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The Effect of Minimum Wages on Labour Market Outcomes: County-Level Estimates from the Restaurant-and-Bar Sector

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Abstract

We use US county-level data on employment and earnings in the restaurant-and-bar sector to evaluate the impact of minimum-wage changes in low-wage labour markets. Our estimated models are consistent with a simple competitive model in which supply-and-demand factors affect both the equilibrium outcome and the probability of the minimum wage being binding. Our evidence does not suggest that minimum wages reduce employment once controls for trends in county-level sectoral employment are incorporated. Rather, employment appears to exhibit an independent downward trend in states that have increased their minimum wages relative to states that have not, thereby predisposing estimates towards reporting negative outcomes.

1. Introduction

Does increasing the minimum wage lead to lower employment? The conventional wisdom in the affirmative was challenged in a series of studies by Card (1992a,b), Katz and Krueger (1992), and Card and Krueger (1994) that indicated minimal, even positive employment effects. This new literature exploited geographic variation in the setting of minimum wages, and its findings stood in contrast to an earlier but simpler time-series literature suggesting negative employment effects. Neumark and Wascher (1992) also considered the importance of geographic variation in estimating minimum-wage effects, but in this case their evidence was consistent with conventional time-series estimates.

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Although both lines of research brought into play identification using state minimum-wage laws, they differed in the geographic coverage of their analysis and specific labour market focus. Neumark and Wascher (1992) exploited a long panel of state-level observations on teenager and young-adult employment, without any restriction on the sector of employment. In contrast, Card and Krueger (1994) studied employment among franchised restaurants in the fast-food sector but compared just two states (New Jersey and Pennsylvania) in the context of a 1992 increase in the New Jersey minimum, with only two observations per restaurant surrounding this increase. Both studies allowed for state effects in employment determination, although the Neumark and Wascher estimation assumed these effects were constant over the long period captured in their sample. As we discuss below, the Card and Krueger analysis has been criticized for its narrow geographic focus that makes broad statistical conclusions difficult.

In a recent paper, Dube *et al.* (2008) have extended the type of border comparison inherent in the Card and Krueger (1994) analysis to a national sample of cross-border minimum-wage comparisons in the 1991–2006 period. Their findings support the original Card–Krueger conclusions that minimum wages have no clear effect on employment in the restaurant sector. Like Dube *et al.*, we employ county-level data to study the impact of minimum wages, albeit for a larger sample of counties and for the full restaurant-and-bar sector. However, we study minimum wages in an econometric design that has more in common with Neumark and Wascher (1992) than with Card and Krueger. Using a large sample of county-level employment, we estimate the minimum-wage effect on employment in a model that allows for a county-specific effect (allowed to trend over time), and with county-level economic controls that allow us to consider the consistency of the estimated models with competitive market forces in this sector. In general, our findings do not suggest that minimum wages reduce employment in the overall restaurant-and-bar sector. That said, our estimates are otherwise consistent with a competitive model in which the labour demand elasticity is very small.

2. Statistical problems in the minimum-wage literature

There is a potential statistical complication in much of the existing research using cross-state variation in minimum wages that may have led to an overstatement of the precision of estimates generated in this literature. Bertrand *et al.* (2004) argue that difference-in-difference estimates often involve policy-related independent variables that are measured at a higher level of aggregation than the dependent variable. For example, in the Card and Krueger (1994) regressions the dependent variable is measured for a given restaurant in a given time period, while the minimum wage varies only at the more aggregated state/time-period level. In this situation, Bertrand, Duflo and Mullainathan show that the assumption that error terms are uncorrelated across restaurants in the same state/time period can lead to a severely biased inference if the actual correlation in these observations is non-zero, as the standard errors for the coefficient estimates on the more aggregated policy variables will tend to be understated (often dramatically) in this case.

