How Will a $15 Minimum Wage Affect Employment in California?*

February 2018

William E. Even
Raymond E. Glos Professor of Economics
Miami University
Oxford, OH 45056
evenwe@muohio.edu
(513)-529-2865

David A. Macpherson
E.M. Stevens Professor of Economics
Trinity University
One Trinity Place
San Antonio, TX 78212
dmacpher@trinity.edu
(210)-999-8112

Abstract

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 the current law which will gradually increase the minimum wage to $15.00 in 2022. The simulations suggest that the $15.00 minimum could cause a loss of approximately 400,000 jobs in California. Approximately one-half of the job loss is projected to occur 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.

* Employment Policies Institute provided funding for this research.

Conflicts of Interest: The authors declare that they have no conflict of interest.

Keywords: minimum wage; employment; California; labor demand;

JEL: J23; J30; J38

Introduction

Since 1980, the state of California has passed several minimum wage laws that increased the minimum wage beyond the federal level. Some would suggest that a higher minimum wage could be justified in California because of its relatively high cost of living compared to the typical state. On the other hand, one might be concerned about whether the higher minimum wage in California causes job loss for low skilled workers, and whether the effects differ in the cities where the cost of living and wages are relatively high as compared to rural areas or less expensive cities.

This study examines the effect of California's state minimum wage laws since 1990. It tests for an effect of a higher minimum wage by examining whether a minimum wage increase is associated with a slowdown in employment growth in county-industry pairs (CIPs) with a greater share of low wage workers. Relying on several different empirical models, our analysis finds that the minimum wage increases that occurred in California over time caused a reduction in employment. Our study simulates the effect of the current law that is scheduled to raise the minimum wage to \$15.00 by 2022. The simulations suggest that the \$15.00 minimum could cause a loss of about 400,000 jobs in California[1]. The job loss is not spread evenly. Approximately one-half of the job loss is projected to be in two industries: accommodation and food services, and retail trade. 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 number of workers that would be affected by the minimum wage hike.

---

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

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 fluctuated since 2000 as both the state and federal minimum wages increased. As of 2017, California's $10.50 minimum is second only to the $11.00 minimum in the states of Washington and Massachusetts. Moreover, under current law, California's will increase its minimum wage 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 history of the U.S.[2]

This study uses the California experience between 1994 and 2016 as a way to gauge the effect of the upcoming increases in the minimum wage on employment in California. While numerous studies have examined the effect of minimum wage hikes on employment [see Neumark and Washer (2008)l; 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

---

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

differences in the cost of living and wages across counties. Second, unlike much of the recent research that estimates the effect of minimum wage hikes by comparing employment trends across states that differ regarding their minimum wage laws, we compare employment growth across county-industry pairs (CIPs) within California to determine the effects. That is, we obtain a measure of the extent to which the minimum wage should be binding in each CIP and test whether a minimum wage increase slows employment growth most where the minimum wage binds the most.

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. Self-employed workers are not included in the QCEW data.

Our analysis of employment trends uses employment by county for each 2-digit NAICS industry. We convert to annual employment measures by averaging across the quarterly employment counts to remove seasonality in the data. Since employment counts are masked for confidentiality reasons when a given county-industry pair (CIP) has a low level of employment, we restrict our analysis to those CIPs that have employment reported in every quarter between 1990 and 2016.

For our analysis, we need a measure of how much the minimum wage binds in each CIP. The QCEW reports total payroll and the number of workers. Given this aggregate level of data and the lack of information on hours worked, the QCEW earnings data is not suitable for estimating the share of workers earning a wage close to the minimum. To obtain an estimate, we use the Current Population Survey Outgoing Rotation Groups files between 1996 and 2016.[3] We estimate the percentage of workers in an industry that we define as "low wage workers" – which we define as anyone earning no more than between $0.25 below the state minimum (in nominal dollars) and $1 above (in 1990 dollars).

Unfortunately, the CPS identifies only 31 of the 58 California counties and our analysis is thus restricted to this subset. To help improve the accuracy of our wage estimate for a CIP, we drop any county that contains a city minimum wage law that causes its minimum wage to differ from the California state minimum wage and simultaneously differ within the county.[4] While San Francisco has a minimum wage above the state level, this is a county-wide minimum wage so we include it in our analysis.

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 CPS sample. The sample also excludes any CIP that has incomplete employment data over 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 any county when the total employment for the included industries covered less than

[3] We choose a starting date of 1996 for the CPS data because the counties identified in the CPS changed in 1996. We also had to map census codes for industry to match those in the QCEW and account for the fact that industry codes changed in both the CPS and QCEW over time.
[4] 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.

one-half of private sector employment in the county in 2016. Finally, we eliminate any CIP that shows more than a 25 percent change in employment between years. Such changes are clear outliers in the data and may reflect changes in reporting behavior by a firm that has multiple establishments.[5]

Table 1 provides a list of the 24 counties that fit our requirements for inclusion along with the employment level in each county. In total, there are 11.2 million private sector wage and salary workers in the 24 counties included. Because we drop CIPs that have missing data on employment in any year between 1994 and 2016, we lose some CIPs. Nevertheless, 90.5 percent of the private sector employment in these 24 counties is covered in our sample, and it represents 72.0 percent of statewide private sector wage and salary employment. While a large share of employment is included in our sample, the exclusion restrictions admittedly result in small rural counties being underrepresented since data is more likely to be suppressed when employment counts are low.

