ECON 483 - Econometric Applications
Eunyoung Ashby, Ellen Chang, Jacob Kovacs, Emily Shettel
4/22/2014

Effects of minimum wages on employment

Introduction

As it is taught in introductory classes, economic theory seems to give a clear answer to the question: will raising the minimum wage increase unemployment? So long as the minimum wage price floor is set above market equilibrium, the basic model depicts the supply of labor exceeding demand, with the least employable (and presumably, neediest) workers suffering the unintended consequences. Evidently this answer has never quite persuaded many members of the American public, since a minimum wage policy has been enforced by the federal government since 1938 and 22 states currently set their minimum wage in excess of the federal standard (U.S. DOL, n.d.; U.S. DOL, 2014). Recent intensification of political action around the minimum wage (Fox, 2013; Valdes, 2014; 15 Now, n.d.) signals there is fresh interest in minimum wage policy as a tool to address poverty and inequality.

Moreover, the textbook answer is not a product of consensus among economists. Minimum wage is one of the most heavily researched topics in the discipline (Schmitt, 2013), but these efforts have so far yielded mixed and much-contested conclusions. Beyond the basic supply and demand model that unambiguously predicts disemployment effects from a binding market floor, a monopsony labor market model such as Card and Kreuger's (1995) allows the possibility for positive effects on employment. Detailed by Partridge and Partridge (1998), the complicated ways in which workers and employers may respond to a minimum wage make modelling inherently difficult. These complications include migration of workers across sectors, since minimum wages generally make exceptions for certain sectors and occupations; the exit of discouraged workers from the ranks of the officially unemployed; the substitution of skilled for unskilled or adult for teenaged workers; and reduction of hours or benefits rather than outright elimination of jobs.

Eras of minimum wage research

Rising to the challenge presented by labor market complexities, minimum wage (MW) research has evolved over the years to make use of increasingly sophisticated econometric techniques. Schmitt (2013) provides a helpful summary of four generations of research efforts, foregrounding key papers from each era. As he reports, consensus of the earliest time series-based research is captured by the Minimum Wage Study Commission's 1977 review, which suggested the negative effect of raising the MW is small and borne mainly by teenagers. A second era of MW researchers introduced new empirical methods and consequent new findings. Famously, Card and Kreuger's use of natural experiments (1994, 2000) and Card's cross-state comparisons (1992) found no negative effects on employment following an increase in MW. In response, several economists including Neumark and Wascher (2000, 2007) launched a third era of research with renewed roots in time series analysis. The debate has now entered its fourth generation with a heritage of contradictory empirical findings and various choice of methods.

Represented by Hirsch, Kaufman, and Zelenska (2011), this latest generation has taken small but encouraging steps toward integrating the debate—in particular, considering the possibility that prior contradictory findings reflect different possible outcomes that arise from the interplay of multiple adjustment mechanisms. This research identifies some adjustment channels as relatively significant and worth more attention, namely changes in workforce turnover, improved efficiency, decreased pay for above-MW earners, and price increases. These channels may absorb some or all of the disemployment tendencies of a higher MW. But precisely because there are so many adjustment mechanisms at work, Schmitt suggests, the net effect of changes in MW policies may remain essentially unpredictable.

Survey of study specifications

Despite the generational progression of MW research outlined above, appropriate methods for investigating MW effects are still a point of lively debate. The spatiality of labor markets and regional clustering of MW policies lead some researchers to assert that panel data is inadequate to identify actual MW effects. These researchers favor case studies and more spatially-precise econometric techniques (e.g. Allegretto, Dube, and Reich, 2011; Dube, Lester, and Reich, 2010; Card, 1992; Card and Kreuger, 1994; Kalenkoski and Lacombe, 2011; Stewart, 2002; Williams, 1993). In this respect, the literature on MW is a microcosm of a larger debate in econometrics, sparked by Leamer (1983) and described by Stafford (1986) and Angrist and Pischke (2010) in their summary of the "credibility revolution" in econometrics. This credibility revolution relies on quasi-experimental research design and has directly influenced at least one prominent researcher who favors the case study approach for investigating MW effects (Dube, 2014). The debate over methods is far from trivial, since panel data-based studies commonly find negative effects from MW increases while other approaches mostly find no or positive effects (Dube, 2011; Schmitt, 2013).

Table 1 summarizes and compares a few specifications used in the literature, all representing a panel data approach. In addition, Allegretto et al. (2013) describe five alternative specifications that improve on the "canonical two-way fixed effects model"[1] by better accounting for spatial heterogeneity. Their recommended models rely on dummy variables deployed—with equally satisfactory results—at either a cross-county, within-commuting-zone, or within-region scale. They further endorse the use of state and year fixed effects, lagged dependent variables, synthetic controls, and different values for the autoregressive coefficient.

Study specifications

The methods and designs recommended by Allegretto et al. (2013) were not feasible for the constraints of our study, which relies on more readily available panel data. We tried to incorporate their criticisms of panel data by making the following adjustments: (1) We conducted our analysis at multiple scales, to permit comparison of how this changed our results; (2) We added regional controls alongside state and year fixed effects, where applicable. Our analysis used the following specifications—model 1 for state-level analysis, model 2 for regional analysis, and model 3 for national analysis:

$$\text{(1)} \qquad \mathbf{U_{ti} = \beta_1 + \beta_2 MW_{ti} + \beta_3 CP_{ti} + \beta_4 RX_{ti} + \beta_5 I_{ti} + \beta_6 R_{ti} + \beta_7 GDP_{ti} + \beta_8 BC_t + \sigma_i + \tau_t + u_{ti}}$$

In this state-level model, t and i are indices for time and state, respectively; U is the natural log of the unemployment rate; MW is the natural log of state i's effective minimum real wage (max of state or federal) at time t; CP (natural log of civilian population), RX (natural log of real exports of goods and services), and I (natural log of inflation) are control variables for the unemployment rate; R is a dummy, controlling for region-specific trends; σ and τ are fixed effects for states and years and u is an error term.

[1] $Y_{it} = \alpha + \beta\, MW_{jt} + X_{it}\Lambda + \gamma_j + \tau_t + u_{it}$, where some dependent variable (for instance, teen unemployment) is regressed on the variable of interest (minimum wage), a vector of controls, and fixed effects for time and place.