When there is the potential for a high degree of correlation in the error terms within cross-sectional units over time, an increasingly common approach to statistical inference with panel data is to use 'clustered standard errors'. Bertrand *et al.* (2004) note that this is a strategy that can work relatively well, as long as the number of cross-sectional units (here, the number of states) is relatively large. The results of Neumark and Wascher (1992) are only partially robust to this type of correction (a negative employment effect is found only for minority male teenagers in the re-analysis by Neumark and Wascher 2007). A further weakness of the Card and Krueger (1994) approach is that the number of cross-sectional units considered is quite small (only New Jersey and Pennsylvania). If there is any tendency for error terms to be correlated across restaurants in the same state, inference using the difference-in-difference regression estimated by Card and Krueger is likely to be unreliable. Furthermore, Donald and Lang (2007) argue that given the limited geographic focus in the Card and Krueger study, the statistical analysis of the policy impact is not even based on a well-defined probability distribution.

The issue of a limited geographic focus is not a concern in the very recent analysis of Dube *et al.* (2008). Using data from the restaurant sector, their approach is based on comparisons of state-border counties assuming a county-pair effect specific to each time period. One difficulty they encounter in their modelling of employment determination within border counties is that there are typically multiple counties in the border state to which any given county in the sample could be matched. The Dube *et al.* approach includes that county's employment as a dependent variable multiple times in the sample, each time matched with another county from the border state. The peculiarity of this approach is that it models a single county's employment as a function of a fixed effect from one border-county match and then models that same employment level as a function of a different fixed effect from a match with a different border county (the original fixed effect having been removed from the model for the county's employment in this second observation in the data). Except in the unlikely event that all three counties have the same county/period effect, the same employment level will have been included twice in the sample each time with different controls.

By contrast, the approach in our article is closer to that of Neumark and Wascher (1992), although restricted to the restaurant-and-bar sector. As in Neumark and Wascher, we study a panel that allows for the incorporation of geographic-specific economic factors as potential employment determinants, along with a geographic fixed effect. We differ in that our analysis is focused at the county level, allowing for a more precise control for local economic factors than Neumark and Wascher are able to incorporate in their state-level models. Another key extension of our analysis is that we allow for county-specific trends in employment and earnings in the restaurant-and-bar sector. Addison *et al*. (2009) showed that for the retail sector (not including restaurants), this approach works well, while the Dube *et al*. method yields considerably imprecise estimates that are often of an unbelievably large magnitude. As discussed in the next section, estimation of our models also allows us to assess the extent to which our results are consistent with a competitive-model explanation of employment and earnings determination.

3. Theoretical framework: competitive-market effects of minimum wages

Empirical studies of minimum-wage effects are typically motivated by a simple one-sector model of low-wage labour markets that assumes the minimum wage exceeds the market-clearing wage. Our following stylized model of low-wage labour markets explicitly takes into account the possibility that some of the labour markets investigated may actually have market-clearing wages above the minimum. We assume constant-elasticity forms for labour supply and demand, in particular,

$$E^d = w^{\beta} X,$$

where E^d is the number of workers desired at wage w, and

$$E^S = w^{\gamma} Z,$$

where E^S is the number of workers supplied. The parameter β represents the labour-demand elasticity, and γ the labour-supply elasticity. X and Z are positive-valued indices that shift demand and supply, respectively.

If the minimum wage ($w_{\min}$) is not binding, equilibrium provides

$$w^* = \left(\frac{X}{Z}\right)^{\frac{1}{\gamma-\beta}},$$

and

$$E^* = X^{\frac{\gamma}{\gamma-\beta}} Z^{\frac{-\beta}{\gamma-\beta}}.$$

However, if $w^* < w_{\min}$, the minimum wage is effective and employment is now given by the demand curve

$$E_{\min} = w_{\min}^{\beta} X.$$

If we let d be an indicator function equal to one when the minimum wage is effective, the log of observed employment can be expressed as

$$\log(E^o) = d\log(E_{\min}) + (1-d)\log(E^*)$$
$$= d\beta\log(w_{\min}) + \frac{\gamma - d\beta}{\gamma-\beta}\log(X) - \frac{\beta - d\beta}{\gamma-\beta}\log(Z).$$

Conditioning on $w_{\min}$, X, and Z, the expected value of the log of observed employment becomes

$$E(\log(E^o|w_{\min}, X, Z)) = p\beta\log(w_{\min}) + \frac{\gamma - p\beta}{\gamma-\beta}\log(X) - \frac{\beta - p\beta}{\gamma-\beta}\log(Z), \tag{1}$$

where $p = E(d \mid w_{\min}, X, Z)$ is the probability that the labour market has an effective minimum wage.