Table 2 provides a list of 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 73.7% of statewide employment in these industries. The industries with the highest share of state-wide employment covered by our sample are those that have sufficient data to be covered by a large number of counties.

---

[5] 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 might have 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

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 accommodation and food services (55% low wage) and agriculture, forestry, fishing and hunting (46 percent low wage). At the other extreme, the two industries with the lowest share of workers earning low wages are utilities, and finance and insurance (both at 5 percent).

Within a given industry, there is a substantial variation in the share of workers earning low wages across counties. For example, in accommodation and food services, the share ranges from 36 to 74 percent; in agriculture, the range is from 24 to 61 percent. As a result, the extent to which a minimum wage increase binds will vary 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 increases in the state minimum wages 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 8% earning low wages) are classified as high wage CIPs. Those in the top quartile of the distribution -- with more than 27% 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 8 and 27% earning low wages) are classified as medium wage industries.

The employment measure is an index set to 100 in 1990. Based on the information provided, employment since 1990 grew by 37, 18, and 15 percent in low, medium, and high wage CIPS since 1990. 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 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 control for these factors and attempt 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 assumptions implicit in each model depends on the specific controls included. In the first specification, we estimate

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

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

The coefficient of interest is β_1 that measures the effect of the natural log of the minimum wage ($\mathrm{lmin}_{\mathrm{it}}$) interacted with the fraction of workers earning low wages in CIP ij ($\mathrm{low\_wage}_{\mathrm{ij}}$) The expectation is that minimum wages will have a larger negative employment effect in the industries that employ 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. 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, during a recession, employment in health services tends to fall less than that in manufacturing since health spending is less cyclical. The year-specific time 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 effects (α_{ij}) capture the effect of variables influencing employment that are fixed over time in a CIP. For example, differences in population, geography, or natural resources might cause a specific industry to have unusually high or low employment in a county over time. For example, being located near an interstate highway system might lead to more employment in transportation; fertile land could lead agricultural employment to be high.

While this model contains only two observable variables as controls, it controls for unobserved factors that lead to a county-specific time trend, industry-specific time trend, or a CIP-specific fixed effect.

We also consider models that include more flexibility in terms of 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.

In the third model, we adjust the second model by dropping industry-specific time trends and replace them with CIP-specific time trends. This model allows, for example, a different time trend for manufacturing in each county. In the final model, we include both industry-specific and county-specific year effects, in addition to CIP specific fixed effects.

Table 3 presents estimates of our 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 .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 -0.98 to -1.46. 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 were being driven by outliers in the data. To find outliers, we examined whether the coefficients changed sharply by eliminating any given CIP, industry, or county. We discovered that manufacturing in Los Angeles (LA) County had an especially strong impact on the estimated effect of the minimum in some specifications. More careful examination of the data revealed that manufacturing in LA county had a more rapid downward trend than any other county in the state, that it was also the county with the highest share of low-wage workers in manufacturing, and is the county with the highest level of manufacturing employment. The combination of these facts causes the estimated effect of the minimum wage to be less negative when LA county manufacturing is removed from the data. Since we are uncomfortable with LA manufacturing having such a large effect on the estimates, we also present results with LA county manufacturing removed from the data. The coefficient estimates are substantially reduced in three of the four specifications, remain negative in all four specifications, but become statistically insignificant (at the .10 level) in the fourth specification which arguably has the highest degree of collinearity. In specification 3, the exclusion of LA manufacturing has little effect on the estimated minimum wage effect. This result is to be expected since this specification allows for a CIP specific time trend which allows LA manufacturing to have a different time trend than the manufacturing industries in other counties.

As a second check for robustness, we considered different start dates for the estimation. As noted by Neumark et al. (2014), 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. It is worth noting that the statistically insignificant results only occur when the start year is pushed to 2000. This is the shortest sample period considered and also eliminates a very large increase in the minimum wage that occurred in 1998.

If LA county manufacturing is removed from the sample due to its unusually large influence on some of the estimates, all 12 coefficient estimates remain negative though they achieve statistical significance (at the .05 level) in only 7 of the 12 models. The first two specifications (which have less flexibility and less collinearity) are, however, much more stable across all variations considered – whether LA county manufacturing is excluded or the starting year is varied. This finding is not surprising as the third and fourth specifications have more collinearity (and flexibility in fitting in the data) and this makes results more sensitive to changes in the data sample.

