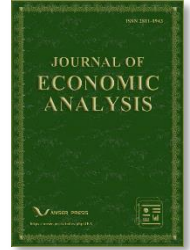




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Inflation's Reduction of the Real Minimum Wage and Unemployment in the USA: 1987 to 2021

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ABSTRACT

Hundreds of articles have been written that include empirical estimates of the dis-employment effects of minimum wages; however, many of these articles find statistically insignificant effects, some find significant negative effects, and a few find significant positive effects. Most of these studies use multivariate analyses which can be criticized for omitting key variables. The omitted variables problem ruins all statistics and estimates. This paper uses reiterative truncated projected least squares (RTPLS), a solution to the omitted variables problem, to estimate the percentage increase in unemployment due to a one percent increase in the real minimum wage using monthly data for the 50 states of the USA from 1987 to 2021. RTPLS produces a separate elasticity for every observation where differences in these estimates are due to omitted variables. We argue that RTPLS solves most of the econometric problems that David Neumark identified in his keynote address at a minimum wage conference in Berlin in 2018. We find that the percentage change in the unemployment rate due to a one percent change in the minimum wage ranges between 1.156 and 3.389, that the elasticities for different states tend to move together over time, and that all these elasticities are statistically significant at a 95 percent confidence level.

KEYWORDS

Real minimum wage; unemployment rate; omitted variable problem; reiterative truncated projected least squares; USA; inflation

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1. Introduction

Twenty three states and Washington DC increased their minimum wages sometime between October 2022 and the first week of January 2023. These increases are expected to affect 11.4 percent of US employees or 8.4 million workers. The most important factor behind these increases was inflation—all state legislatures are probably concerned about the impact of inflation on real minimum wages and 13 states automatically tie their minimum wages to the Consumer Price Index.

Supported by one of economics' most foundational models, supply and demand, economists tend to believe that minimum wages increase unemployment. However, when many economists have tried to empirically estimate the size of this effect, they have found no statistically significant relationship between unemployment and minimum wages. For example, one would expect that a higher minimum wage would increase unemployment more in a county that was contiguous to another county with a lower minimum wage. However, Dube, Lester, and Reich (2010) compared all contiguous county pairs in the United States that straddle a state border and found no adverse employment effects from minimum wages on the earnings and employment in restaurants and other low wage sectors – the very sectors in which one would expect the highest impact of minimum wages. Furthermore, their results are robust when allowing for long term effects of changes in minimum wage. Research finding no dis-employment effects from minimum wages could be used to justify positions taken by major influential international organizations. For example, a joint report from the IMF (international monetary fund), World Bank, OECD (organization for economic co-operation and development), and ILO (international labour organization) stated.

Combined with in-work benefits and measures to reduce the non-wage cost of low-paid jobs, a statutory minimum wage set at an appropriate level may raise labour force participation at the margin, without adversely affecting demand, thus having a net positive impact especially for workers weakly attached to the labour market. Maintaining the purchasing power of minimum wages at around 30 to 40 per cent of median wages sustains demand and reduces poverty and income inequalities (ILO, 2012, p. 12).

Note that the reasoning given by the IMF, World Bank, OECD, and ILO includes the idea that minimum wages may have a positive effect on employment by increasing aggregate demand. Indeed a few researchers have empirically found a positive relationship between employment and minimum wages (for example, Card and Krueger, 1994 and McHenry and Mellor, 2022).

However, other researchers have estimated negative employment effects from increased minimum wages (for examples, Neumark, Salas, and Wascher, 2014 and Paun, et al 2021). A survey of the massive literature on the dis-employment effects of minimum wage will not be attempted in this paper. Surveys and meta-studies of the minimum wage literature include Belman and Wolfson (2013), Neumark and Wascher (2008), and Schmitt (2013) for surveys and Chletsos and Giotis (2015), Doucouliagos and Stanley (2009), and Leonard, Stanley and Doucouliagos (2014) for meta-studies.

David Neumark (2018, pp. 1-2), in his keynote address for the "Evaluation of Minimum Wages" conference DIW Berlin July 4-5, 2018, said,

[T]he debate among researchers about whether minimum wages reduce employment, and if so by how much, remains intense and unsettled....My main goal in this paper is to delve into the econometrics and economics of past research on the effects of minimum wages on employment in the United States....[M]y intent is to try to identify key questions raised in the recent literature, and some in the earlier literature, that I think hold the most promise for understanding the conflicting evidence and arriving at a more definitive answer about the employment effects of minimum wages.

In this paper, we will argue that many of the issues that Neumark (2018) raises are grounded in the omitted variables problem of regression analysis. We will use Reiterative Truncated Projected Least Squares (RTPLS), a solution to the omitted variables problem, to estimate the dis-employment effects of minimum wages in the 50 states of the USA from 1987 through 2021 using monthly data. We find statistically significant but relatively small dis-employment effects. Specifically, we find that the percentage change in the unemployment rate due to a one percent change in the minimum wage ranges between 1.156 and 3.389 and that these elasticities vary more over time than they do between different states of the union. We also find that these elasticities fall during recessions. In addition to these estimates and the temporal patterns that they reveal, this paper adds to the minimum wage literature by arguing that (1) when other researchers use control areas, first differencing, and/or adding trend terms the underlying problem that their efforts are trying to address is often one due to omitted variables, (2) when estimating the effects of minimum wages, other researchers using control variables like a measure of the aggregate labor market and/or the percent of the population that are young eliminates from the resulting estimates part of the effect of minimum wages, and (3) when considering the effects of raising minimum wages, researchers need to address the relative needs of those who get the higher minimum wage versus the needs of those who lose their jobs (many of which are young people living with their parents). Finally, this paper adds to the literature a study that

examines the effect of minimum wages on total unemployment, in contrast to the current literature which tends to focus on the effects of minimum wages on the employment of the most vulnerable populations (e.g. teenagers and restaurant workers). We believe that RTPLS solves many, but not all, of the issues raised by Neumark (2018). One important issue not solved is how to forecast the effects of large increases in the minimum wage using analyses that have focused on relatively small changes.

