions

This study uses California employment data from 1990 through 2016 to test whether the state's minimum wage increases over the past 25 years led to a loss of low-wage jobs. Our empirical approach identifies the effects of minimum wage increases by comparing the evolution of employment across county-industry pairs (CIPs). We find fairly robust evidence that, when the minimum wage increases, employment growth is slowed in low-wage relative to high-wage CIPs. While our models are parsimonious in terms of the controls for observed economic conditions, our models allow for a variety of different types of fixed effects and/or time trends that control for any common shocks that impact all industries across counties, or all industries within a county. We also examined the data for outliers that might have unusually large effects on our estimates.

Across a wide range of specifications, we find statistically significant negative effects of the California minimum wage increases on employment growth, particularly in low-wage industries. We admit, however, that if we expand the list of controls to the point of having a highly saturated model, the estimates become statistically insignificant. We do not view these insignificant results as evidence against a minimum wage effect. Rather, we believe that if an empirical model includes large numbers of fixed effects, there is too much collinearity in the model and too little identifying variation left to identify the effect of minimum wage movements.

Our preferred estimates, which exclude Los Angeles county manufacturing as an outlier, suggest that a 10% increase in the minimum wage would lead to a 3.4% reduction in employment. The percentage job loss is greater in accommodations and food services, and retail trade industries. While the most populated counties of California would be expected to incur the largest employment loss regarding the number of workers, the smaller counties experience a larger percentage point loss in employment due to the lower wages and the greater share of workers that would be affected by the minimum wage hike.

While our model provides fairly convincing evidence that minimum wage increases cause job loss, it's important to note that it is based on historical data and that the models assume that the only factor that determines the response of an industry to a minimum wage hike is its share of low wage workers. In reality, the response elasticities of firms to minimum wage hikes will depend on factors such as their ability to replace labor with capital, or labor's share of the firm's total cost. The easier it is to substitute capital for labor and the more labor intensive the firm is, the greater the expected response to a change in the minimum wage. Moreover, a firm's ability to pass on the cost of a minimum wage hike may vary over time as new technologies are developed. As a result, our estimates should be considered with some caution given the simplifying assumptions of our model. Nevertheless, we feel that our estimates of job loss are consistent with the employment loss associated with previous minimum wage increases in California.