Table 1. Survey of study specifications

Study	*LHS*	*RHS: Variable of interest*	*RHS: Controls*
Kalenkoski & Lacombe (2011)	log(%unemp. teens)	log(effective[a] real MW)[b]	adult unemp. rate; teen share of pop.; matrix of controls for spatial dependence state and year fixed effects
Partridge & Partridge (1998)	log(%unemp. teens)	log(effective MW)	coverage [d]; avg. mfgtr. wage; INDMIX EMP[e]; state and year fixed effects; age
Williams (1993)	log(%emp. teens)	(1) MW/avg. mfgtr. wage (2) effective real MW fed. real MW[c]	adult unemp. rate; teen share of pop.; enrollment rate[f]; welfare exp. per capita; gross state product per capita; %unionized
Neumark & Wascher (1992)	%emp. teens	[many complex manipulations of MW]	state & year fixed effects; enrollment rate; prime-age male unemp. rate; teen share of pop.

[a] Effective minimum wage is max of state or federal minimum wage.
[b] Converted nominal to real using urban CPI.
[c] Converted nominal to real using regional CPI, allocated to states within each region.
[d] Share of workforce affected by minimum wage.
[e] Proxy for business cycle: state's growth rate, imputed from national growth rates according to industries.
[f] Teen enrollment in schools.

$$(2) \qquad \mathbf{U_{tr} = \beta_1 + \beta_2 MW_{tr} + \beta_3 CP_{tr} + \beta_4 RX_{tr} + \beta_5 I_{tr} + \beta_6 GDP_{tr} + \beta_7 R_t + \tau_t + u_{tr}}$$

In this regional model, *t* and *r* are indices for time and region, respectively; *U* is the natural log of the unemployment rate; *MW* is the natural log of region *r*'s effective real minimum wage at time *t* (the regional average, weighted by states' labor forces); *CP* (natural log of civilian population), *RX* (natural log of real exports of goods and services), and *I* (natural log of inflation) are control variables for the regional unemployment rate (the regional average, weighted by states' labor forces); *R* is a dummy, controlling for region-specific trends; τ is a year fixed-effect; and *u* is an error term.

$$(3) \qquad \mathbf{U_t = \beta_1 + \beta_2 MW_t + \beta_3 CP_t + \beta_4 RX_t + \beta_5 I_t + \beta_6 GDP_t + \tau_t + u_t}$$

In this national model, *t* is an index for time; *U* is the natural log of the national unemployment rate; *MW* is the natural log of national MW (average of state real MWs, weighted by states' labor forces); *CP* (natural log of civilian population), *RX* (natural log of real exports of goods and services), and *I* (natural log of inflation) are control variables for the unemployment rate; τ is a year fixed-effect; and *u* is an error term.

Since teenagers are among the populations most affected by changes in MW (BLS, 2012), it is common in the literature to use some measurement of teen employment or unemployment as the left-hand side variable (see Table 1). We were unable to obtain this data at all our study scales, and thus used general unemployment as our left-hand side variable. For this same reason, our control variables differ from the specifications in Table 1, where variables like "teen share of population" and "enrollment" are popular. With general unemployment as our left-hand side variable, we drew on Merz and Wells (n.d.) to identify controls of unemployment. Based in Keynesian theory, their unemployment forecasting model uses civilian population, real exports of goods and services, and inflation as explanatory variables, achieving an adjusted R^2 of .95 (see Appendix 1 for further discussion). Our specifications use real MW rather than a

Kaitz index[2] or some measure of relative MW (e.g. state MW divided by federal MW or by average wage). Finally, in keeping with many of the studies outlined in Table 1, we chose a log specification.

Breusch-Pagan/Cook-Weisberg tests indicate that our state-level data exhibits heteroscedasticity, but that our regional and national data is homoscedastic. To address this, we fit our state-level model using robust standard errors. With Breusch-Godfrey tests we determined that our regional and national data exhibit autocorrelation, and thus fit these data with Newey-West standard errors. (STATA code for these tests is presented in the Appendix 2). Following the literature (e.g. Allegretto et al., 2013), we expect unobserved spatial and temporal heterogeneity and attempt to correct for it through use of regional, state and year fixed effects. Omitted variable bias is also a concern due to the difficulty in identify all possible determinants of unemployment rates; we attempt to minimize it by using variables identified as adequate by other researchers (e.g. Merz and Wells, n.d.) See Appendix 1 for a more complete discussion of omitted variables.

Data collection and preparation

We gathered data at the state, regional, and national levels. Our state data is limited to the period from 1997 to 2012 (fifteen years), while national data covers the period from 1984 to 2013 (twenty-nine years) Since much of our regional data emerges from state-level data, our regional analysis is also confined to the period from 1997 to 2012. Basic summary statistics for our variables are presented in Tables 2 and 3.

Table 2. Summary statistics (state)

Variable	***Mean***	***Standard deviation***	***Max***	***Min***
Unemployment rate	5.50%	2.05%	13.80%	2.30%
Real minimum wage	$6.20	$1.54	$11.53	$3.52
Civilian population	4,449,502	4,848,846	29,176,513	364,826
Real exports of goods and services	$1082M	$1666M	$16544M	$6M
Inflation rate	0.73%	12.96%	31.62%	-100.00%

Table 3. Summary statistics (national)

Variable	***Mean***	***Standard deviation***	***Max***	***Min***
Unemployment rate	6.30%	1.59%	9.60%	4.00%
Civilian population	208,274.1	22113.25	245679	174,215.3
Real exports of goods and services	$1085.035Bn	$510.2067Bn	$2010.05Bn	$340.38Bn
Inflation rate	2.4%	1.0%	5.1%	0.0%

[2] [Minimum wage / Avg. adult wage] * % Labor force covered by MW

Data for left-hand side variable

Minimum wage workers are largely youth (BLS, 2012), and so most specifications use some measure of youth unemployment as their left-hand side variable. Though youth unemployment figures were available at the national level from the Bureau of Labor Statistics ("(Seas) unemployment rate", 2014), we were unable to find similar data at state or regional levels. To keep our models consistent across scales, we opted to execute our national level analysis with general unemployment data that was likewise available at state and regional levels. All data on unemployment rates was obtained through querying the Bureau of Labor Statistics' data retrieval tool (n.d.). Data on state labor force size, obtained from the same BLS source, was used to calculate a weighted average for each region. (We obtained our regional classification scheme, depicted in Figure 1, from the Bureau of Economic Analysis, 2004.) Taking natural logs of national and state unemployment rates was the final step in preparing our dependent variable data for analysis.