2. Methods

If a researcher studying the relationship between raising the minimum wage and the unemployment rate did not consider the percent of the labor force currently employed at the minimum wage, then his results would not be reliable because the relationship between minimum wages and unemployment would surely be affected by the percent of the labor force at or near the current minimum wage. In this case, the researcher has an omitted variables problem that ruins all his or her statistics and estimates. However, if that same researcher did not include the average travel time (the “time cost” not the “monetary cost”) to places of work (and its variability) when estimating the relationship between minimum wages and unemployment, then his or her estimates are probably not ruined – average travel time (and its variability) probably does affect unemployment but does not affect the relationship between minimum wages and unemployment. In this case, average travel time to work would just add “random” variation to the dependent variable (unemployment) without affecting the estimates on how the included independent variable (minimum wage) affects the dependent variable (unemployment). However, for those earning at or near the current minimum wage, the “monetary cost” (in contrast to the “time cost”) of travelling to and from work would probably affect the relationship between minimum wages and unemployment, creating an omitted variables problem.

In other words, omitting variables from an estimation is a “problem” only if the omitted variables interact with the included independent variables. Thus, if a researcher estimates equation (1) while ignoring equation (2), the resulting estimate of β_1 (how minimum wages affect unemployment) is a constant when in truth β_1 varies with q_i (the percent of the labor force at or near the current minimum wage), and this ignoring of equation (2) creates an omitted variables problem. The α s and β s are coefficients to be estimated, Y is the dependent variable, X is the explanatory variable, u is random error, and “ q_t ” represents the combined influence of all omitted variables plus any random variation in β_1 itself.

$$Y_t = \alpha_0 + \beta_1 X_t + u \quad (1)$$

$$\beta_1 = \alpha_1 + \alpha_2 q_t \quad (2)$$

One convenient way to model the omitted variable problem is to combine equations (1) and (2) to produce equation (3).

$$Y_t = \alpha_0 + \alpha_1 X_t + \alpha_2 X_t q_t + u_t \quad (3)$$

Consider the following derivation.

$$\left(\frac{dY}{dX}\right)^{true} = \alpha_1 + \alpha_2 q_t \text{ Derivative of equation (3)} \quad (4)$$

$$\frac{Y_t}{X_t} = \frac{\alpha_0}{X_t} + \alpha_1 + \alpha_2 q_t + \frac{u_t}{X_t} \text{ Equation (3) divided by } X_t \quad (5)$$

$$\alpha_1 + \alpha_2 q_t = \frac{Y_t}{X_t} - \frac{\alpha_0}{X_t} - \frac{u_t}{X_t} \text{ Equation (5) rearranged} \quad (6)$$

$$\left(\frac{dY}{dX}\right)^{true} = \frac{Y_t}{X_t} - \frac{\alpha_0}{X_t} - \frac{u_t}{X_t} \text{ From Equations (4) and (6)} \quad (7)$$

Recall that u_t is random error which should be relatively small, and u_t/X_t even smaller if X is greater than one. Leightner, Inoue, and Lafaye de Micheaux (2021) show that eliminating u_t/X_t from equation (7) does not bias the results, and that elimination produces equation (8).

$$\frac{dY}{dX} = \frac{Y_t}{X_t} - \frac{\alpha_0}{X_t} \quad (8)$$

Reiterative Truncated Projected Least Squares (RTPLS) peels the data down layer by layer (like an onion) to produce slope estimates for every layer; each Y_t/X_t is then subtracted from the corresponding layer's slope to

produce a new dependent variable; and then a final regression is run between that new dependent variable and $1/X_t$ to find an α_0 which is then plugged into equation (8) along with Y_t and X_t to generate a separate slope estimate for every observation. The differences in these slope estimates are due to omitted variables. RTPLS produces estimates that include all the ways that the dependent and independent variable are correlated (i.e. it produces total derivatives) in contrast to partial derivatives (which hold all the other included independent variables constant). The mathematical equations underlying RTPLS are explained in Leightner (2015).

The best way to explain RTPLS is with a diagram like Figure 1. To construct Figure 1, one hundred values for a known independent variable (X) and one hundred values for an “omitted variable” (q) were randomly generated. Then a dependent variable (Y) was generated as equal to $500 + 10X + 0.8Xq$. In this example, the omitted variable (q) makes a 900 percent difference to the true slope: the true slope (dY/dX) is $10 + 0.8q$, thus when $q = 0$, the true slope is 10 and when $q = 100$, the true slope is 90. Figure 1 plots the values for Y versus the values for X and identifies each point with the value of the omitted variable (q). For this example, the values for q are known; however, imagine that a researcher does not know the values for q because q is immeasurable, q is the combined effect of hundreds of other variables for which the researcher cannot model with any certainty the interactions of, or because the researcher does not know what omitted variables affect the dependent variable. Even when q is unknown, unmeasurable, or its effects cannot be modelled, Figure 1 shows that the relative vertical position of each observation contains information about q . Specifically, the observations in the upper left part of Figure 1 correspond to the largest q s (98, 98, 99, 99, 95, and 95) and the observations in the lower right correspond to the lowest values for q (2, 1, 0, 1, 4, and 9). Note, that if $0.8Xq$ had been subtracted from $500 + 10X$ instead of added when calculating Y , then the smallest values for q would have been at the top of Figure 1 and the highest values for q at the bottom of Figure 1; either way, the relative vertical position of the observations contains information about the omitted variable, q . Another way to think about this vertical position of observations is to examine the values for q as one moves from the top of Figure 1 to the bottom for a given value of X . For example, when X is approximately 65, the corresponding values for q , reading from the top to the bottom, are 76, 66, 57, 50, 40, 23, 13, and 10 – the fact that these values are declining show that the relative vertical position of observations contains information about the impact of important variables omitted from the analysis.