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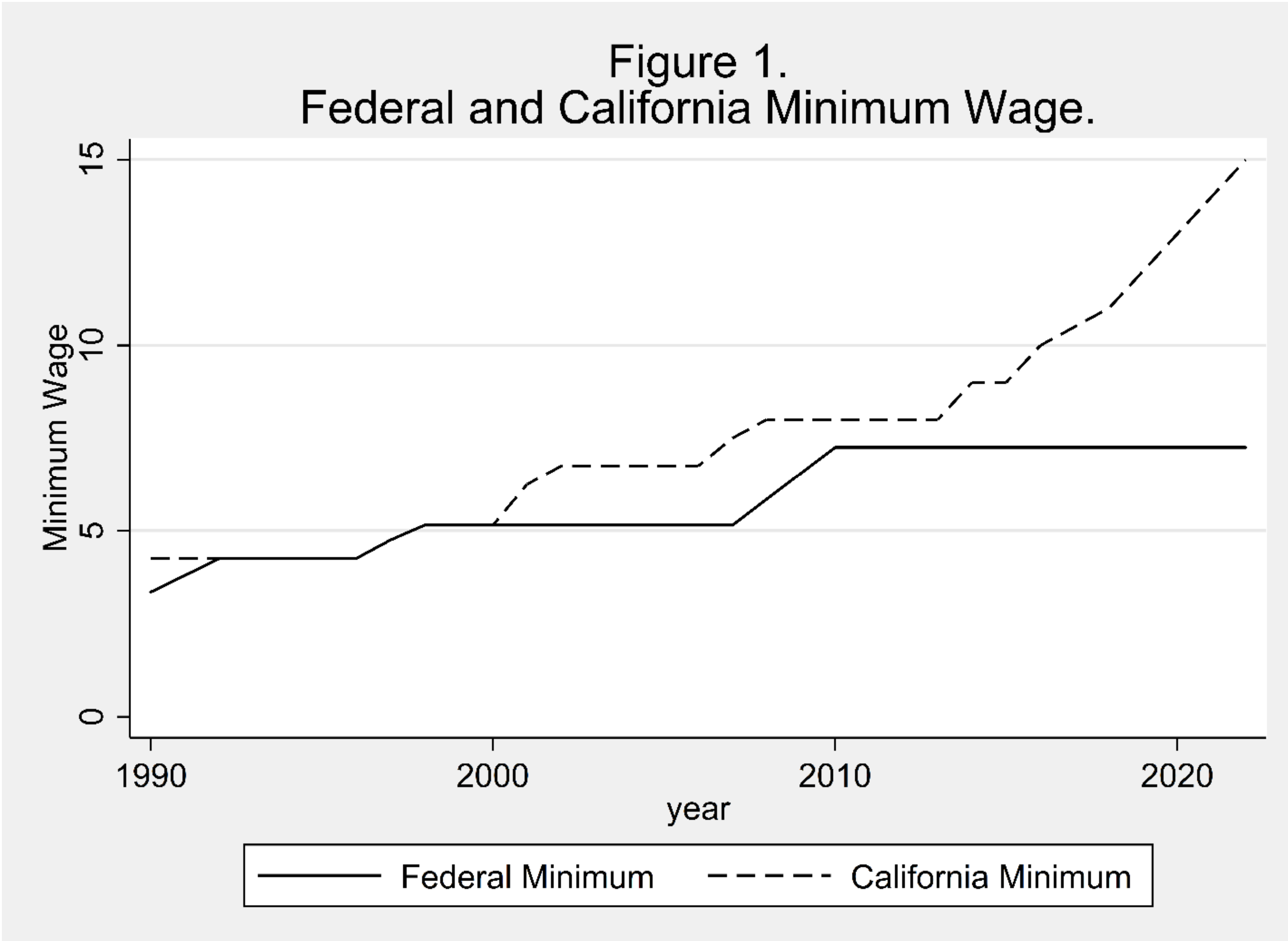