As yet another test of robustness, we consider the methodology proposed by Meer and West (2016). Their method was designed to address the possibility that a change in the minimum wage would affect 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) $\Delta_{\mathrm{r}} lemp_{ijt} = \beta_0 + \beta_1 \Delta_{\mathrm{r}} \mathrm{lmin} * \ \mathrm{low\_wage}_{\mathrm{ijt}} + u_{ijt}$

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 are in table 4. The estimated models correspond to the time-differenced versions of the four specifications in our earlier analysis of employment levels. In the first four specifications, all observations are included and we present results for the 5-year time difference. In all four specifications, the coefficient estimates imply a statistically significant (at .01 level) negative effect of minimum wage increases on employment growth. We also considered shorter and longer time differences. For most specifications considered, the effects were statistically significant for both shorter and longer time differences.[6]

Time-differenced models were also estimated with LA county manufacturing excluded. These are shown in the lower panel of table 4 for a five-year time difference. The first three specifications all yield statistically significant negative minimum wage effects, though the fourth specification is statistically insignificant at the .10 level with a coefficient that is less than one-half of that found in the other three specifications.

Finally, to assure that the minimum wage effects estimated are not capturing some omitted factor, we examine whether leading and lagging values of the minimum explain employment. If leading values explain employment, one might be concerned that the model is capturing a spurious relationship between the minimum and employment levels. Alternatively, it might be that employers begin reducing low wage employment in anticipation of the minimum wage rising.

Table 5 provides estimates of the same models used in table 3, but adds a one year lead and lag of lmin* low_wage to the model. In the model including all CIPs, the lagged value of the minimum wage has a statistically significant negative effect for all four specifications, the contemporaneous minimum wage is never statistically significant, and the leading value is never

[6] The one exception was the fourth specification where the results were statistically significant only for time differences of 5 years or more.

statistically significant at the .05 level.[7] When the LA county manufacturing CIP is excluded, the lagged minimum is significant at .05 level in all four models. The leading and contemporaneous effects of the minimum are small and never significant at the .05 level.

In review, we have considered numerous regression models to estimate the effect of minimum wage increases on employment. We find some evidence that the negative effects of the minimum wage are much larger with the inclusion of the LA county manufacturing CIP. Nevertheless, after excluding this CIP, most specifications still yield statistically significant (but smaller) negative effects. The most sensitive specifications tend to be those with the most collinearity which leads to less identifying variation in the minimum wage variable. The results are fairly similar in magnitude whether we use employment levels or time-difference the data. We also find little evidence that leading values of the minimum wage explain changes in employment.

While we consider the results quite 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 industries. We turn to the size of these effects in the next section.

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 50% of the workers are paid within $1 of the minimum wage (in 1990 dollars), a 10% increase in the minimum causes a 5% decrease in employment. For the average CIP in our sample, the proportion of workers

[7] The leading value is statistically significant at the .10 level in one of the four specifications.

with low wages is .21. As a consequence, our estimated coefficient of -0.89 from our preferred specification (2) with LA county manufacturing excluded implies that a 10% increase in the minimum wage reduces employment in the average industry by 1.9%. This translates into a minimum wage elasticity of -0.19 for all workers. 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 others. Their analysis of the 2016 Seattle Washington minimum wage increase estimates a minimum wage elasticity of -0.23 to -0.28 for all workers. [8] Overall, our estimated elasticity of -0.19 for all workers 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.

Simulations of Employment Loss from a $15 Minimum Wage

California's minimum wage is scheduled to rise from $10.50 in 2017 to $11.00 in 2018, and then increase $1 per year until it reaches $15 in 2022. In this section, we use our earlier econometric estimates to simulate how many jobs would be lost as a result of this increase. To

[8] 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.

perform the simulation, we estimate the effect of switching to $15 in the 2016 labor market. Since wages will grow over time, we convert the 2022 minimum of $15 into 2016 dollars by assuming that prices will grow at 2.2% per year, which is consistent with the CBO forecast for 2016 to 2022.[9] We then use the second specification from table 3 that excluded the LA county manufacturing sector to simulate employment loss. This is accomplished by estimating the change in the log of employment that would occur if the minimum wage is increased from the 2016 value of $10.00 (except in San Francisco county where it was $12.25 until July 2016). We then convert the estimated change in log-employment into the change in the level of employment.

The results of this simulation are presented by industry in table 6. In total, we estimate that raising the minimum wage to $12.88 (the real equivalent of $15 in 2022) will result in a loss of 398,228 jobs in the CIPs included in our sample. This represents 4.1% of the employment in the included CIPs. As a percentage of employment, the estimated job loss is greatest in the two industries with the largest share of low-wage workers – agriculture, forestry and fishing; and accommodation and food services. In these industries, we project 10.7 and 9.5 percent of jobs will be eliminated as a result of a $15 minimum. The size of the predicted job loss is greatest in accommodation and food services (123,000) and retail trade (77,000). These two industries account for half of the predicted job loss in our sample of CIPs.