One implication of equation (1) is that the coefficient on the log of the minimum-wage equation identifies the labour-demand elasticity if corrected by dividing the estimated coefficient by an estimate of the percentage of the labour market that actually receives the minimum wage (this type of correction is noted in Brown 1999). Alternatively, an equation for the average wage in the labour market could be estimated, as the reduced-form log-wage equation is

$$E(\log(w)|w_{\min}, X, Z) = p\log(w_{\min}) + (1-p)\frac{1}{\gamma-\beta}\log(X/Z). \tag{2}$$

Dividing the minimum-wage coefficient in the employment equation by the coefficient in the wage equation provides the labour-demand elasticity.

While this approach is appropriate for infinitesimal changes in the minimum wage, it ignores the fact that observed changes in the minimum wage also increase the likelihood that the minimum wage is effective in a market, thereby causing p to change. A simple strategy is to model this probability as a linear function of characteristics that would shift supply or demand, given that

$$p = P(w^* \le w_{\min}) = P\left(w_{\min} - \left(\frac{X}{Z}\right)^{\frac{\beta}{\gamma-\beta}} \ge 0\right).$$

In practice, we specify

$$p = \alpha_0 + \alpha_1\log(w_{\min}) + \alpha_2\log(X) + \alpha_3\log(Z).$$

Substituting in equation (1) provides an equation with interactions between all variables, given that p appears as part of the coefficient for each variable. In our estimated models, we primarily handle the varying impact of minimum wages on employment by including interactions of all variables with the minimum wage.

4. Data and statistical approach

The primary data source for the estimation of our models is the Quarterly Census of Employment and Wages (QCEW) from the Bureau of Labor Statistics (BLS). The QCEW reports quarterly county-level payroll data on private employment and earnings for narrowly defined industries, and covers 99.7 per cent of all wage and salary civilian employment. The public-use data from the QCEW do not provide information at the establishment level but instead aggregate information on employment and payroll within industries at the county level. These data have many advantages over other employment surveys. They provide census observations of employment and earnings for detailed industrial specifications within a large number of narrowly defined geographic regions. Also, the county level of aggregation provides a reasonable approximation of a labour market, especially for the restaurant-and-bar sector. Even in metropolitan areas with several counties, the large number of employers in this sector within a county (lowering the necessity of long commutes) suggests that potential employees would typically look to nearby establishments as a source of employment.

That said, the QCEW is not without its weaknesses. The survey does not distinguish between part-time and full-time employees, and there is no measure of hours worked or the average wage. The sole earnings measure available is data on the average quarterly payroll of establishments by sector in the county, which we divide by total employment in the corresponding sector to construct a measure of average (weekly) earnings per worker. This measure does include most wage-like compensation, including tips, bonuses, stock options and employer contributions to retirement plans. Further, we are unable to examine the possibility that minimum wages may be affecting hours worked for workers who remain employed, although previous research using other data has not provided any evidence of such an effect (see Zavodny 2000). Even so, the QCEW does provide accurate and comprehensive measures of employment and earnings in highly disaggregated markets, and has been underutilized in minimum-wage research.