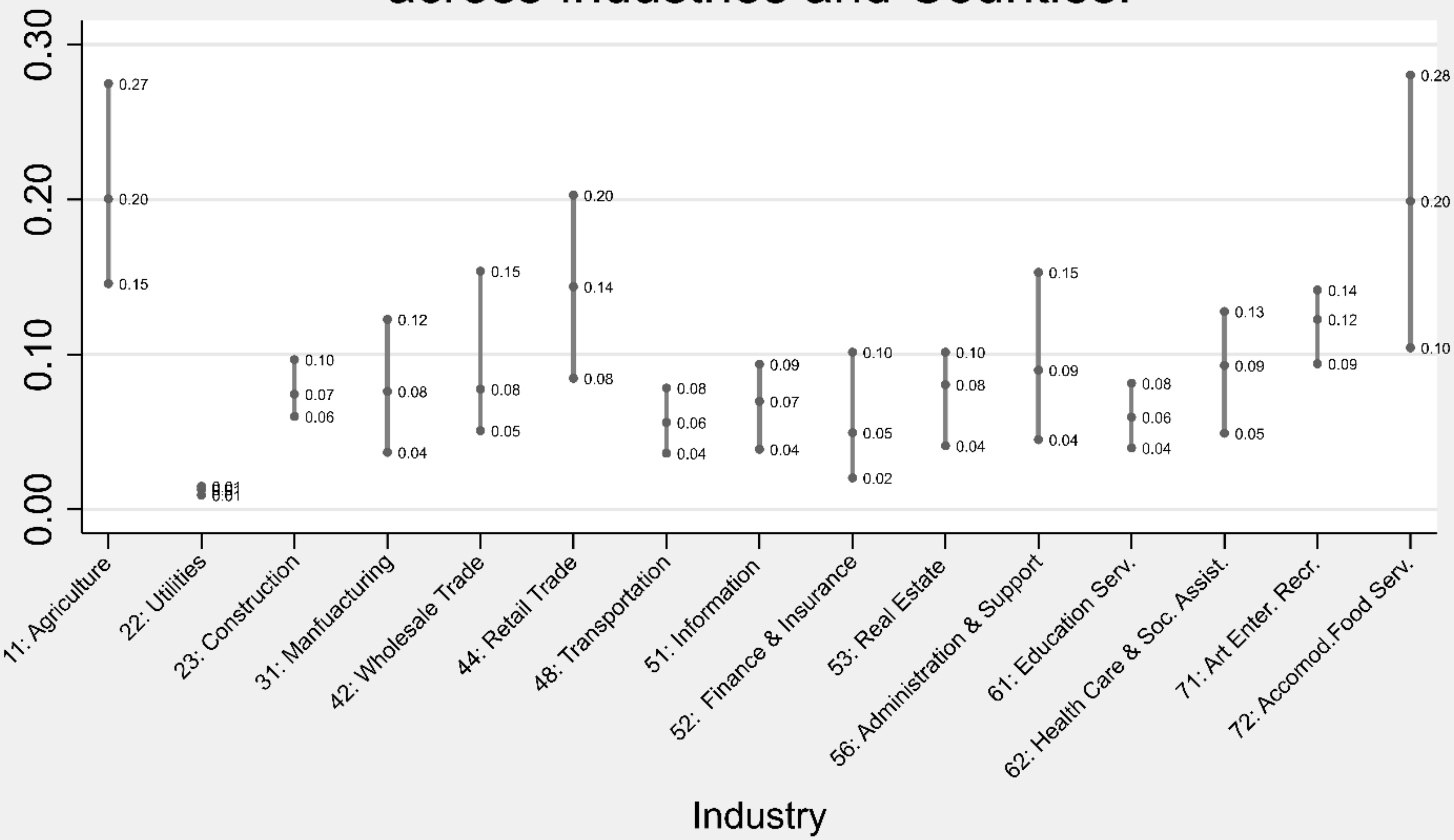
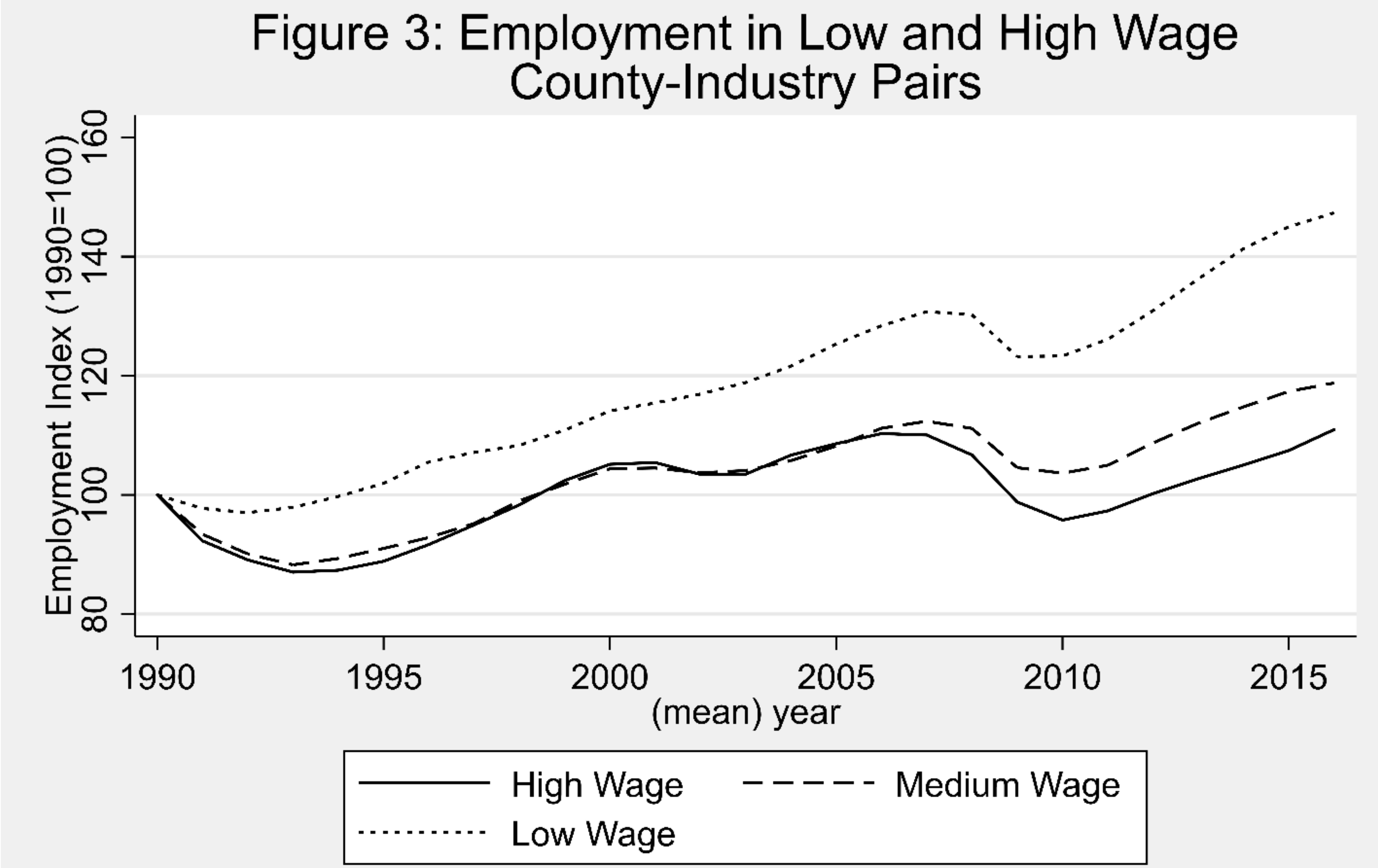