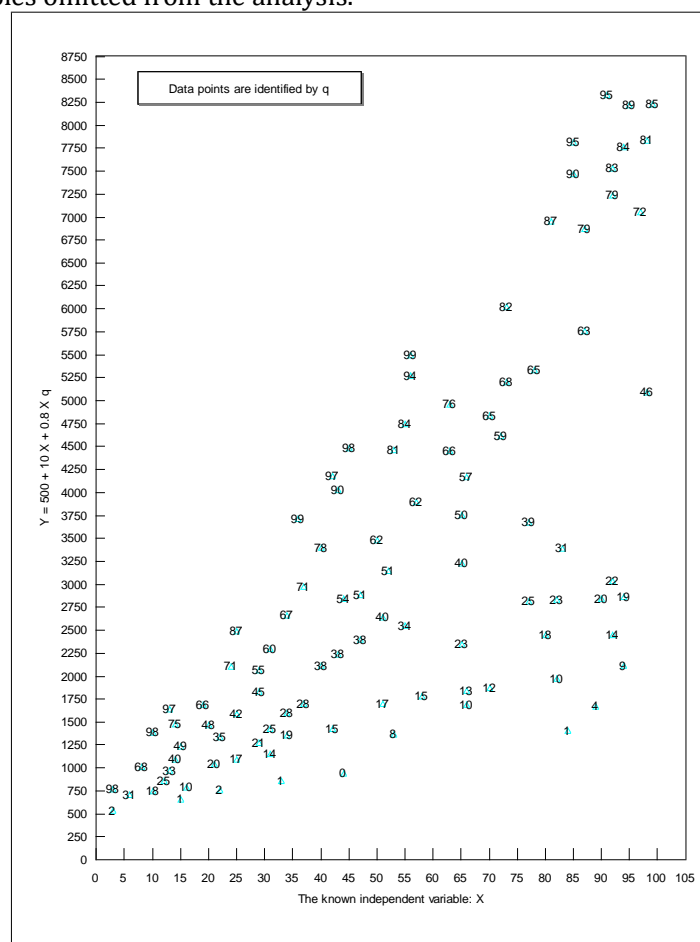


Figure 1. The Intuition underlying RTPLS.

RTPLS uses the relative vertical position of observations to capture the effect of omitted variables on estimated slopes. The RTPLS procedure starts by drawing a frontier around the upper left observations (the ones with the largest values for q in Figure 1). RTPLS then projects all other observations to that frontier and then runs an ordinary least squares (OLS) regression through the frontier observations and the observations projected to that frontier. The slope estimates generated by this OLS regression (called TPLS estimates) are then appended to the data for the frontier observations. Note that the first layer's slope is "identified" by being on the upper most frontier. The frontier observations are then deleted, and the procedure repeated, producing a slope estimate for the observations with the second highest values for q . Again the second layer's slope is "identified" by being on the upper most frontier after the first layer was deleted. This process is reiterated peeling the data down layer by layer until there are 10 or fewer observations remaining. Next RTPLS starts over with the original data and peels from the bottom to the top until there are only 10 observations remaining at the top. RTPLS then runs a final OLS regression where the dependent variable is the TPLS estimates from the peeling down and up process $(dY/dX)^{\wedge}$ minus Y/X and the independent variable is $1/X$ as per equation (9) which is a rearrangement of equation (8).

$$(dY/dX)^{\wedge} - Y_t/X_t = -\alpha_0/X_t \quad (9)$$

The resulting α_0 obtained from this final regression along with values for Y and X are plugged into equation 8 to produce an estimated slope value for each observation where differences in these slope estimates are due to omitted variables, q . The purpose of this final regression is to create more accurate estimates. If every observation on every frontier in the peeling down and up process corresponded to exactly the same value for q (for example, 99, 99, 99, and 99 for the first iteration and 95, 95, 95, and 95 for the second iteration, etc.), then the TPLS estimates would be 100 percent accurate. This final regression eliminates most of the inaccuracy added to the TPLS estimates by the q values along a given frontier not being identical.

Someone might ask, "What happens if the government increases spending, reducing unemployment, at the same time as the government increases the minimum wage?" In this case government spending is an omitted variable (one of many) that would tend to move an observation closer to the frontier of the data—the frontier that shows the observations that had the highest minimum wages combined with the lowest unemployment.

If instead of using RTPLS, OLS is used to estimate the relationship between Y and X for the data underlying Figure 1 and q was omitted, OLS produces the following estimate: $Y = 284.8 + 54.28X$ with the standard error of X being 5.319 and the R^2 being 0.515. Since the estimated coefficient for X is highly significant and 51.5 percent of the variation in Y is explained, this regression looks successful, but it is not. Remember the correct equation is $500 + 10X + 0.8Xq$. The OLS regression did the best it could given its assumption of a constant dY/dX ; indeed OLS produced an estimated dY/dX in the ballpark of $10 + 0.8E[q]$ where $E[q]$ is the expected (or mean) value for q . For Figure 1, $E[q]$ is 48.59 and $10 + 0.8E[q]$ is 48.87 which is in the ballpark of the estimated 54.28.

Leightner, Inoue, and Lafaye de Micheaux (2021) ran 5000 simulations each for the 27 combinations of the omitted variable making a 10 percent, 100 percent, and 1000 percent difference to the true slope, with random error being 0 percent, 1 percent, and 10 percent of the standard deviation of X , and with sample sizes of $n=100$, 250, and 500. Leightner, Inoue, and Lafaye de Micheaux found that RTPLS noticeably outperformed assuming that there are no omitted variables and using OLS except when random error effected the equation as much as the omitted variables affect it. This exception makes sense since RTPLS uses the relative vertical position of observations to capture the effects of omitted variables and relatively large amounts of random error would make it impossible to distinguish between the influence of omitted variables and randomness.