Our basic econometric model is

$$\log(\mathrm{Y}_{\mathrm{ist}}) = \varphi \log(\mathrm{MW}_{\mathrm{st}}) + \gamma \mathrm{X}_{\mathrm{ist}} + \mu_{\mathrm{i}} + \tau_{\mathrm{t}} + \varepsilon_{\mathrm{ist}}, \tag{3}$$

where $\mathrm{Y}_{\mathrm{ist}}$ denotes either industry employment or earnings in county i and state s during period t, $\mathrm{MW}_{\mathrm{st}}$ is the real minimum wage, $\mathrm{X}_{\mathrm{ist}}$ is a vector of supply and demand factors, μ_{i} and τ_{t} are fixed county and time effects, and $\varepsilon_{\mathrm{ist}}$ is the idiosyncratic error term. Given the inclusion of county and time effects, the controls included in X should reflect how a county's labour market might vary over time in a manner that differs from other counties.

The primary dependent variables are formed from an extract of quarterly observations of county-level employment and earnings for the *Food Service and Drinking Places* sector (North American Industrial Coding System

(NAICS) sector number 722) in the years 1990–2005. (According to the 2005 CPS-ORG, the *Restaurants and other Food Services* sector, which comprises most of NAICS 722, had the highest percentage of workers at or below the relevant effective minimum wage in the country (14.4 per cent). Moreover, fully 42 per cent of the workers in this sector worked for less than the minimum wage plus two dollars.) The sector includes traditional full-service restaurants, fast food restaurants, cafeterias and stand-alone bars.

The BLS converted from Standard Industrial Classification (SIC) to NAICS coding in 2001, and subsequently reconstructed all pre-2001 QCEW data from SIC into NAICS definitions using establishment information at the time of the transition. Concerns do arise in using the NAICS coding in the pre-2001 data when establishments are identified as operating in very specific sectors. This is particularly the case for establishments in the pre-2001 data that were not extant as of 2001, as there would be no indication in the post-2001 data of the precise NAICS sector for the establishment. Fortunately, a relatively easy match exists between the two industrial coding systems for the *Food Service and Drinking Places* sector as a whole, so this is not a real concern at the level of aggregation we primarily utilize. That said, the retrospective recoding of establishments into *Food Service and Drinking Places* sub-sectors may be less accurate, as a breakdown of this sector was not part of the SIC coding under which the data were originally collected. This creates the potential for measurement errors when looking at these individual sub-sectors separately in the pre-2001 data, as is the case in section 6 when we offer an extension of the primary results. We also note that Dube *et al*. (2008) use an aggregation of the QCEW data that sums the limited-service and full-service restaurant employment levels in their analysis, which in addition limits their sample size as it requires valid data within each of the sub-sectors in a county.

The BLS does censor sector-specific observations on employment and earnings if the number of establishments in the county is below a certain level (typically, fewer than three to five establishments). We perform our estimation on a balanced panel of counties, and so exclude any counties that did not meet the censoring threshold in any of the quarters from 1990 to 2005. Most counties either have valid observations for all 64 quarters or for no quarter, but there are 634 counties with valid observations for part but not all of the time period. (In estimates provided upon request, we show that our results are not sensitive to the balanced panel restriction and that the censoring of counties is not related to the level of the minimum wage.) For the general restaurant-and-bar sector, we have a balanced panel of 1,825 counties, providing 116,800 quarterly observations — or roughly 58 per cent of the potential sample of 3,143 counties in the United States.

The minimum wage variable is calculated as the higher of the state minimum wage (if one exists) and the federal minimum wage. Information on state minimum wages was collected from the discussion of state labour-law changes presented annually in the January edition of the *Monthly Labor*

Review, along with previously published information on state minimum wages at the start of our sample period (see Addison and Blackburn 1999). In the first quarter of 1990, there were 15 states with minimum-wage levels above the federal mandate of \$3.35. Over the next 63 quarters there were 75 state-level increases in the minimum wage exceeding the federal standard, as well as 4 separate federal minimum wage increases. (A table of state minimum wages will be provided upon request.)

Although the use of fixed-effects deals with many of the problems caused by differences in county characteristics that are unchanging over the sample period, the inclusion of additional controls is needed to capture the effects of other factors that might influence employment or earnings and change across the sample over time. The QCEW survey can be used to construct total county employment and average weekly earnings for all industries combined. The inclusion of total county employment and earnings helps to control for the county-level status of the labour market, with the average earnings variable potentially reflecting any equilibrium tendency towards high wages in general in a county.