Figure 1.
Federal and California Minimum Wage.
Minimum Wage
0
5
10
15
1990
2000
2010
2020
year
Federal Minimum
California Minimum

Figure 2. Share of Workers Earning Low Wages across Industries and Counties.



Plots show minimum, mean and maximum value of the percent of workers earning low wages across counties, by industry. See text for details.



The share of workers with low wages in low, medium and high wage CIPs are respectively >14%, 7-14%, and <7%. See text for details.

Table 1. Counties Included in Analysis.[a]

County	County FIPS Code	2016 Employment Covered by Industries with complete data for 1990-2016[b]	Total County Employment in 2016	Share of 2016 employment covered in data.
Butte	7	48,587	64,366	75.5%
El Dorado	17	21,196	42,494	49.9%
Fresno	19	277,789	303,441	91.5%
Humboldt	23	22,048	34,745	63.5%
Kern	29	222,285	243,339	91.3%
Los Angeles	37	3,665,722	3,756,230	97.6%
Marin	41	74,296	98,383	75.5%
Merced	47	26,785	57,991	46.2%
Monterey	53	120,784	154,346	78.3%
Napa	55	28,064	64,715	43.4%
Orange	59	1,352,394	1,397,182	96.8%
Placer	61	74,812	136,349	54.9%
Riverside	65	476,896	559,878	85.2%
Sacramento	67	443,498	461,371	96.1%
San Bernardino	71	534,508	577,448	92.6%
San Diego	73	1,085,212	1,167,110	93.0%
San Francisco	75	504,224	600,645	83.9%
San Joaquin	77	155,085	194,765	79.6%
San Luis Obispo	79	72,654	93,057	78.1%
San Mateo	81	254,753	356,677	71.4%
Santa Barbara	83	145,047	161,737	89.7%
Santa Cruz	87	63,034	85,288	73.9%
Shasta	89	32,734	51,478	63.6%
Solano	95	83,331	110,002	75.8%
Sonoma	97	144,232	173,130	83.3%
Stanislaus	99	109,527	152,909	71.6%
Tulare	107	60,233	127,898	47.1%
Ventura	111	249,571	275,707	90.5%
Yolo	113	32,388	67,438	48.0%
All Included Counties		10,381,689	11,570,119	89.7%
California			14,126,759	73.5%

[a] 2016 data is based on January through June of 2016 QCEW data.
[b] For a given county-industry pair to be included, the QCEW must report employment in every year over the sample period (1990-2016).