Specifically, Leightner, Inoue, and Lafaye de Micheaux found that when the effect of the omitted variables was ten times bigger than random error, using OLS while assuming there are no omitted variables produced approximately 3.8 times the error produced by RTPLS. Furthermore, when the effect of the omitted variables was one hundred times the size of random error, using OLS while ignoring omitted variables produced more than 27 times the error from using RTPLS. In the most extreme case examined (omitted variables made 1000 percent difference to the true slope, zero random error, and $n = 100$) using OLS while ignoring the omitted variables problem produced 2138 times the error produced by RTPLS.

RTPLS finds total derivatives that show all the ways that the dependent and independent variables are related. Confidence intervals for RTPLS estimates can be calculated using the central limit theorem.

$$\text{Confidence interval} = \text{mean} + \left(\frac{s}{\sqrt{n}} \right) t_{n-1, \alpha/2} \quad (10)$$

In equation (10), " s " is the standard deviation, " n " is the number of observations, and $t_{n-1, \alpha/2}$ is taken off the standard t table for the desired level of confidence. Leightner, Inoue, and Lafaye de Micheaux (2019) used an estimate along with the 4 estimates before it and a 95% confidence level to create a moving confidence interval

(much like a moving average) for a given set of RTPLS estimates. This 95% confidence interval can be interpreted as meaning that there is only a five percent chance that the next RTPLS estimate will lie outside of this range if omitted variables maintain the same amount of variability that they recently have.

Published applications of RTPLS can be found in *Journal of Risk and Financial Management*, *Biomedical Journal of Scientific & Technical Research*, *International Journal of Contemporary Mathematical Sciences*, *Economics Bulletin*, *European Journal of Operations Research*, *Journal of Central Banking Theory and Practice*, *International Journal of Financial Research*, *Economies*, *China Economic Policy Review*, *Applied Economic Letters*, *Frontiers of Economics in China*, *China & World Economy*, *Pacific Economic Review*, *The Japanese Economy: Translations and Studies*, *Journal of Productivity Analysis*, *Economy*, *International Economics & Finance Journal*, *Advances in Decision Sciences*, *International Journal of Economic Issues*, *Global Economy Journal*, *Journal of Financial Economic Policy*, and *Contemporary Social Science*.

David Neumark (2018) in his keynote address for the “Evaluation of Minimum Wages” conference in Berlin, July 4-5, 2018 focused his remarks on two issues: (1) the proper specification of control areas and (2) the inclusion of trends. In the context of minimum wages, an ideal “control area” or “counterfactual” would be identical to the area with a higher minimum wage with only one difference – the minimum wage. Under these ideal conditions, any variable omitted from the analysis of the area with the higher minimum wage would also be omitted from the analysis of the counterfactual making any difference in the results due to the one difference in the areas – the minimum wage. In reality, it is impossible to achieve this ideal for the analysis of minimum wages. However, if we had a perfectly specified model that included all the ways that minimum wages are correlated with unemployment, correctly modeled, then there would be no need for a counterfactual. The purpose of using a counterfactual is to address the omitted variables problem.

The second issue professor Neumark (2018) addresses is the inclusion of trends in minimum wage analyses. Neumark (2018, p.19) says, “the appeal to including trends is typically based on the hypothesized influence of omitted variables that underlie these trends.” First differencing the data and/or adding a trend term are common ways of handling autocorrelation. Autocorrelation occurs when the errors from an estimation (the vertical distance from the best fit line and the actual observations) is related to time. Econometricians tend to test for autocorrelation and then apply methods to solve it (often adding a trend, and/or first differencing the data). However, an important question (usually not asked) is “why is there autocorrelation?” Autocorrelation can be caused by omitting some important variable that changes over time.

Furthermore, when a researcher first differences the data and/or adds a trend term, he or she maybe eliminating a major part of the relationship he or she is attempting to estimate. Consider real minimum wages (minimum wages corrected for inflation). Inflation reduces real minimum wages, and first differencing the data or adding a trend term eliminates part of the influence of inflation on real minimum wages, destroying part of what the researcher is trying to estimate. Figure 2 depicts the real federal minimum wage from 1987 to 2021 for the four regions of the USA analyzed in this paper using December 2021 as the base year. In January 1987, this federal minimum wage was binding in all but three states (three states had higher state imposed minimum wages); by December 2021 this federal minimum wage was binding in only 20 states (30 states had higher state imposed minimum wages).

However, Figure 2 clearly shows that first differencing the data would eliminate much of the influence of inflation on real minimum wages, cutting from the analysis a lot of useful information. Adding a trend term that restarted every time the federal minimum wage was increased would eliminate a similar amount of information. Thus, the need for a “counterfactual” group for comparison purposes and the use of either first differencing the data and/or adding a trend term could be due to omitted variables. However, our problems with the unemployment effects of minimum wage literature does not end with just “omitted variables.” We think this literature also has a “mis-specified included variables” problem. Neumark (2018, pp. 19-20) says, “most employment equation specifications in the minimum wage literature use quite measured parsimonious controls, often including only an aggregate labor market indicator and a relative supply variable (like the share of the young population in the total population).” However, *ceteris paribus*, as the aggregate labor market increases, the unemployment effects of a binding minimum wage should also increase. In other words, part of the effect on unemployment of an increase in minimum wages is probably due the labor supply increasing (while labor demand decreases) resulting in the estimated coefficient for the aggregate labor market variable capturing part of the effect of rising minimum wages on unemployment (one paper that estimates how the minimum wage increases labor supply is Martin, 2021). Likewise, control variables like “the share of the young in the total population” could be strongly correlated with increased unemployment from increased minimum wages because the wage rates paid to the young tend to be closer to the minimum wage than the wage rates paid to their elders. Of course, if the model is correctly specified where the relationship between these control variables and minimum wages are correctly modelled, then using