Data for explanatory variable (minimum wages)

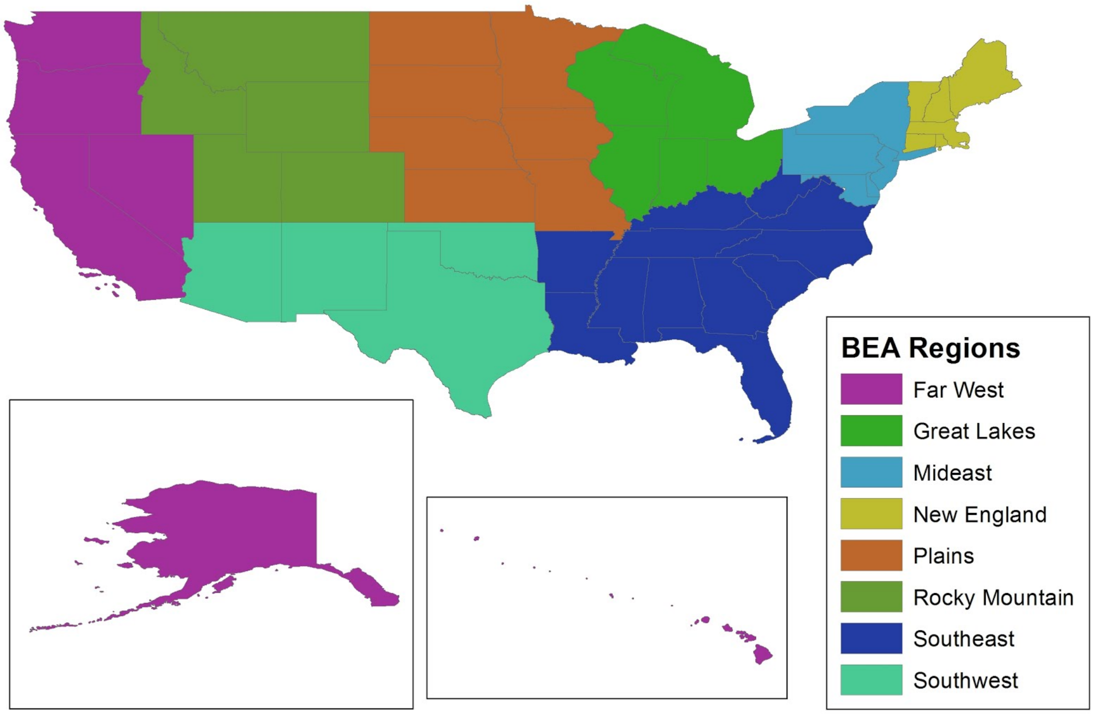
Our explanatory variable is different minimum wage levels. We obtained this data from the U.S. Department of Labor (2013), showing changes in federal and state MW policies over time. From this data, we calculated effective MW for each state (the maximum of state or federal MW at time *t*), then used CPI data (described below) to convert effective MW values from nominal to real. We used states' real MW values weighted by the size of states' labor forces (BLS, n.d.) to calculate both regional MW averages and the national MW average. We took natural logs for all our MW data.

Data for control variables

Our review of the literature (e.g. Allegretto, Dube, and Zipperer, 2013) indicated that regional controls have a significant impact on MW findings. This effect arises due to the presence of spatial heterogeneity above and beyond that which can be captured by level state fixed effects. To introduce regional controls into our models (where applicable), we located regional designations from the Bureau of Economic Analysis (2004; see Figure 1) and coded seven regional dummy variables for each state, choosing the Far West region as our reference category.

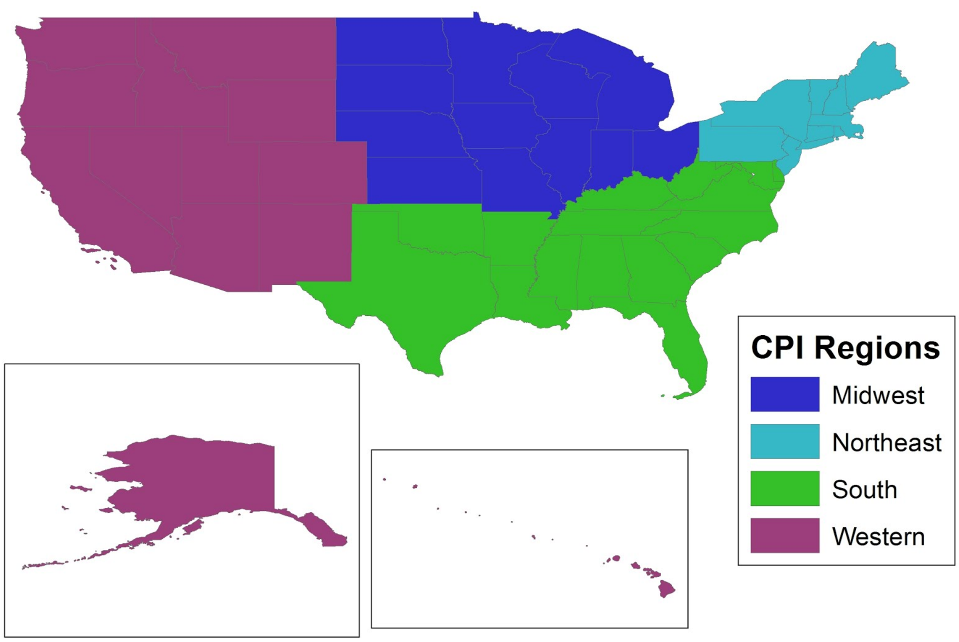
Following Merz and Wells (n.d.), we collected data on non-institutional civilian population, real exports of goods and services, and inflation as control variables for general unemployment rate. We collected data on national and state civilian populations from the Bureau of Labor Statistics (2014e, 2014g). Regional civilian populations were calculated through summing the relevant states' civilian populations. Data on national real exports of goods and services came from the Federal Reserve Bank of St. Louis (FRED, 2014, "Real exports"); state-level data on real exports of goods and services came from the Census Bureau (n.d.). Again, regional figures for real exports of good and services were obtained by summing the relevant states' exports. Finally, as our last control for general unemployment rate, we collected national urban CPI data (FRED, 2014, "Consumer Price Index") and used it to calculate national annual inflation rates. Since CPI is not published at the state-level (OFM, 2012), we imputed regional CPI (BLS 2014a; BLS 2014b; BLS 2014c; BLS 2014d) to the states contained within each region, using the Bureau of Labor statistics' regional classification scheme (see Figure 2). We then computed regional and state-level inflation. Natural logs for civilian population, real exports, and inflation figures were also calculated.