Table 2. Industries Covered in Analysis.[a]

Industry	NAICS Code	Number of Counties with required data[b].	2016 Covered Employment Total	Average share of county employment in 2016	Covered Employment Share of State Employment Total	2016 State Employment Total
Agriculture, Forestry, Fishing and Hunting	11	10	243,584	10.7%	59.6%	408,690
Mining	21	0	0	0.0%	0.0%	22,557
Utilities	22	3	17,068	0.4%	29.1%	58,578
Construction	23	9	388,844	6.0%	51.7%	752,044
Manufacturing	31-33	26	1,000,522	8.7%	77.5%	1,291,140
Wholesale Trade	42	17	522,376	4.2%	73.3%	713,060
Retail Trade	44-45	29	1,391,195	13.5%	84.4%	1,647,523
Transportation and Warehousing	48-49	11	337,350	3.5%	67.9%	496,663
Information	51	8	281,177	2.3%	54.5%	515,558
Finance and Insurance	52	18	418,272	3.4%	77.8%	537,898
Real Estate and Rental and Leasing	53	11	202,201	2.0%	74.1%	272,963
Management of Companies and Enterprises	55	0	0	0.0%	0.0%	225,185
Administrative and Support and Waste Management and Remediation Services	56	22	1,676,475	12.9%	73.9%	2,268,315
Educational Services	61	18	228,457	1.9%	74.4%	307,270
Health Care and Social Assistance	62	29	2,230,956	20.0%	83.8%	2,661,619
Arts, Entertainment, and Recreation	71	6	180,743	2.1%	61.7%	292,972
Accommodation and Food Services	72	27	1,336,112	12.0%	85.0%	1,571,030
Unclassified industries	99	0	0	0.0%	0.0%	83,690
Total			10,381,689		73.5%	14,126,759

[a] Employment counts are for the counties included in the analysis. See table 1 for list of counties. 2016 data is based on January through June of 2016 QCEW data.

[b] For a given county-industry pair to be included, the QCEW must report employment in every year over the sample period (1990-2016).

Table 3. Estimates of Employment Effects of Minimum Wage Increase.[a]				
	All Observations			
	(1)	(2)	(3)	(4)
Log(minimum wage)* Low wage share[b]	-4.517***	-4.616***	-2.421***	-5.366***
	(0.221)	(0.919)	(0.542)	(1.352)
Observations	6,588	6,588	6,588	6,588
Number of county-industry pairs	244	244	244	244
Within Group R^2	0.806	0.830	0.920	0.866
Overall Adjusted R^2	0.997	0.997	0.998	0.997
Number of Controls	84	783	984	1119
	Excluding Los Angeles Manufacturing			
	(1)	(2)	(3)	(4)
Log(minimum wage)* Low wage share[b]	-3.555***	-3.525***	-2.365***	-3.834**
	(0.227)	(0.976)	(0.546)	(1.562)
Observations	6,561	6,561	6,561	6,561
Number of county-industry pairs	243	243	243	243
Within Group R^2	0.788	0.814	0.912	0.852
Overall Adjusted R^2	0.996	0.996	0.998	0.997
Number of Controls	84	783	983	1,119
County-Industry Pair Effects?	Yes	Yes	Yes	Yes
Year Effects?	Yes	No	No	No
County-Specific Year Effects?	No	Yes	Yes	Yes
County-Specific Time Trend?	Yes	No	No	No
County-Industry Specific Time Trend?	No	No	Yes	No
Industry-Specific Year Effects?	No	No	No	Yes
Industry-Specific Time Trend?	Yes	Yes	No	No
Industry-Specific Unemployment Rate Effects?	Yes	Yes	Yes	No

[a] Dependent variable is log(employment) for a given county-industry pair. The sample is restricted to counties and industries described in text. Standard errors are in parentheses and are corrected for clustering by CIP. *, **, and *** indicate significance levels of .1, .05 and .01, respectively.

[b] Low wage share is the percentage of workers in the county-industry pair earning between (mw- $0.25) and (mw+$1) where mw is the minimum wage measured in 1990 dollars.

Table 4. Estimated Effects of Minimum Wage on Employment Growth with Year Effects[a]

	(1)	(2)	(3)	(4)
Δ(Log(minimum wage) * low wage share)[b]	-3.484***	-3.332***	-3.086***	-2.354*
	(0.524)	(0.566)	(0.614)	(1.364)
Observations	5,103	5,103	5,103	5,103
Number of county/industry pairs	243	243	243	243
Overall R^2	0.481	0.558	0.619	0.766
County-Industry Pair Effects?	No	No	Yes	No
Year Effects?	Yes	No	No	No
County-Specific Year Effects?	No	Yes	Yes	Yes
County-Specific Effects?	Yes	No	No	No
Industry-Specific Effects?	Yes	Yes	No	No
Industry-Specific Unemployment Rate Effects?	Yes	Yes	Yes	No
Industry-Specific Year Effects?	No	No	No	Yes

[a] Dependent variable is five year change in log(employment). The sample is restricted to years 1996 forward. The sample is restricted to counties and industries described earlier. Standard errors are in parentheses and corrected for clustering by CIP. *, **, and *** indicate significance levels of .1, .05 and .01, respectively.
[b] Low wage share is the percentage of workers in the county-industry pair earning between (mw- $0.25) and (mw+$1) where mw is the minimum wage measured in 1990 dollars.