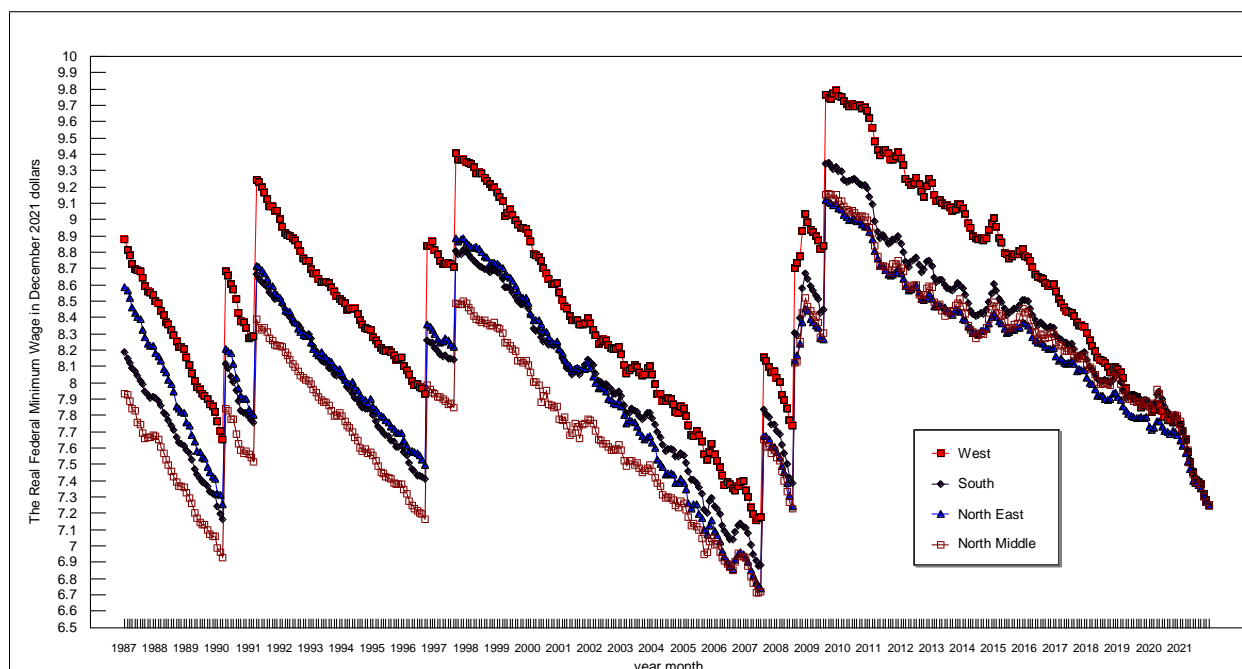


Figure 2. The Real Federal Minimum Wage over time, December 2021 as base.

these control variables is not a problem. However, the minimum wage literature usually does not model the potential interaction between these control variables and the minimum wage.

What is needed is a statistical technique that solves the omitted variables problem and that produces total derivatives that capture all the ways that unemployment and minimum wages are correlated—what is needed is RTPLS.

3. The Data and Results

Monthly unemployment data for each state of the USA was retrieved from the FRED economic database which was sourced from the U.S. Bureau of Labor Statistics. Monthly minimum wage data for each state was retrieved from the U.S. Department of Labor, Wage and Hour Division. For all observations, whichever minimum wage was higher – federal or state – that minimum wage was used because it would be the binding one. The federal minimum wage came from <https://dol.gov/agencies/whd/minimum-wage/history>. When states had minimum wages rates that only applied to women and minors, the federal minimum wage was used. When states had minimum wage rates that applied to only employers with two (or four, or six) or more employees then the state minimum wage was used if it was higher than the federal minimum wage. For the years 1988 to 1990, Minnesota had a two-tier schedule with the higher rate applicable to employers covered by the FLSA and the lower rate to employers not covered by the FLSA; for those years the higher rate was used. The Federal Minimum Wage was used when a state's minimum wage did not apply to a majority of the state's employers or employees. Any minimum wage rate changes that were enacted not on the 1st of the month were calculated as $((\text{Previous Minimum Wage} \times \text{Number of Days In Effect Since the 1st}) + (\text{New Minimum Wage} \times \text{Number of Days Till End of Month}) / \text{Total Days in Month})$. This new numerical value was included as that month's minimum wage.

Unfortunately, we could not find monthly consumer price index (CPI) data for each state. We were forced to use monthly CPI data by region. We used the CPI data that was not seasonally adjusted which came from the U.S. Bureau of Labor Statistics database.

Estimates for $d(\text{unemployment rate})/d(\text{real minimum wage})$ were generated by Reiterative Truncated Projected Least Squares (RTPLS) which were then multiplied by $(\text{real minimum wage}/\text{unemployment rate})$ to calculate an elasticity – the percentage change in the unemployment rate due to a one percent change in the real minimum wage $[\%d(\text{unemployment rate})/\%d(\text{real minimum wages})]$. Remember RTPLS produces a separate slope estimate for every observation where differences in these slope estimates are due to omitted variables. How the estimated $\%d(\text{unemployment rate})/\%d(\text{real minimum wages})$ elasticities changed over time are depicted in Figures 3 through 6. All of the $\%d(\text{unemployment rate})/\%d(\text{real minimum wage})$ elasticities were statistically significant (see equation 10) at a 95 percent confidence level. The analysis was conducted 4 times – once for each region of the USA because the CPI data was different for each region (also Even and Macpherson (2019) found that

different regions of California having different employment characteristics led to different effects of minimum wages, and these regions of the US also have different employment characteristics). The unemployment rate, instead of the employment rate, was used because using the unemployment rate fits with the most important issue – how minimum wages affect unemployment, the most important issue is not how minimum wages affect employment.