Figure 1. Regional classification scheme (for analysis)



Source: Bureau of Economic Analysis, 2004.

Figure 2. Regional classification scheme (for CPI imputation)



Source: Bureau of Labor Statistics, 2014a; 2014b; 2012c; 2014d.

Results

Regression results are presented in Appendix 3. Taken together, the outputs illustrate the wide range of conclusions that emerge depending on the unit of analysis (state, regional, or national). In addition, we ran two models at each scale, the first without any dummy variables, and the second with some combination of dummy variables to account for regional, state and year fixed effects (STATA code is provided in Appendix 2). Details of each output are summarized and discussed below.

State-level results

Working with a sample size of 529, we first ran OLS and robust versions of our state-level regressions *without* dummy variables for region, state, and year. Shown in Appendix 3 (Outputs 1.a.i, 1.a.ii), these regression yielded nearly identical results. In particular, they both show a significant coefficient for our MW variable (P=0.000), suggesting that general unemployment is expected to *increase* 0.59 percentage points for a 1 percent increase in minimum wage, all other factors held constant. This model has a significant but fairly low value of R^2 (0.253). We then added in regional, state and year dummies and ran two more regressions (OLS and robust), resulting in a much higher and still significant R^2 (0.850). Shown in Appendix 3 (Outputs 1.b.ii, 1.b.ii), these other specifications produced a very different but still significant estimate of the coefficient of MW (P=0.013; P=0.019), predicting a 0.14 percent *decrease* in unemployment for a 1 percent increase in MW, other factors held constant. While not all dummy variables in the second specification were significant, an F test of the explanatory power of the additional variables[3] allowed us to reject the null (no effect) by a wide margin. Worth noting is that STATA automatically dropped seven state dummies due to a high degree of collinearity; the sample size reported here accounts for this.

Regional results

Similarly, working at the regional level with a sample size of 63, we first ran OLS and Newey-West regressions without regional and year dummies. Shown in Appendix 3 (Outputs 2.a.i, 2.a.ii) these models failed to produce a significant estimate of the MW coefficient (P=0.922, P=0.927). The OLS model without dummies exhibits large standard errors for all its right-hand side variables, only one of which proves significant (civilian population, with P=0.002); the overall explanatory power of the model is low (R^2=0.169) albeit significant. Adding dummy variables for region and year does not cause meaningful improvement[4]. Shown in Appendix 3 (Outputs 2.b.i, 2.b.ii), the coefficient of MW remains insignificant (P=0.076, P=0.085), standard errors remain high, and the apparent increase in overall fit (R^2=0.489 for the OLS model) is insignificant.

National results

Shown in Appendix 3 (Outputs 3.a.i, 3.a.ii), our national model (n=30) was run as OLS and Newey-West regressions, first without dummies. Our OLS model produced a significant coefficient for MW (2.525, with P=0.001), yet the standard error was high (0.636). The model has a significant R^2 of 0.636. Similarly, our national Newey-West model gave a significant coefficient of MW (again 2.525, with

---

[3] $F = \dfrac{(44.4720 - 8.9669) / 70}{8.9669 / (529 - 74)} = 25.75 \quad > \quad F_{crit} = 1.31$

[4] $F = \dfrac{(4.9293 - 3.0333) / 21}{3.0333 / (63 - 25)} = 1.13 \quad < \quad F_{crit} = 1.75$

P=0.000) with a high standard error (0.583). Attempting to add year fixed effects within an OLS regression caused STATA to drop five variables for collinearity, and also resulted in an output lacking t statistics, P values, and confidence intervals. This unintelligible output could not be compared with the first specification and is not included in Appendix 3. Attempting to add year fixed effects under Newey-West yielded an error message (“matrix missing values”).

Interpretation

Our most reliable results come from the state-level regressions, based on a much larger sample size and more detailed data. After elimination of observations due to collinearity, our regional and national regressions are based on insufficient sample sizes and warrant little attention.

Our state-level results illustrate precisely the major point of debate within the literature: when regional, state and year effects are controlled, an increase in minimum wage is associated with slightly *higher* levels of employment, but if these controls are judged unimportant, then regression analysis indicates that an increase in minimum wage is associated with slightly *lower* levels of employment. Choosing among these specifications requires a degree of econometric sophistication beyond the scope of this study. Even if these two conclusions could be reconciled, though, there remains the problem of identification, for which quasi-experimental study designs (e.g. Card and Krueger, 1994) are essential. The limitations of this study, then, are clear. Minimum wage is a fundamental and persistent question within labor economics, and will likely continue to occupy researchers for years to come.

Conclusion

Several generations of economic research on the consequences of minimum wage policies have yet to yield conclusive and unambiguous guidance for policy makers, though such guidance is certainly in demand. This paper has summarized some fundamental points of difference within the MW literature. Our own regression estimates give some indication of the varying results that may be obtained from working at different scales, underscoring the need for spatially-sensitive econometrics (such as employed by Kalenkoski and Lacombe, 2011) and better identification strategies.

An interesting point is raised by Levin-Waldman and Whalen (2007). In short, they argue that seemingly disproportionate political passions surrounding minimum wage policies—given that the estimated direct impacts of such policies, positive or negative, are usually very small—signal something important. The minimum wage, they suggest, serves as a key point of reference, anchoring the wages of higher earners in the labor market. Thus the whole population affected by changes in the minimum wage (through “contour effects”) is much larger than the small number of workers directly affected. They cite Spriggs and Klein as finding that many “firms merely maintain their internal wage structures in response to changes in the statutory minimum wage” (Levin-Waldman and Whalen, 2007, p. 64), and estimate that roughly 12.3% of the total American workforce—including many primary earners, and essential secondary earners—should be considered members of an “effective minimum wage” population that would be affected by shifting wage structures. Their argument both reinforces the need for more conclusive research on minimum wage effects and points these efforts in a promising direction. Future work in this area might marry Hirsch, Kaufman, and Zelenka’s (2013) pioneering approach (using establishment-level payroll data) with Levin-Waldman and Whalen’s (2007) concern to identify the whole population affected by minimum wage policies. A much clearer picture of *how* the minimum wage affects the labor market and *who* it affects is desirable. That these two essential aspects of the minimum wage issue are yet largely unknown reveals how far the literature is from supplying a foundation for current public debates.