Table 5. Estimates of Employment Effects of Minimum Wage Increase with Leads and Lags.[a]

	(1)	(2)	(3)	(4)
Log(minimum wage$_t$)* Low wage share[b]	-1.125	-1.797***	-1.522***	0.826
	(0.922)	(0.654)	(0.457)	(0.731)
Log(minimum wage$_{t+3}$)* Low wage share	-0.764	-0.718	-1.836	-0.992
	(0.498)	(0.878)	(1.163)	(1.332)
Log(minimum wage$_{t+2}$)* Low wage share	-0.679	-0.293	-0.107	0.0338
	(0.830)	(0.451)	(0.426)	(0.939)
Log(minimum wage$_{t+1}$)* Low wage share	-0.812	-0.00768	-0.753	0.00857
	(0.894)	(0.568)	(0.629)	(0.858)
Log(minimum wage$_{t-1}$)* Low wage share	-0.467	0.382	-0.287	-1.055
	(0.925)	(0.965)	(0.719)	(0.843)
Log(minimum wage$_{t-2}$)* Low wage share	-1.159	-1.719**	-1.246**	-0.170
	(0.835)	(0.799)	(0.510)	(1.754)
Log(minimum wage$_{t-3}$)* Low wage share	0.397	-0.357	-1.203*	-2.706
	(0.515)	(0.736)	(0.651)	(1.760)
Observations	6,561	6,561	6,561	6,561
Number of county-industry pairs	243	243	243	243
Number of Controls (including				
Within Group R^2	0.789	0.815	0.913	0.853
Overall Adjusted R^2	0.996	0.996	0.998	0.997
p-value for F-Test for Leads	0.000	0.613	0.435	0.636
p-value for F-Test for Lags	0.007	0.000	0.000	0.099
County-Industry Pair Effects?	Yes	Yes	Yes	Yes
Year Effects?	Yes	No	No	No
County-Specific Year Effects?	No	Yes	Yes	Yes
County-Specific Time Trend?	Yes	No	No	No
County-Industry Specific Time Trend?	No	No	Yes	No
Industry-Specific Year Effects?	No	No	No	Yes
Industry-Specific Time Trend?	Yes	Yes	No	No
Industry-Specific Unemployment Rate Effects?	Yes	Yes	Yes	No

[a] Dependent variable is log(employment). Sample is restricted to counties and industries described earlier. Standard errors are in parentheses and are corrected for clustering by CIP. *, **, and *** indicate significance levels of .1, .05 and .01, respectively.
[b] Low wage share is the percentage of workers in the county-industry pair earning between (mw- $0.25) and (mw+$1) where mw is the minimum wage measured in 1990 dollars.