These simulations are based on what we consider to be the most robust and parsimonious regression model. As we noted, however, the empirical estimates are somewhat sensitive to the types of controls included and the starting point for the sample period. In all, we estimated 24 different specifications of the employment regression (4 different sets of controls x 3 different

---

[9] Congressional Budget Office, www.cbo.gov

starting years x 2 samples that either include or exclude LA county manufacturing). Averaging across these 24 different specifications results in a slightly larger job loss of 445,000.

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 have led to the 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 our ability to control 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 4.5% reduction in employment in an industry if one-half of its workers earn low-wages. We use these estimates to simulate the number of jobs that would be lost for the CIPs included in our sample if the minimum wage is increased to $15 in 2022. Our results suggest that approximately 400,000 jobs would be lost in the CIPs included in our sample. This represents about a 4.1% reduction in employment. Approximately one-half of the job loss occurs in accommodations and food services, and retail trade.

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.

References.

Autor, DH, and Dorn, D (2013) The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review* 103(5): 1553-1597.

Autor, DH, Dorn, D, and Hanson, GH (2013) The China Syndrome: local labor market effects of import competition in the United States. *American Economic Review* 103 (6): 2121-2168.

_______________ (2015) Untangling trade and technology: evidence from local labor markets. *The Economic Journal* 125 (584): 621–646.

Baily, MN, and Bosworth, BP (2014) U.S. manufacturing: understanding its past and its potential future. *The Journal of Economic Perspectives* 28(1): 3-25

Congressional Budget Office (2014) The effects of a minimum-wage increase on employment and family income. Congressional Budget Office, Washington DC.

Jardim, E, Long, MC, Plotnick, R, Inwegen, EV, Vigdor, J, and Wething, H (2017) Minimum wage increases, wages, and low-wage employment: evidence from Seattle." NBER Working Paper Number 23552, June 2017.

Pierce, JR, and Schott, PK (2016) The surprisingly swift decline of US manufacturing employment. *American Economic Review* 106 (7): 1632-62.

Meer, J, and West, J (2016) Effects of the minimum wage on employment dynamics. *Journal of Human Resources* 51(2): 500-522.

Neumark, D (2015) The effects of minimum wages on employment. *FRBSF Economic Letter* December 21, 2015.

_____________., Salas, JMI, and Wascher, W (2014) Revisiting the minimum wage-employment debate: throwing out the baby with the bathwater? *Industrial and Labor Relations Review* 67(3): 608-648.