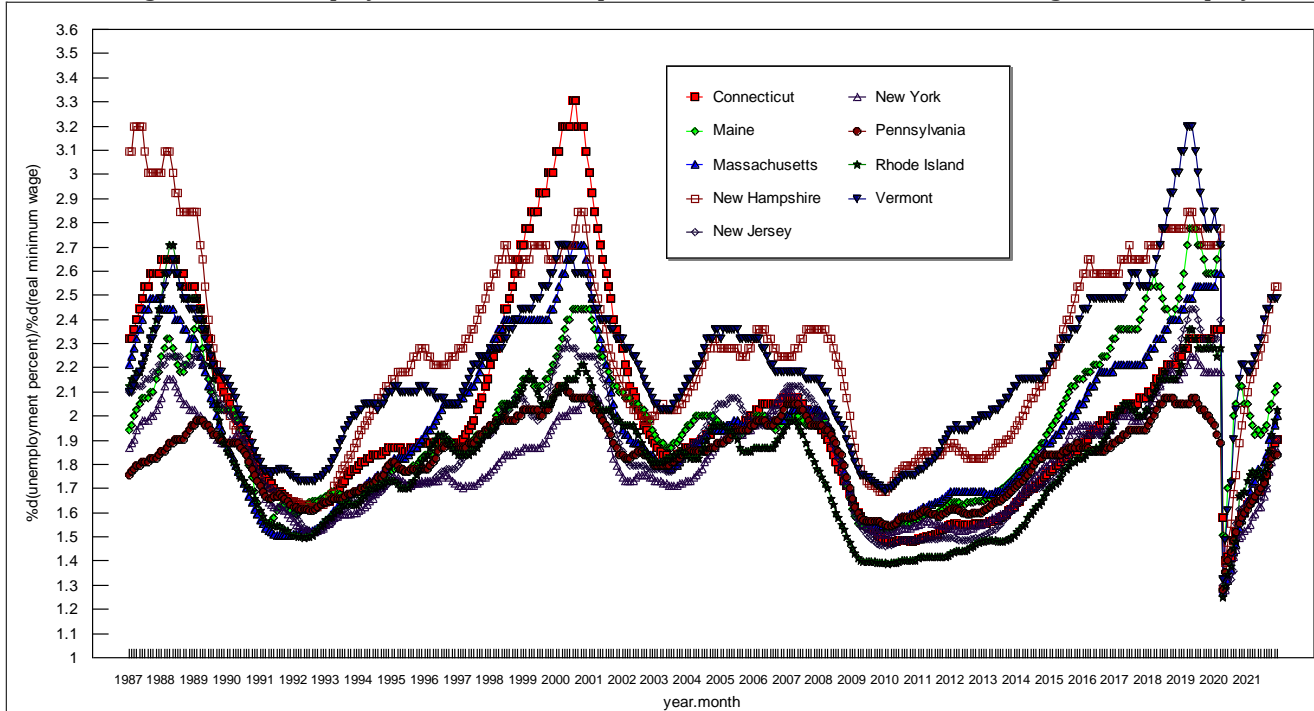


Figure 3. Empirical Estimates for Northeastern States.

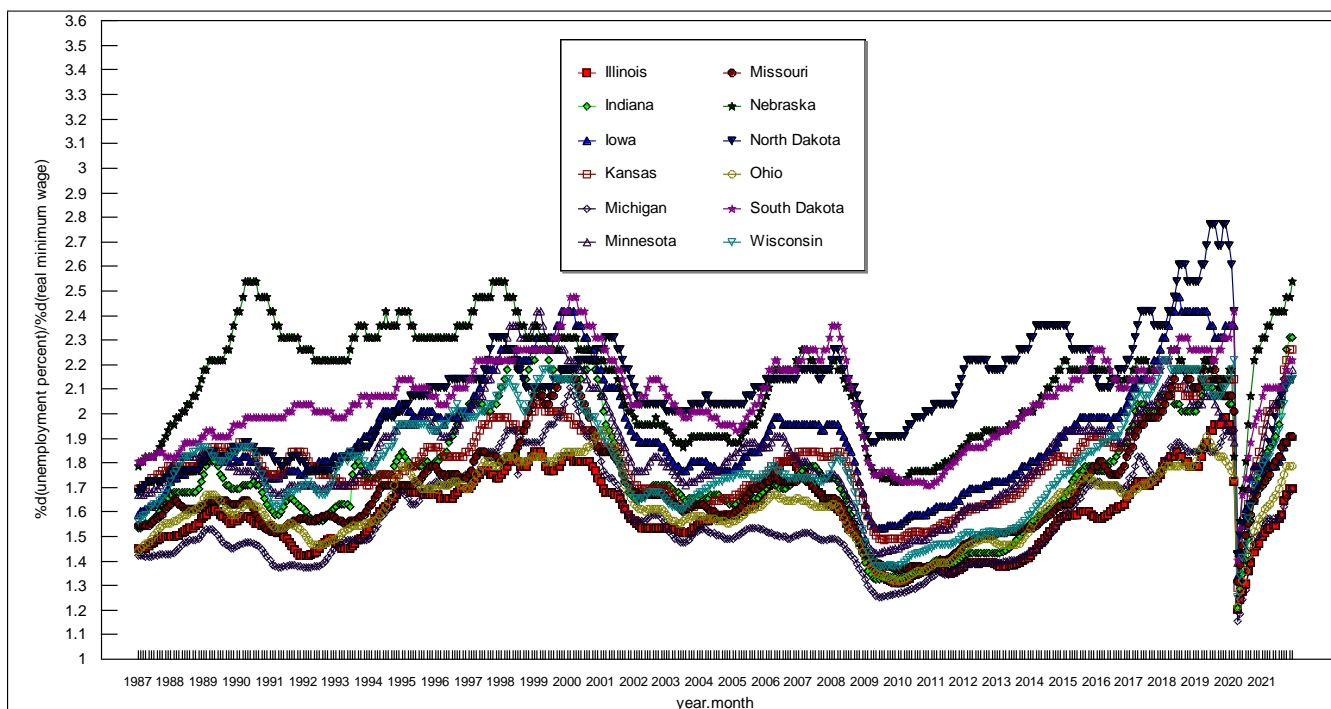


Figure 4. Empirical Estimates in Northern Middle States.