Appendix 1: Discussion of omitted variables

Selection of control variables

We drew on Merz and Wells (n.d.) in choosing variables to control for our left-hand side variable (general unemployment rate). Merz and Wells' model was developed for forecasting purposes, and achieves an R^2 of .95. Theoretically grounded in Keynesian models and the Phillips curve, their model explains variations in unemployment rate as a function of three variables: civilian population, real exports of goods and services, and inflation rate.

Starting with the basic Keynesian model, GDP is described as a function of real exports:

$$\mathbf{Y = C + I + G + (I - X) \rightarrow Y = f(X)}$$

Then, from a classic production function, unemployment is expressed as a function of GDP, and therefore as a function of real exports:

$$\mathbf{Y = f(L, K) \rightarrow Y = f(U)}\text{, since U and L are related} \rightarrow \mathbf{U = f(Y) = f(X)}$$

The Phillips curve simply *is* a relation between unemployment and inflation:

$$\mathbf{U = f(i)}$$

Finally, by definition, unemployment is some proportion of the civilian population:

$$\mathbf{U = f(CP)}$$

Thus,

$$\mathbf{U = f(X, i, CP).}$$

Rejected control variables and potential effect (omitted variable bias)

Omitted variable cannot be truly ruled out as a concern for our models. In searching for desired control variables, we faced serious data limitations. In particular, we thought that a valid approach to researching minimum wage impacts *must* operate at the state level; but many of our desired variables were available only at the national level. The trade-off we faced was between developing an unacceptably abstract national specification with many variables, or a state-level model with available data. We opted to build a state-level model then repeat our analysis across regional and national scales. Here, we review and discuss the possible impacts of some control variables that were dropped during the course of our research.

Variable: MW coverage (percent of labor force employed at minimum wage)

In states where a comparatively large share of the workforce is employed at minimum wage, we would expect MW increases to have a stronger impact on unemployment. Since there is a positive correlation between this variable and MW, we believe there is bias in our MW coefficient, such that the effects of MW increases may be overestimated. With more time, we may have been able to explore the suitability of proxies for MW coverage. Specifically, since minimum wage workers tend to be clustered in specific occupations, chiefly foodservice (BLS, 2012), we may have been able to gather data on foodservice share of the workforce and use it as a proxy, reducing the impact of omitted variable bias.

Variable: Changes in unemployment benefits/Relative generosity of welfare benefits

An increase in unemployment or welfare benefits, or relaxation of eligibility criteria of welfare or unemployment benefits could possibly increase unemployment rate. The potential for omitted variable bias arises if we suspect that minimum wage increases correlate with generous social benefits, for instance of states with majority Democrat governance are more likely to offer both high minimum wages and robust benefits as part of an ambitious social safety net. Without further exploration of this potential correlation, we cannot estimate the likelihood of omitted variable bias for this variable.

Variable: Changes in labor force composition (Immigration/Aging)

Changes in the demographic composition of the workforce may plausibly change MW coverage (if less-skilled workers make up a higher share of the state workforce), and thereby have an indirect effect on unemployment. As with MW coverage itself, there is a possibly that omitted variable bias results from our inability to include this data in our regressions.

Variable: Changes in trade, and offshoring trends.

Since the adoption of free trade agreements such as NAFTA, exports of U.S. manufactured goods have decreased, and imports of similar goods from other countries (particularly China) have increased. If we investigated the relationship between the unemployment rate and trade liberalization, we might expect at least a temporary surge in unemployment following adoption of new trade agreements. Relatedly, we expect that an increase in offshoring of jobs (such as telemarketing) will raise the unemployment rate. However, since we would not expect these changes to correlate with MW policies, we can rule out omission of this variable as a potential source of bias.

Variable: Manufacturing productivity

If productivity in a certain state is high, it might increase unemployment as productivity means less demand for labor, other factors constant. Again, though, we would not necessarily expect this phenomenon to correlate with MW policies, and so feel justified in dropping it as a control variable from our models.

Appendix 2: STATA code

State-level regression and testing

We ran two regressions at the state level, one without fixed effects or dummy variables, and the other including regional dummy variables plus state and year fixed effects. Dummies were coded in Excel, while state and year fixed effects were generated automatically within STATA:

(1.a) **regress LNUnemprate LnRealMW LnRealexports LnCivPop LNInfrate**
(1.b) **regress LNUnemprate LnRealMW LnRealexports LnCivPop LNInfrate, robust**
(2.a) **xi: regress LNUnemprate LnRealMW LnRealexports LnCivPop LNInfrate Region1 Region2 Region3 Region4 Region5 Region6 Region7 i.State i.Year**
(2.b) **xi: regress LNUnemprate LnRealMW LnRealexports LnCivPop LNInfrate Region1 Region2 Region3 Region4 Region5 Region6 Region7 i.State i.Year, robust**

We checked our data for heteroscedasticity using the Breusch-Pagan/Cook-Weisberg test as follows, and were led to reject our null hypothesis (homoscedasticity):

(3) **hettest LnRealMW LnRealexports LnCivPop LNInfrate**

We checked our data for autocorrelation using the Breusch-Godfrey test as follows, and were unable to reject our null hypothesis (no serial correlation):

(4)
```
gen time = _n
tsset time
estat bgodfrey, lag(1)
```

Regional regression and testing

We ran two regressions at the regional level, one without fixed effects or dummy variables, and the other including regional dummy variables plus year fixed effects. Regional dummies and year fixed effects were generated automatically within STATA:

(1.a) **regress LGunemployment LnWeightedRealMW LnRealexports LGcp LGinflation**
(1.b) **newey LGunemployment LnWeightedRealMW LnRealexports LGcp LGinflation, lag(0)**
(2.a) **xi: regress LGunemployment LnWeightedRealMW LnRealexports LGcp LGinflation i.Region i.Year**
(2.b) **xi:newey LGunemployment LnWeightedRealMW LnRealexports LGcp LGinflation i.Region i.Year, lag(0)**