_____________., and Wascher, W (2008) *Minimum wages*. Cambridge, MA: MIT Press.

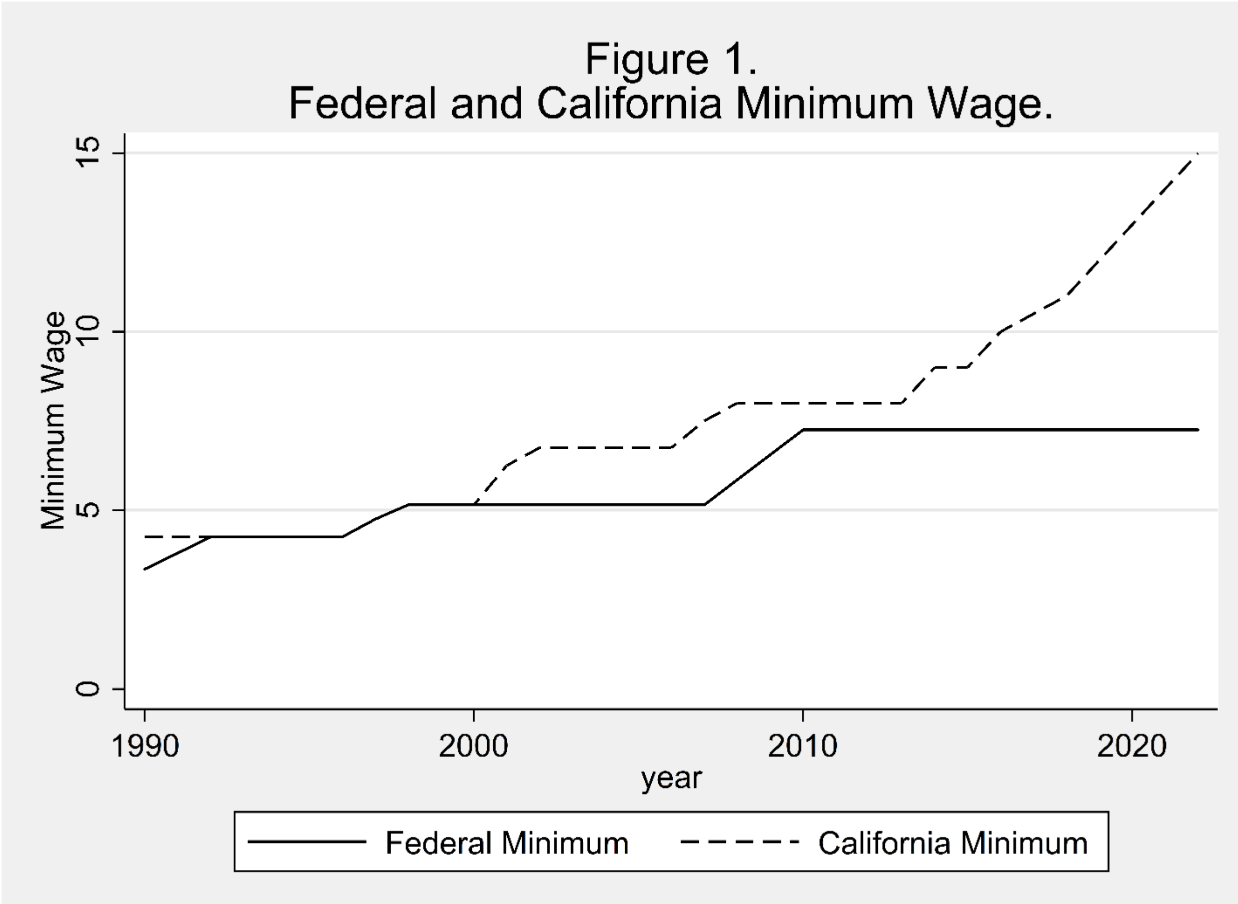
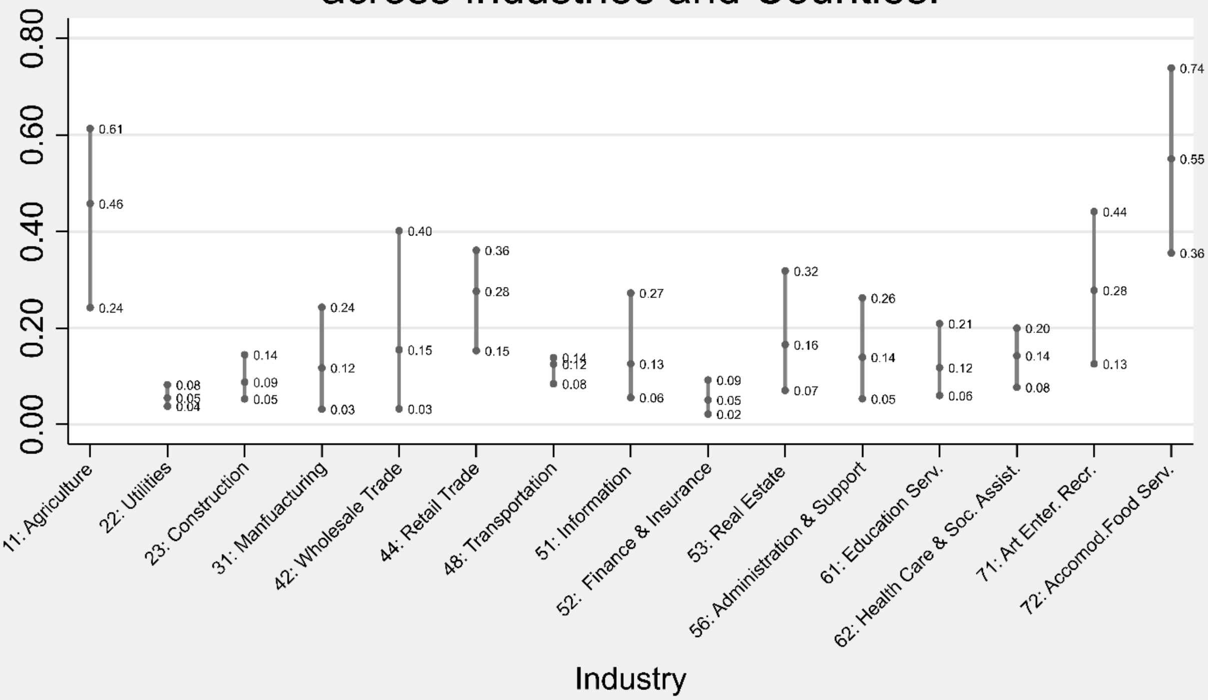