Other measures that may be relevant to outcome indicators in low-wage labour markets were obtained from sources other than the QCEW. We take county population from the US Census Bureau's Population Estimates Program. Unemployment rates at the county level are available from the Local Area Unemployment Survey. School enrolment rates comprise the percentage of individuals aged 16–24 years enrolled, and are measured at the state level using the Current Population Survey.

Detailed summary statistics for all variables included in our models are given in Table 1. Data from all 50 states (the District of Columbia is excluded) are contained in our samples. Average employment in the restaurant-and-bar sector is about 8 per cent of average total private employment. Average weekly earnings in restaurants and bars is only 31 per cent of the total average. In those counties in our sample where the state minimum exceeded the federal minimum at any time over the period studied, the difference between the state and federal averaged \$0.33 (it was \$0.90 in the quarters where the state was actually above the federal value). The most noticeable difference is that both total employment and population in these counties were more than twice as large as in counties always at the federal minimum. Above-federal-minimum states tend to have a small number of highly populous counties, as reflected in the fact that 38 per cent of states are in the above-federal-minimum category but only 28 per cent of our county/quarter observations come from these states. This is largely a reflection of the historical tendency towards smaller counties in the southern part of the United States, an area with no state minimum-wage increases, while counties in the West tend to be much larger (e.g. Los Angeles county has over 9 million people) and more densely populated in the Northeast. The substantial difference in population size led us to consider weighted least squares estimation of our models, as discussed in the next section.

TABLE 1
Descriptive Statistics for the County Sample: 1990–2005

Variable	*Mean (standard deviation)*		
	All counties	*Counties with federal minimum wage effective throughout sample*	*Counties with state minimum wage above federal level (at least one quarter)*
Restaurant-and-bar employment	3,883 (10,493)	2,927 (7,255)	6,292 (15,784)
Restaurant-and-bar average weekly earnings	167 (44)	162 (39)	178 (51)
Total private employment	50,712 (151,268)	36,491 (97,652)	86,767 (235,121)
Total private average weekly earnings	536 (135)	521 (123)	571 (154)
Population (annual)	135,949 (365,589)	97,096 (214,599)	234,482 (587,047)
Unemployment rate (all industries)	5.86 (2.71)	5.80 (2.71)	6.02 (2.69)
Real minimum wage (2005 dollars)	5.66 (0.44)	5.57 (0.30)	5.90 (0.60)
Enrolment rate (state-level)	0.46 (0.11)	0.46 (0.10)	0.48 (0.11)
Sample size	116,800	83,776	33,024

Note: All wage and earnings variables are in 2005 dollars.
Sources: Bureau of Labor Statistics, Quarterly Census of Employment and Wages; Bureau of Labor Statistics, Monthly Labor Review; Bureau of Labor Statistics, Local Area Unemployment Survey; US Bureau of the Census, Population Estimates Program; and US Bureau of the Census, Current Population Survey.

5. Estimation results

Basic Models

As a first examination of the correlations in the data, we estimated models that incorporate fixed county and time effects but for which the only right-hand side variable is the log of the minimum wage. The dependent variables are, respectively, the log of employment, and the log of average weekly earnings, both for the restaurant-and-bar sector. Standard errors are adjusted for clustering at the state level. The employment effects are reported in the first column of Table 2 and point to a statistically significant negative effect of the minimum wage on restaurant-and-bar employment. The estimates in the second column strongly support the notion that increases in the minimum wage feed through into average weekly earnings in the restaurant-and-bar sector. The implied estimate of the elasticity of labour demand in this sector is roughly –0.9. This is calculated as the ratio of the minimum-wage coefficient estimate in the employment equation to the minimum-wage coefficient estimate in the earnings equation, as suggested by equations (1) and (2). The estimated coefficient for the minimum-wage variable is of a magnitude similar to that reported in most analyses using state-level panel data