We checked our data for heteroscedasticity using the Breusch-Pagan/Cook-Weisberg test as follows, and were unable to reject our null hypothesis (homoscedasticity):

(3) **hettest LnWeightedRealMW LnRealexports LGcp LGinflation**

We checked our data for autocorrelation using the Breusch-Godfrey test as follows, and were led to reject our null hypothesis (no serial correlation):

(4) **gen time = _n**
tsset time
estat bgodfrey, lag(1)

National regression and testing

We ran two regressions at the regional level, one without fixed effects or dummy variables, and the other including regional dummy variables plus year fixed effects. Regional dummies and year fixed effects were generated automatically within STATA:

(1.a) **regress LGunemployment LGrealminwage LGrealexport LGcp LGinflation**
(1.b) **newey LGunemployment LGrealminwage LGrealexport LGcp LGinflation, lag(0)**
(2.a) **xi: regress LGunemployment LGrealminwage LGrealexport LGcp LGinflation i.Year**

We checked our data for heteroscedasticity using the Breusch-Pagan/Cook-Weisberg test as follows, and were unable to reject our null hypothesis (homoscedasticity):

(3) **hettest LGrealminwage LGrealexport LGcp LGinflation**

We checked our data for autocorrelation using the Breusch-Godfrey test as follows, and were led to reject our null hypothesis (no serial correlation):

(4) **gen time = _n**
tsset time
estat bgodfrey, lag(1)

Appendix 3: STATA outputs

Output 1.a.i. State-level OLS regression (excluding dummies and fixed effects)

Source	**SS**	**df**	**MS**	
				Number of obs = 529
				F(4, 524) = 44.42
Model	15.1729003	4	3.79322507	**Prob > F** = 0.0000
Residual	44.7419955	524	.085385488	**R-squared** = 0.2532
				Adj R-squared = 0.2475
Total	59.9148958	528	.113475181	**Root MSE** = .29221

LNUnemprate	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**	
LnRealMW	.5895521	.058153	10.14	0.000	.4753105	.7037937
LnRealexports	.0071506	.0146774	0.49	0.626	-.0216833	.0359844
LnCivPop	.0687677	.0204326	3.37	0.001	.0286278	.1089076
LNInfrate	.0305959	.0133883	2.29	0.023	.0042946	.0568971
_cons	-.4915514	.2590065	-1.90	0.058	-1.00037	.0172674

Output 1.a.ii. Robust state-level regression (excluding dummies and fixed effects)

Number of obs = 529
F(4, 524) = 42.78
Prob > F = 0.0000
R-squared = 0.2532
Root MSE = .29221

LNUnemprate	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**	
LnRealMW	.5895521	.0571899	10.31	0.000	.4772025	.7019017
LnRealexports	.0071506	.013669	0.52	0.601	-.0197022	.0340034
LnCivPop	.0687677	.0193661	3.55	0.000	.0307229	.1068125
LNInfrate	.0305959	.0126329	2.42	0.016	.0057785	.0554133
_cons	-.4915514	.2527884	-1.94	0.052	-.9881546	.0050519

Output 1.b.i. State-level OLS regression (including dummies and fixed effects)

Source	**SS**	**df**	**MS**	
				Number of obs = 529
				F(68, 460) = 38.44
Model	50.94804	68	.749235882	**Prob > F** = 0.0000
Residual	8.96685578	460	.019493165	**R-squared** = 0.8503
				Adj R-squared = 0.8282
Total	59.9148958	528	.113475181	**Root MSE** = .13962

LNUnemprate	**Coef.**	**Std. Err.t**	**P>|t|**	**[95% Conf. Interval]**		
LnRealMW	-.1392907	.0556576	-2.50	0.013	-.2486653	-.0299161
LnRealexports	-.015958	.0088338	-1.81	0.071	-.0333176	.0014015
LnCivPop	.501411	.2040984	2.46	0.014	.1003301	.9024919
LNInfrate	.0148707	.0088943	1.67	0.095	-.0026079	.0323493
…						
_cons	-6.362371	3.471497	-1.83	0.067	-13.18433	.4595881

Note: Output has been edited for concision (for instance, by excluding dummy variable results).

Output 1.b.ii. Robust state-level regression (including dummies and fixed effects)

Number of obs = 529
F(68, 460) = 56.13
Prob > F = 0.0000
R-squared = 0.8503
Root MSE = .13962

LNUnemprate	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**	
LnRealMW	-.1392907	.0590565	-2.36	0.019	-.2553446	-.0232367
LnRealexports	-.015958	.008975	-1.78	0.076	-.0335952	.0016791
LnCivPop	.501411	.2199802	2.28	0.023	.0691204	.9337016
LNInfrate	.0148707	.0096559	1.54	0.124	-.0041044	.0338458
…						
_cons	-6.362371	3.747338	-1.70	0.090	-13.72639	1.001652

Note: Output has been edited for concision (for instance, by excluding dummy variable results).

Output 2.a.i. Regional OLS regression (excluding dummies and fixed effects)

Source	**SS**	**df**	**MS**
Model	1.00504805	4	.251262012
Residual	4.92934799	58	.084988759
Total	5.93439604	62	.095716065

Number of obs = 63
F(4, 58) = 2.96
Prob > F = 0.0272
R-squared = 0.1694
Adj R-squared = 0.1121
Root MSE = .29153

LGunemployment	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**	
LnWeightedRealMW	-.0195568	.1991454	-0.10	0.922	-.4181895	.379076
LnRealexports	-.0010059	.0024357	-0.41	0.681	-.0058816	.0038697
LGcp	.1311564	.0397613	3.30	0.002	.0515655	.2107474
LGinflation	-.0115031	.0347085	-0.33	0.742	-.0809797	.0579735
_cons	-.4282101	.7381004	-0.58	0.564	-1.905679	1.049258

Output 2.a.ii. Regional Newey-West regression (excluding dummies and fixed effects)

Regression with Newey-West standard errors
maximum lag: 0

Number of obs = 63
F(4, 58) = 3.50
Prob > F = 0.0126

LGunemployment	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**	
LnWeightedRealMW	-.0195568	.2138596	-0.09	0.927	-.4476433	.4085298
LnRealexports	-.0010059	.0023882	-0.42	0.675	-.0057865	.0037747
LGcp	.1311564	.0358344	3.66	0.001	.0594262	.2028867
LGinflation	-.0115031	.0317273	-0.36	0.718	-.0750122	.0520059
_cons	-.4282101	.7227974	-0.59	0.556	-1.875046	1.018626