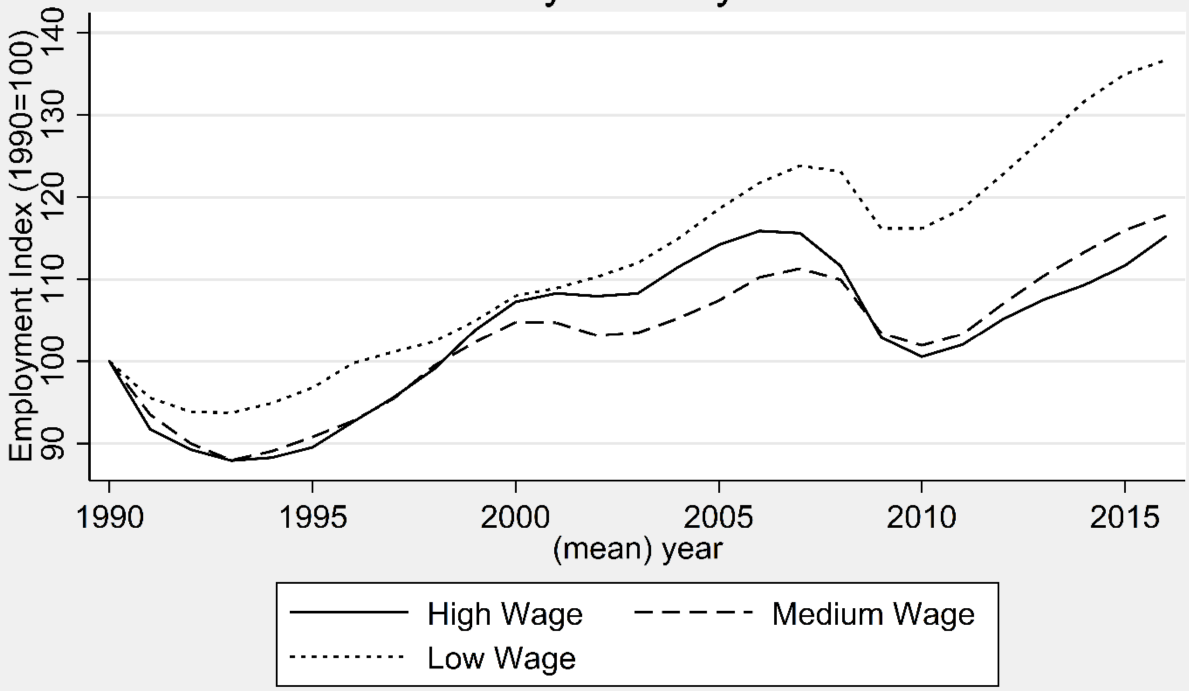
Figure 1.
Federal and California Minimum Wage.
Minimum Wage
0
5
10
15
1990
2000
2010
2020
year
Federal Minimum
California Minimum

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.

Figure 3: Employment in Low and High Wage County-Industry Pairs



The share of workers with low wages in low, medium and high wage CIPS are respectively >27%, 8-27%, and <8%. See text for details.

Table 1. Counties Included in Analysis.

County	County FIPS Code	2016 Employment Covered by Industries with complete data for 1990-2016	Total County Employment in 2016	Share of 2016 employment covered in data.
Butte	7	51,800	64,366	80.5%
El Dorado	17	21,196	42,494	49.9%
Fresno	19	233,795	303,441	77.0%
Kern	29	229,155	243,339	94.2%
Los Angeles	37	3,665,722	3,756,230	97.6%
Merced	47	32,320	57,991	55.7%
Monterey	53	126,861	154,346	82.2%
Orange	59	1,352,394	1,397,182	96.8%
Placer	61	89,314	136,349	65.5%
Riverside	65	461,702	559,878	82.5%
Sacramento	67	446,642	461,371	96.8%
San Bernardino	71	528,594	577,448	91.5%
San Diego	73	1,085,212	1,167,110	93.0%
San Francisco	75	518,639	600,645	86.3%
San Joaquin	77	160,204	194,765	82.3%
San Luis Obispo	79	82,302	93,057	88.4%
San Mateo	81	254,753	356,677	71.4%
Santa Barbara	83	151,470	161,737	93.7%
Solano	95	44,465	110,002	40.4%
Sonoma	97	151,004	173,130	87.2%
Stanislaus	99	113,895	152,909	74.5%
Tulare	107	65,967	127,898	51.6%
Ventura	111	255,966	275,707	92.8%
Yolo	113	42,136	67,438	62.5%
All Included Counties		10,165,508	11,235,510	90.5%
California			14,126,759	72.0%

Table 2. Industries Covered in Analysis.[1]

Industry	NAICS Code	Number of Counties	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	236,073	11.2%	57.76%	408,690
Utilities	22	4	14,662	0.4%	25.03%	58,578
Construction	23	9	382,413	5.5%	50.85%	752,044
Manufacturing	31-33	22	968,080	8.4%	74.98%	1,291,140
Wholesale Trade	42	16	497,847	4.1%	69.82%	713,060
Retail Trade	44-45	24	1,342,088	13.1%	81.46%	1,647,523
Transportation and Warehousing	48-49	9	304,198	3.7%	61.25%	496,663
Information	51	10	279,017	1.9%	54.12%	515,558
Finance and Insurance	52	19	416,762	3.4%	77.48%	537,898
Real Estate and Rental and Leasing	53	20	219,649	1.8%	80.47%	272,963
Administrative and Support and Waste Management and Remediation Services	56	17	1,621,333	13.5%	71.48%	2,268,315
Educational Services	61	14	217,638	1.8%	70.83%	307,270
Health Care and Social Assistance	62	24	2,155,078	19.3%	80.97%	2,661,619
Arts, Entertainment, and Recreation	71	14	216,502	1.9%	73.90%	292,972
Accommodation and Food Services	72	23	1,294,168	11.8%	82.38%	1,571,030
Total			10,165,508		73.69%	13,795,321

[1.] 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 data.