Table 6. Employment Loss from a 10% Increase in the Minimum Wage.[a]					
			Percent Employment Loss from a 10% Increase in the Minimium Wage		
County	Percent Low Wage in county.	2016 Employment Covered by Industries with complete data for 1990-2016	All covered industries in county.	Retail Trade	Accommodation and Food Services[a]
Butte	16.0%	48,587	-5.2%	-5.5%	-8.5%
El Dorado	12.7%	21,196	-4.1%	-4.2%	-5.2%
Fresno	14.6%	277,789	-4.7%	-4.9%	-7.7%
Humboldt	15.6%	22,048	-5.0%	-5.4%	-6.9%
Kern	14.4%	222,285	-4.7%	-5.2%	-7.7%
Los Angeles	10.2%	3,306,128	-3.3%	-4.5%	-6.1%
Marin	6.8%	74,296	-2.2%	-3.3%	-3.6%
Merced	13.4%	26,785	-4.3%	-6.2%	---
Monterey	12.5%	133,206	-4.1%	-4.7%	-4.4%
Napa	8.1%	28,064	-2.7%	-4.5%	---
Orange	8.9%	1,352,394	-2.9%	-4.0%	-6.1%
Placer	11.7%	74,812	-3.8%	-5.1%	-4.7%
Riverside	11.3%	476,896	-3.7%	-4.4%	-6.0%
Sacramento	10.7%	443,498	-3.5%	-4.5%	-7.2%
San Bernardino	10.7%	534,508	-3.5%	-4.8%	-6.6%
San Diego	10.9%	1,108,415	-3.6%	-4.8%	-6.2%
San Francisco	7.3%	504,224	-2.4%	-2.7%	-4.5%
San Joaquin	12.8%	155,085	-4.2%	-4.5%	-7.0%
San Luis Obispo	13.6%	72,654	-4.4%	-5.9%	-6.9%
San Mateo	6.9%	266,634	-2.3%	-3.3%	-5.1%
Santa Barbara	13.1%	149,464	-4.3%	-5.0%	-6.9%
Santa Cruz	10.8%	63,034	-3.5%	-4.8%	-5.8%
Shasta	15.3%	32,734	-5.0%	-5.6%	-7.0%
Solano	9.2%	83,331	-3.0%	-3.3%	-6.5%
Sonoma	10.8%	147,551	-3.5%	-4.7%	-6.4%
Stanislaus	13.3%	109,527	-4.3%	-5.0%	-7.6%
Tulare	15.8%	71,034	-5.1%	-4.7%	-8.9%
Ventura	11.1%	249,571	-3.6%	-4.6%	-6.7%
Yolo	13.6%	39,988	-4.4%	-6.5%	-7.1%
All Included Counties	10.5%	10,095,738	-3.4%	-4.5%	-6.2%

[a] Employment loss estimates are based on the average coefficient on log(minimum wage)*low_wage_share from the specifications in table 4.
[b] Data for accommodation and food services is not available for Merced and Napa counties.

Appendix Table A1. Federal and California State Minimum Wage

Year	Federal Minimum Wage	California Minimum Wage[a]
1939	$0.25	$0.33
1940	$0.40	$0.33
1941	$0.40	$0.33
1942	$0.40	$0.33
1943	$0.40	$0.33
1944	$0.40	$0.45
1945	$0.40	$0.45
1946	$0.40	$0.45
1947	$0.40	$0.45
1948	$0.40	$0.65
1949	$0.40	$0.65
1950	$0.75	$0.65
1951	$0.75	$0.65
1952	$0.75	$0.65
1953	$0.75	$0.75
1954	$0.75	$0.75
1955	$0.75	$0.75
1956	$0.75	$0.75
1957	$1.00	$0.75
1958	$1.00	$1.00
1959	$1.00	$1.00
1960	$1.00	$1.00
1961	$1.00	$1.00
1962	$1.15	$1.00
1963	$1.15	$1.00
1964	$1.15	$1.25
1965	$1.15	$1.30
1966	$1.15	$1.30
1967	$1.15	$1.30
1968	$1.40	$1.30
1969	$1.60	$1.65
1970	$1.60	$1.65
1971	$1.60	$1.65
1972	$1.60	$1.65
1973	$1.60	$1.65
1974	$1.60	$1.65
1975	$2.10	$2.00
1976	$2.30	$2.00
1977	$2.30	$2.50
1978	$2.65	$2.50
1979	$2.90	$2.90
1980	$3.10	$3.10
1981	$3.35	$3.35
1982	$3.35	$3.35
1983	$3.35	$3.35
1984	$3.35	$3.35
1985	$3.35	$3.35
1986	$3.35	$3.35

1987	$3.35	$3.35
1988	$3.35	$3.35
1989	$3.35	$4.25
1990	$3.35	$4.25
1991	$3.80	$4.25
1992	$4.25	$4.25
1993	$4.25	$4.25
1994	$4.25	$4.25
1995	$4.25	$4.25
1996	$4.25	$4.25
1997	$4.75	$4.75
1998	$5.15	$5.15
1999	$5.15	$5.75
2000	$5.15	$5.75
2001	$5.15	$6.25
2002	$5.15	$6.75
2003	$5.15	$6.75
2004	$5.15	$6.75
2005	$5.15	$6.75
2006	$5.15	$6.75
2007	$5.15	$7.50
2008	$5.85	$8.00
2009	$6.55	$8.00
2010	$7.25	$8.00
2011	$7.25	$8.00
2012	$7.25	$8.00
2013	$7.25	$8.00
2014	$7.25	$9.00
2015	$7.25	$9.00
2016	$7.25	$10.00
2017	$7.25	$10.50
2018	$7.25	$11.00
2019	$7.25	$12.00
2020	$7.25	$13.00
2021	$7.25	$14.00
2022	$7.25	$15.00

[a] Between January 2017 and January 2023, California state law has a lower minimum wage for employers with 25 employers or less.