Output 2.b.i. Regional OLS regression (including dummies and fixed effects)

Source	**SS**	**df**	**MS**	
				Number of obs = 63
				(24, 38) = 1.51
Model	2.9010909	24	.120878788	**Prob > F** = 0.1235
Residual	3.03330514	38	.079823819	**R-squared** = 0.4889
				Adj R-squared = 0.1660
Total	5.93439604	62	.095716065	**Root MSE** = .28253

LGunemployment	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**	
LnWeightedRealMW	-1.684298	.9228224	-1.83	0.076	-3.552454	.1838585
LnRealexports	-.0163177	.0193336	-0.84	0.404	-.0554566	.0228211
LGcp	.0514323	.075813	0.68	0.502	-.1020431	.2049078
LGinflation	.0084227	.0444169	0.19	0.851	-.0814947	.0983401
…						
_cons	4.99204	2.541339	1.96	0.057	-.1526322	10.13671

Note: Output has been edited for concision (for instance, by excluding dummy variable results).

Output 2.b.ii. Regional Newey-West regression (including dummies and fixed effects)

Regression with Newey-West standard errors
maximum lag: 0

Number of obs = 63
F(24, 38) = 7.35
Prob > F = 0.0000

LGunemployment	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**	
LnWeightedRealMW	-1.684298	.9511799	-1.77	0.085	-3.609861	.2412652
LnRealexports	-.0163177	.0218129	-0.75	0.459	-.0604757	.0278402
LGcp	.0514323	.0721262	0.71	0.480	-.0945795	.1974442
LGinflation	.0084227	.0435705	0.19	0.848	-.0797812	.0966267
…						
_cons	5.094274	2.519616	2.02	0.050	-.0064214	10.19497

Note: Output has been edited for concision (for instance, by excluding dummy variable results).

Output 3.a.i. National OLS regression

Source	**SS**	**df**	**MS**
Model	1.14601172	4	.286502931
Residual	.656162971	25	.026246519
Total	1.80217469	29	.062143955

Number of obs = 30
F(4, 25) = 10.92
Prob > F = 0.0000
R-squared = 0.6359
Adj R-squared = 0.5776
Root MSE = .16201

LGunemploymt	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**	
LGrealminwage	2.525371	.6358144	3.97	0.001	1.215887	3.834855
LGrealexport	-1.032571	.2520707	-4.10	0.000	-1.55172	-.5134214
LGcp	2.75531	1.50182	1.83	0.078	-.3377457	5.848365
LGinflation	-.121421	.0833887	-1.46	0.158	-.2931632	.0503212
_cons	-29.51792	16.16864	-1.83	0.080	-62.81786	3.782027

Output 3.a.ii. National Newey-West regression

Regression with Newey-West standard errors
maximum lag: 0

Number of obs = 30
F(4, 25) = 14.79
Prob > F = 0.0000

LGunemploym~t	**Coef.**	**Std. Err.**	**t**	**P>|t|**	**[95% Conf. Interval]**	
LGrealminwage	2.525371	.5832308	4.33	0.000	1.324185	3.726557
LGrealexport	-1.032571	.2070896	-4.99	0.000	-1.45908	-.6060617
LGcp	2.75531	1.15304	2.39	0.025	.3805792	5.130041
LGinflation	-.121421	.0908267	-1.34	0.193	-.3084821	.0656401
_cons	-29.51792	12.42479	-2.38	0.025	-55.10725	-3.928581

References

15 Now. (n.d.). *15 Now in your area.* Retrieved from http://15now.org/get-involved/in-your-area/

Allegretto, S. A., Dube, A., Reich, M., & Zipperer, B. (2013). *Credible research designs for minimum wage studies* (Working Paper Series). Berkeley, CA: Institute for Research on Labor and Employment, UC Berkeley.

Allegretto, S. A., Dube, A., & Reich, M. (2011). Do minimum wages really reduce teen employment? Accounting for heterogeneity and selectivity in state panel data. *Industrial Relations, 50*(2), 205-240.

Angrist, J. D., & Pischke, J. (2010). The credibility revolution in empirical economics: How better research design is taking the con out of econometrics. *Journal of Economic Perspectives, 24*(2), 3-30.

Card, D. (1992). Using regional variation in wages to measure the effects of the federal minimum wage. *Industrial and Labor Relations Review, 46*(1), 22-37.

Card, D., Katz, L. F., & Krueger, A. (1994). Comment on David Neumark and William Wascher, "Employment effects of minimum and subminimum wages: Panel data on state minimum wage laws". *Industrial and Labor Relations Review, 47*(3), 487-496.

Card, D., & Krueger, A. (1994). Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania. *American Economic Review, 48*(4), 772-793.

Card, D., & Kreuger, A. (1995). *Myth and measurement: The new economics of the minimum wage.* Princeton, NJ: Princeton University Press.

Card, D., & Krueger, A. (2000). Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania: Reply. *American Economic Review, 90*(5), 1397-1420.

Dube, A. (2011). Review of *Minimum wages* by David Neumark and William Wascher. *Journal of Economic Literature, 49*(3), 762-766.

Dube, A. (2014, Jan. 22). *The poverty of minimum wage "facts"*. Retrieved from http://arindube.com/2014/01/22/the-poverty-of-minimum-wage-facts/

Dube, A., Lester, T. W., & Reich, M. (2010). Minimum wage effects across state borders: Estimates using contiguous counties. *Review of Economics and Statistics, 92*(4): 945–964.