The estimated elasticities ranged from 1.1559 for Michigan in April 2020 to 3.3891 for Hawaii in October 2017. These numbers imply that if Michigan's real minimum wage (with December 2021 as the base year) had increased ten percent from \$10.59 to \$11.65 in April 2020 then Michigan's unemployment rate would have increased from 22.7 percent to 25.3 percent (22.7 times 1.11559). Alternatively, if Michigan's real minimum wage had fallen ten

percent due to inflation from \$10.59 to \$9.53 in April 2020 then Michigan's unemployment rate would have fallen from 22.7 percent to 20.1 percent. Likewise, if Hawaii's real minimum wage (with December 2021 as the base year) had increased ten percent from \$10.65 to \$11.72 in October 2017 then Hawaii's unemployment rate would have increased from 1.9 percent to 2.5 percent (1.9 times 1.33891). Alternatively, if Hawaii's real minimum wage had fallen ten percent due to inflation from \$10.65 to \$9.59 in October 2017 then Hawaii's unemployment rate would have fallen from 1.9 percent to 1.3 percent. These numerical examples represent the extremes (Michigan in April 2020 had the smallest elasticity and Hawaii in October 2017 had the largest).

There are several interesting features common to Figures 3 through 6. First, except for the North, middle states (Figure 4) the $\%d(\text{unemployment rate})/\%d(\text{real minimum wages})$ estimates vary more over time than between states even when comparing across regions that had different inflation rates. Second, the US has suffered four recessions during the time period of this analysis: July 1990 to March 1991, March 2001 to November 2001, December 2007 to June 2009, and February 2020 to April 2020. A close look at Figures 3 through 6 reveals that the $\%d(\text{unemployment rate})/\%d(\text{real minimum wages})$ estimates fell during all of these recessions. Leightner (2022) argues that RTPLS can be used to improve macroeconomic modelling. Likewise, RTPLS can be used to improve the econometrics used in estimating the effects of the minimum wage on unemployment. The relationship between recessions and $\%d(\text{unemployment rate})/\%d(\text{real minimum wages})$ leads us to recommend that instead of adding trend terms when estimating the effects of minimum wages on unemployment, researchers should add another control variable that captures the strength of the US economy.

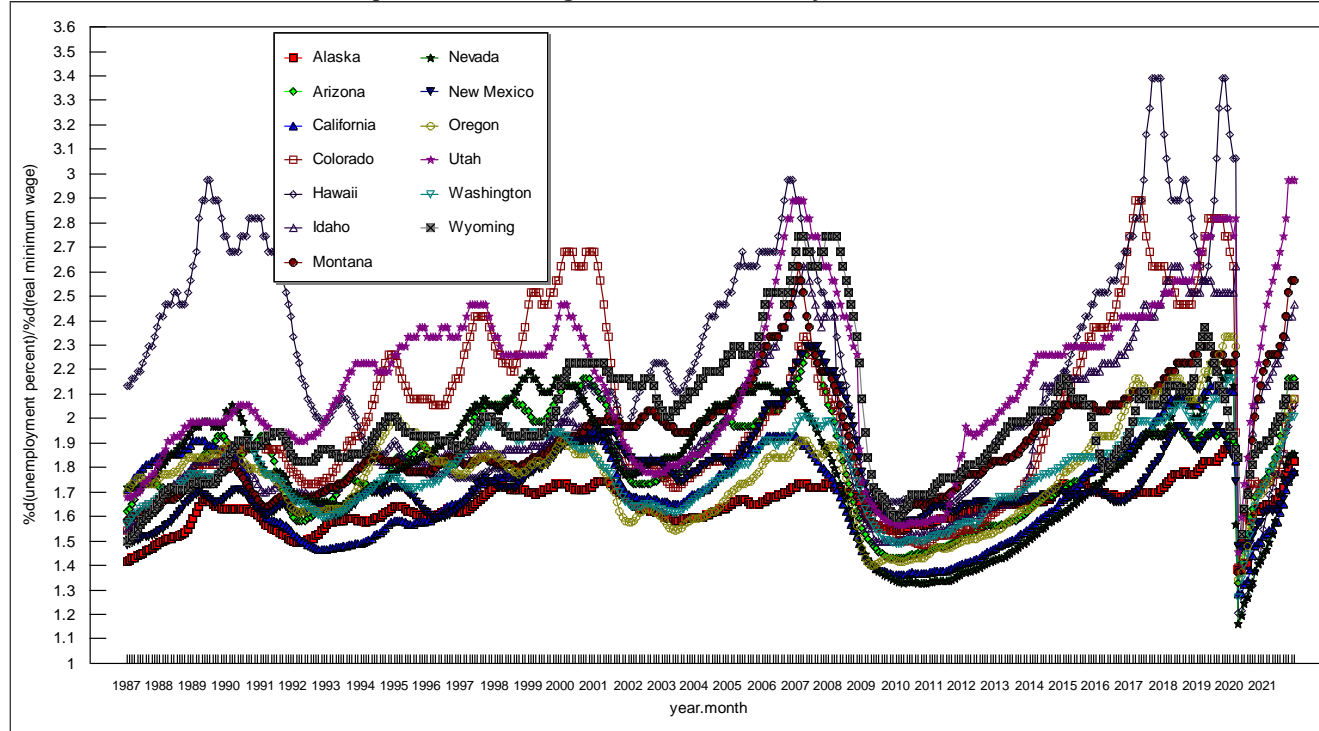


Figure 5. Empirical Estimates for Western States.

As the federal minimum wage was increased three times between July 24, 2007 and July 24, 2009, for a total nominal change of 40.8 percent from \$5.15 to \$7.25, $\%d(\text{unemployment rate})/\%d(\text{real minimum wages})$ elasticities fell for all 50 states (see figures 3 through 6). This decline in elasticities even occurred in the twelve states that by July 24, 2009 still had state mandated minimum wages that exceeded the federal minimum wage – California, Colorado, Connecticut, Illinois, Massachusetts, Michigan, New Mexico, Ohio, Oregon, Rhode Island, Vermont, and Washington. An increase of the binding minimum wage in 38 states (especially increases of 40.8 percent for some of them) would likely cause inflation across the USA. Note, Harasztosi and Lindner (2019) find that in Hungary 75 percent of minimum wages are passed to customers and 25 percent is absorbed by firm owners. Since inflation reduces the real minimum wage, inflation acts as a dampening force on the relationship between real minimum wages and unemployment, which is one possible explanation for the August 2007 through July 2009 fall in $\%d(\text{unemployment rate})/\%d(\text{real minimum wages})$ in all fifty states. For a survey of the literature on the effect of minimum wages on prices see Lemos (2008).