Appendix Table A2. Estimates of Employment Effects of Minimum Wage Increase by Start Year.[a]

		1990-2016		
	(1)	(2)	(3)	(4)
Log(min wage)* Low wage share[b]	-3.555***	-3.525***	-2.365***	-3.834**
	(0.227)	(0.976)	(0.546)	(1.562)
Observations	6,561	6,561	6,561	6,561
Number of CIPS	243	243	243	243
Within Group R^2	0.788	0.814	0.912	0.852
		1995-2016		
Log(minimum wage)* Low wage share[b]	-3.744***	-3.697***	-2.532***	-4.094**
	(0.240)	(0.820)	(0.541)	(1.610)
Observations	5,346	5,346	5,346	5,346
Number of CIPS	243	243	243	243
Within Group R^2	0.760	0.788	0.896	0.834
		2000-2016		
Log(min wage)* Low wage share[b]	-3.271***	-2.776***	-0.0862	-4.808**
	(0.321)	(0.982)	(0.586)	(1.898)
Observations	4,131	4,131	4,131	4,131
Number of CIPS	243	243	243	243
Within Group R^2	0.721	0.749	0.885	0.801
County-Industry Pair Effects?	Yes	Yes	Yes	Yes
Year Effects?	Yes	No	No	No
County-Specific Year Effects?	No	Yes	Yes	Yes
County-Specific Time Trend?	Yes	No	No	No
County-Industry Specific Time Trend?	No	No	Yes	No
Industry-Specific Year Effects?	No	No	No	Yes
Industry-Specific Time Trend?	Yes	Yes	No	No
Industry-Specific Unemployment Rate Effects?	Yes	Yes	Yes	No

[a] Dependent variable is log(employment). Sample is restricted to counties and industries described earlier. Standard errors are in parentheses and based on standard errors corrected for clustering by CIP. *, **, and *** indicate significance levels of .1, .05 and .01, respectively.

[b] Low wage share is the percentage of workers in the county-industry pair earning between $0.25 less than the minimum wage and less than or equal to $1 above the minimum wage om 1990 dollars.

Appendix Table A3. Estimates of Employment Effects of Minimum Wage Increase using the Four Industries with the Largest Share of Low-Wage Workers.[a]

	(1)	(2)	(3)	(4)
Log(minimum wage)* Low wage share[b]	-1.986***	-1.782	-3.945***	-0.808
	(0.355)	(1.735)	(0.951)	(2.200)
Observations	1,944	1,944	1,944	1,944
Number of county-industry pairs	72	72	72	72
Within Group R^2	0.806	0.830	0.920	0.866
Overall Adjusted R^2	0.998	0.997	0.999	0.997
Number of Controls	62	761	801	833
County-Industry Pair Effects?	Yes	Yes	Yes	Yes
Year Effects?	Yes	No	No	No
County-Specific Year Effects?	No	Yes	Yes	Yes
County-Specific Time Trend?	Yes	No	No	No
County-Industry Specific Time Trend?	No	No	Yes	No
Industry-Specific Year Effects?	No	No	No	Yes
Industry-Specific Time Trend?	Yes	Yes	No	No
Industry-Specific Unemployment Rate Effects?	Yes	Yes	Yes	No

[a] Dependent variable is log(employment) for a given county-industry pair. The sample is restricted to counties and industries described in text. Standard errors are in parentheses and are corrected for clustering by CIP. *, **, and *** indicate significance levels of .1, .05 and .01, respectively. Los Angeles manufacturing is excluded for reasons discussed in text.

[b] Low wage share is the percentage of workers in the county-industry pair earning between (mw- $0.25) and (mw+$1) where mw is the minimum wage measured in 1990 dollars.