Federal Reserve Bank of St. Louis (FRED). (2014). *Consumer Price Index for all urban consumers: All items* [Data file]. Retrieved from http://research.stlouisfed.org/fred2/series/CPIAUCSL

Federal Reserve Bank of St. Louis (FRED). (2014). *Real exports of goods & services* [Data file]. Retrieved from http://research.stlouisfed.org/fred2/graph/?id=EXPGSC1#

Fox, E. J. (2013, November 7). Washington city votes to raise minimum wage to $15. *CNN Money.* Retrieved from http://money.cnn.com/2013/11/06/news/economy/minimum-wage-seatac-new-jersey/

Hirsch, B. T., Kaufman, B., & Zelenska, T. (2011). Minimum wage channels of adjustment. IZA Discussion Paper No. 6132. Germany: Institute for the Study of Labor. Retrieved from http://www2.gsu.edu/~ecobth/IZA_HKZ_MinWageCoA_dp6132.pdf

Kalenkoski, C. M., & Lacombe, D. J. (2011). Minimum wages and teen employment: A spatial panel approach (Discussion Paper No. 5933). *Institute for the Study of Labor (IZA)*. Retrieved from http://www.rri.wvu.edu/wp.../Lacombe_MinimumWagePanelPaper_wp2011_08.pdf

Leamer, E. E. (1983). Let's take the con out of econometrics. *The American Economic Review, 73*(1), 31-43.

Levin-Waldman, O., & Whalen, C. (2007). The minimum wage is a middle-class issue. *Challenge, 50*(3), 59-71.

Mertz, D., & Wells, M. (n.d.). *A two year forecast of unemployment rate.* College of Business, Western Carolina University. Retrieved from http://paws.wcu.edu/mulligan/www/NCES99-11.html

Neumark, D., & Salas, J. M. I. (2013). *Minimum wages: Evaluating new evidence on employment effects.* Washington, D.C.: Employment Policies Institute.

Neumark, D., Salas, J. M. I., & Wascher, W. L. (2013). *Revisiting the minimum wage-employment debate: Throwing out the baby with the bathwater?* (Working Paper No. 18681). Cambridge, MA: The National Bureau of Economic Research.

Neumark, D., & Wascher, W. L. (1992). Employment effects of minimum and subminimum wages: Panel data on state minimum wage laws. *Industrial and Labor Relations Review, 46*(1), 55-81.

Neumark, D., & Wascher, W. L. (1994). Employment effects of minimum and subminimum wages: Reply to Card, Katz, and Krueger. *Industrial and Labor Relations Review, 47*(3), 497-512.

Neumark, D., & Wascher, W. L. (1995). *The effect of New Jersey's minimum wage increase on fast-food employment: A re-evaluation using payroll records* (Working Paper No. 5224). Cambridge, MA: The National Bureau of Economic Research.

Neumark, D., & Wascher, W. L. (2007). Minimum wages and unemployment. *Foundations and Trends in Microeconomics, 3*(1-2), 1-182.

Office of Financial Management (OFM). (2012). *Inflation*. Retrieved from http://ofm.wa.gov/economy/econtopics/inflation/default.asp#what

Partridge, M. D., & Partridge, J. S. (1998). Are teen unemployment rates influenced by state minimum wage laws? *Growth and Change, 29*(4), 359-382.

Sabia, J. J. (2009). Identifying minimum wage effects: New evidence from monthly CPS data. *Industrial Relations, 48*(2), 311-328.

Schmitt, J. (2013). Why does the minimum wage have no discernible effect on unemployment? *Center for Economic and Policy Research.*

Stafford, F. (1986). Forestalling the demise of empirical economics: The role of microdata in labor economics research. In O. Ashenfelter & R. Layard (Eds.), *Handbook of Labor Economics*, Vol. 1 (pp. 387-423). San Francisco: Elsevier.

Stewart, M. B. (2002). Estimating the impact of the minimum wage using geographical wage variation. *Oxford Bulletin of Economics and Statistics*, *64*(supplement), 583-605.

U.S. Bureau of Economic Analysis (BEA). (2004). *BEA regions*. Retrieved from http://www.bea.gov/regional/docs/regions.cfm

U.S. Bureau of Labor Statistics (BLS). (n.d.). *Top picks (Most requested statistics)* [Data file]. Retrieved from http://data.bls.gov/cgi-bin/surveymost?la

U.S. Bureau of Labor Statistics (BLS). (2012). *Minimum wage workers account for 4.7 percent of hourly paid workers in 2012.* Retrieved from http://www.bls.gov/opub/ted/2013/ted_20130325.htm

U.S. Bureau of Labor Statistics (BLS). (2014a). *Consumer Price Index - All urban consumers - Northeast urban* [Data file]. Retrieved from http://data.bls.gov/pdq/querytool.jsp?survey=ln

U.S. Bureau of Labor Statistics (BLS). (2014b). *Consumer Price Index - All urban consumers - Midwest urban* [Data file]. Retrieved from http://data.bls.gov/pdq/querytool.jsp?survey=ln

U.S. Bureau of Labor Statistics (BLS). (2014c). *Consumer Price Index - All urban consumers - South urban* [Data file]. Retrieved from http://data.bls.gov/pdq/querytool.jsp?survey=l

U.S. Bureau of Labor Statistics (BLS). (2014d). *Consumer Price Index - All urban consumers - West urban* [Data file]. Retrieved from http://data.bls.gov/pdq/querytool.jsp?survey=ln

U.S. Bureau of Labor Statistics (BLS). (2014e). *Labor force statistics from the Current Population Survey: Civilian noninstitutional population* [Data file]. Retrieved from http://data.bls.gov/pdq/querytool.jsp?survey=ln

U.S. Bureau of Labor Statistics (BLS). (2014f). *Labor force statistics from the Current Population Survey: (Seas) unemployment rate - 16-19 yrs* [Data file]. Retrieved from http://data.bls.gov/pdq/querytool.jsp?survey=ln

U.S. Bureau of Labor Statistics (BLS). (2014g). *Civilian noninstitutional population and associated rate and ratio measures for model-based areas* [Data file]. Retrieved from http://www.bls.gov/lau/rdscnp16.htm

U.S. Census Bureau. (n.d.). *U.S. exports of goods by state, based on origin of movement, by NAICS-Based Product: Current and historical releases.* Retrieved from http://www.census.gov/foreign-trade/statistics/state/origin_movement/index.html

U.S. Department of Labor (DOL). (2013). *Changes in basic minimum wages in non-farm employment under state law: Selected years 1968 to 2013.* Retrieved from http://www.dol.gov/whd/state/stateMinWageHis.htm

Valdes, M. (2014, May 29). Seattle city council panel OKs $15 minimum wage. *ABC News.* Retrieved from http://abcnews.go.com/US/wireStory/seattle-city-council-panel-oks-15-minimum-wage-23916768

Williams, N. (1993). Regional effects of the minimum wage on teen employment. *Applied Economics, 25*(12), 1517-1528.