Table 3. Estimates of Employment Effects of Minimum Wage Increase.[a]				
	All Observations			
	(1)	(2)	(3)	(4)
Log(minimum wage)* Low wage share[b]	-1.371***	-1.327***	-0.976***	-1.455***
	(0.315)	(0.345)	(0.177)	(0.549)
Observations	6,345	6,345	6,345	6,345
Number of county-industry groups	235	235	235	235
Within Group R^2	0.862	0.877	0.915	0.894
Overall Adjusted R^2	0.997	0.997	0.999	0.998
	Excluding Los Angeles Manufacturing			
	(1)	(2)	(3)	(4)
Log(minimum wage)* Low wage share[b]	-0.967***	-0.892***	-0.954***	-0.777
	(0.299)	(0.325)	(0.174)	(0.545)
Observations	6,318	6,318	6,318	6,318
Number of county-industry groups	234	234	234	234
Within Group R^2	0.799	0.825	0.913	0.862
Overall Adjusted R^2	0.997	0.997	0.999	0.998
Year Effects?	Yes	No	No	No
County-Specific Effects?	Yes	No	No	No
County-Specific Year Effects?	No	Yes	Yes	Yes
County-Industry Specific Time Tend?	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

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

		All Observations		
	(1)	(2)	(3)	(4)
Δ(lmin * low wage share)[b]	-1.344***	-1.231***	-1.142***	-0.995**
	(0.201)	(0.198)	(0.214)	(0.433)
Observations	4,935	4,935	4,935	4,935
Number of county/industry cells	234	234	234	234
Overall R^2	0.552	0.616	0.668	0.804
		Excluding Los Angeles Manufacturing		
Δ_r(lmin * low wage share)[b]	-1.250***	-1.113***	-1.170***	-0.424
	(0.208)	(0.201)	(0.208)	(0.419)
Observations	4,914	4,914	4,914	4,914
Number of county/industry cells	234	234	234	234
Overall R^2	0.487	0.563	0.619	0.773
Year Effects?	Yes	No	No	No
County-Specific Effects?	Yes	No	No	No
Industry-Specific Effects?	Yes	Yes	No	No
Industry-Specific Unemployment Rate Effects?	Yes	Yes	Yes	No
County-Specific Year Effects?	No	Yes	Yes	Yes
County-Industry Effects?	No	No	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 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 cell earning between $0.25 less than the minimum wage and less than or equal to $1 in $1990 above the minimum wage. The change operator represents a 5-year time difference.

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

	All Observations			
	(1)	(2)	(3)	(4)
Log(minimum wage)* Low wage share (t+1)	-0.765*	-0.478	-0.167	-0.725
	(0.404)	(0.439)	(0.227)	(0.581)
Log(minimum wage)* Low wage share(t) [b]	0.0776	0.0164	-0.160	0.671
	(0.254)	(0.278)	(0.108)	(0.485)
Log(minimum wage)* Low wage share (t-1)	-0.911***	-1.045***	-0.926***	-1.473***
	(0.294)	(0.303)	(0.218)	(0.522)
Observations	6,345	6,345	6,345	6,345
Number of county-industry groups	235	235	235	235
Within Group R^2	0.820	0.841	0.924	0.874
Overall Adjusted R^2	0.997	0.997	0.999	0.998
	Excluding Los Angeles Manufacturing			
	(1)	(2)	(3)	(4)
Log(minimum wage)* Low wage share (t+1)	-0.268	0.050	-0.121	0.001
	(0.405)	(0.428)	(0.216)	(0.484)
Log(minimum wage)* Low wage share(t) [b]	-0.212	-0.323	-0.201*	0.325
	(0.251)	(0.267)	(0.108)	(0.478)
Log(minimum wage)* Low wage share (t-1)	-0.630**	-0.716**	-0.890***	-1.155**
	(0.298)	(0.299)	(0.215)	(0.582)
Observations	6,318	6,318	6,318	6,318
Number of county-industry groups	234	234	234	234
Within Group R^2	0.805	0.828	0.917	0.862
Overall Adjusted R^2	0.997	0.997	0.999	0.998
Year Effects?	Yes	No	No	No
County-Specific Effects?	Yes	No	No	No
County-Specific Year Effects?	No	Yes	Yes	Yes
County-Industry Specific Time Tend?	No	No	Yes	No
Industry-Specific Year Effects?	No	No	No	Yes
Industry-Specific Time Trend?	Yes	Yes	No	No
Industry-Specific Unempl. Rate Effects?	Yes	Yes	Yes	No

[a] 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 cell earning between $0.25 less than the minimum wage and less than or equal to $1 in $1990 above the minimum wage.