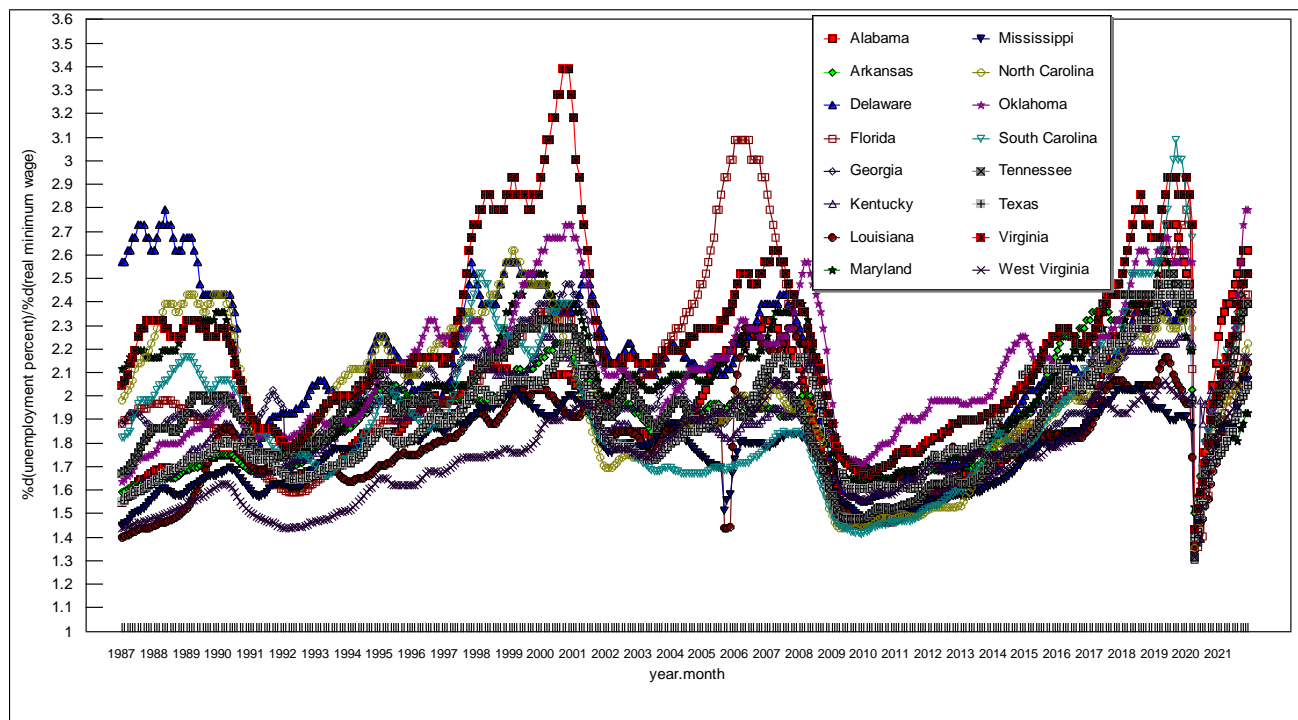


Figure 6. Empirical estimates for southern states.

4. Discussion and conclusion

The massive literature on the unemployment effects of minimum wages primarily uses multivariate analysis which produces partial derivatives (the effect of minimum wages holding all other included variables constant). In this paper, we use reiterative truncated projected least squares (RTPLS) to calculate total derivatives that show all the ways that minimum wages and unemployment are correlated. Multivariate analysis produces one slope or elasticity that is supposed to hold for all observations. RTPLS produces a separate slope or elasticity estimate for every observation where differences in these estimates are due to omitted variables. Thus, RTPLS makes it possible to see how the estimated relationship is changing over time. In this paper, we found extremely strong temporal patterns in the elasticity estimates which are surprisingly consistent over all fifty US states. Many multivariate studies of the employment effects of minimum wages find no statistical relationship between minimum wages and unemployment. All the estimates found in this paper were statistically significant at a 95 percent confidence level. Most of the multivariate analyses of the minimum wage focus on “the most vulnerable employees” – teenagers and restaurant workers. In this paper, we examine the total unemployment rate. Many multivariate studies add a trend term and/or first difference the data. This paper argues that adding a trend term and/or first differencing the data may eliminate much of the influence of inflation, reducing the information content of the data. Inflation reduces the real minimum wage which affects unemployment. We understand that first differencing and/or adding a trend term is often done to correct for autocorrelation; however, a better approach is to find omitted variables that should be included which are related to time which, when included, cause tests of autocorrelation to be negative.

The massive literature on the minimum wage clearly shows that raising minimum wages increases the income of those who keep their minimum wage jobs. When a statistically significant positive relationship is found between minimum wages and unemployment, this literature presents its results as a tradeoff – some workers gain by being paid more while other workers lose their jobs. What is not sufficiently emphasized in this literature is that many of those who lose their jobs—teenagers, for example—may have lower needs than those who are paid more. Many working teenagers live at home with their parents and spend much of their earnings on playing, not on the necessities of life. Indeed, a recent Pew Research Center study showed that the percent of US 18 to 29 year olds living with their parents jumped from 47 percent to 52 percent between February and May 2020. However, Wagner (2021) argues that this jump was due to the pandemic causing some young adults to return home when they got sick, some when their colleges shutdown, and some when they lost their jobs. No matter what the cause, teenagers and young adults living with their parents have less need than those living on their own. The literature dealing with those hurt by the minimum wage versus those helped needs to consider potential differences between the needs of those hurt and those helped.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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