Table 6. Changes in Employment by Industry. [a]

	NAICS Code	Levels Job loss from $15 minimum	Covered Employment in 2016	Percent Job loss from $15 minimum
Agriculture, Forestry, Fishing and Hunting	11	-25,290	236,073	-10.71%
Utilities	22	-149	14,662	-1.02%
Construction	23	-7,643	382,413	-2.00%
Manufacturing	31-33	-15,006	608,488	-2.47%
Wholesale Trade	42	-15,350	497,847	-3.08%
Retail Trade	44-45	-76,529	1,342,088	-5.70%
Transportation and Warehousing	48-49	-8,729	304,198	-2.87%
Information	51	-4,122	279,017	-1.48%
Finance and Insurance	52	-3,767	416,762	-0.90%
Real Estate and Rental and Leasing	53	-4,957	219,649	-2.26%
Administrative and Support and Waste Management and Remediation Services	56	-40,823	1,621,333	-2.52%
Educational Services	61	-4,036	217,638	-1.85%
Health Care and Social Assistance	62	-58,702	2,155,078	-2.72%
Arts, Entertainment, and Recreation	71	-10,275	216,502	-4.75%
Accommodation and Food Services	72	-122,850	1,294,168	-9.49%
Total		-398,228	9,805,916	-4.06%

[a] The simulated job loss assumes an increase in the minimum wage to $15.00 in 2022 dollars (or $12.88 in 2016 dollars). The employment levels simulations are based on the Table 3 model excluding Los Angeles manufacturing with county-specific year effects, industry-specific time trends, and industry-specific unemployment rate effects. The job loss projections are for the CIPs included in our sample.

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

Appendix Table A1. Federal and California State Minimum Wage

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]

	All Observations 1990-2016			
	(1)	(2)	(3)	(4)
Log(min wage)* Low wage share[b]	-1.371***	-1.327***	-0.976***	-1.455***
	(0.315)	(0.345)	(0.177)	(0.549)
Observations	6,345	6,345	6,345	6,345
Number of CIPS	235	235	235	235
Within Group R^2	0.862	0.877	0.915	0.894
	All Observations 1995-2016			
Log(minimum wage)* Low wage share[b]	-1.376***	-1.328***	-1.017***	-1.473**
	(0.263)	(0.292)	(0.174)	(0.570)
Observations	5,170	5,170	5,170	5,170
Number of CIPS	235	235	235	235
Within Group R^2	0.791	0.998	0.908	0.998
	All Observations 2000-2016			
Log(min wage)* Low wage share[b]	-1.073***	-0.929**	-0.0903	-1.588**
	(0.301)	(0.363)	(0.206)	(0.729)
Observations	3,995	3,995	3,995	3,995
Number of CIPS	235	235	235	235
Within Group R^2	0.756	0.998	0.898	0.999
Year Effects?	Yes	No	No	No
County-Specific Fixed Effects?	Yes	No	No	No
County-Specific Year Effects?	No	Yes	Yes	Yes
County-Industry Specific Time Tend?	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

Appendix Table A2 (continued). Estimates of Employment Effects of Minimum Wage Increase by Start Year.[a]				
	Excluding Los Angeles Manufacturing, 1990-2016			
	(1)	(2)	(3)	(4)
Log(min wage)* Low wage share[b]	-0.967***	-0.892***	-0.954***	-0.777
	(0.299)	(0.325)	(0.174)	(0.545)
Observations	6,318	6,318	6,318	6,318
Number of CIPs	234	234	234	234
Within Group R^2	0.799	0.825	0.913	0.862
	Excluding Los Angeles Manufacturing, 1995-2016			
Log(minimum wage)* Low wage share[b]	-1.091***	-1.012***	-1.003***	-0.860
	(0.259)	(0.277)	(0.174)	(0.583)
Observations	5,148	5,148	5,148	5,148
Number of CIPS	234	234	234	234
Within Group R^2	0.770	0.798	0.897	0.844
	Excluding Los Angeles Manufacturing, 2000-2016			
Log(minimum wage)* Low wage share[b]	-0.793***	-0.575*	-0.0792	-0.944
	(0.285)	(0.301)	(0.200)	(0.703)
Observations	3,978	3,978	3,978	3,978
Number of county-industry groups	234	234	234	234
Within Group R^2	0.729	0.760	0.886	0.810
Year Effects?	Yes	No	No	No
County-Specific Effects?	Yes	No	No	No
County-Specific Year Effects?	No	Yes	Yes	Yes
County-Industry Specific Time Tend?	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] 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 cell earning between $0.25 less than the minimum wage and less than or equal to $1 (in 1990 dollars) above the minimum wage.