TABLE 2
Regression Estimates of Employment and Earnings Equations for the Restaurant-and-Bar Sector

Independent variable	*Ordinary least squares (a)*				*Weighted least squares (b)*			
	Employment	*Earnings*	*Employment*	*Earnings*	*Employment*	*Earnings*	*Employment*	*Earnings*
Minimum wage	–0.198**	0.229**	–0.230**	0.223**	–0.115*	0.215**	–0.098**	0.201**
	(0.084)	(0.040)	(0.079)	(0.031)	(0.067)	(0.024)	(0.039)	(0.021)
Population			0.474**	0.072**			0.329**	–0.057
			(0.077)	(0.024)			(0.099)	(0.038)
Total employment			0.518**	0.106**			0.591**	0.156**
			(0.044)	(0.017)			(0.052)	(0.025)
Total average weekly earnings			–0.311**	0.158**			–0.138**	0.194**
			(0.046)	(0.014)			(0.048)	(0.032)
Unemployment rate			0.000	0.000			–0.001	0.001
			(0.001)	(0.001)			(0.002)	(0.001)
Enrolment rate			–0.027	–0.073**			–0.086**	–0.054**
			(0.049)	(0.021)			(0.042)	(0.021)
R^2	0.99	0.91	0.99	0.92	0.99	0.95	0.99	0.96

Notes: All dependent variable and independent variables are in logarithmic form, with the exceptions of the unemployment rate and enrolment rate. The standard errors in parentheses are corrected to allow for possible non-independence of observations within a state. All regressions included fixed-effects for county and quarter. Regressions in panel (b) are weighted by the average population in their respective county. Sample size in all regressions is 116,800.
**,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

(see, in particular, Neumark and Wascher 2006). But to the extent that these studies have mainly looked at teenagers — a higher percentage of whom work at the minimum wage than is the case for overall employment in this sector — our basic estimates are perhaps larger in magnitude than traditionally observed in the literature.

Estimated models that incorporate additional controls for supply-and-demand factors are reported in the third and fourth columns of Table 2. The estimated minimum-wage coefficients are similar to those in the equations without controls and continue to suggest a labour demand elasticity of around –1. Not surprisingly, a larger total employment and county population tend to be associated with increases in restaurant-and-bar employment. They also have small positive effects on sectoral earnings. Counties with higher average earnings in general also appear to have higher sectoral earnings but lower employment, a result that is consistent with an inward shift of the labour supply schedule in this particular labour market. There is little evidence of an enrolment-rate effect on employment, although this variable has a negative coefficient estimate in the average earnings equation. This result could reflect higher enrolment rates increasing supply (with restaurant-and-bar employment conducive to school attendance and work) while attenuating demand. Unemployment rates do not appear to be an important factor in either equation.

Although estimated at the county level, these findings are quite consistent with most of the earlier state-level studies. As much of this early research has used standard errors appropriate only under the assumptions of homoskedasticity and zero intra-state correlations, our findings suggest that negative employment results can still be supported in an analysis that is robust to these assumptions.[1]

Weighted Estimation

Our ordinary least squares estimators implicitly give equal weight to each county, although it is not obvious that the assumption of equal weighting is appropriate. Research using geographically oriented data often uses estimates that incorporate population-based weights. One argument for doing so is that the error variance is related to population, so that correcting for this heteroskedasticity could improve efficiency. The possibility we consider is that the idiosyncratic error terms in the log employment and log earnings equations tend to vary less for larger-sized populations, suggesting that large-population counties should play a greater role in estimation than small-population counties. It is still possible to calculate standard errors that are robust to arbitrary heteroskedasticity and intra-state correlation, such that a misspecification of the weight in our estimation should not lead to invalid inferences.

Our weighted least squares estimates are reported in the final four columns of Table 2. Two things are noteworthy about these estimates. First, the standard errors are considerably smaller for the coefficient estimates of the minimum-wage variable — in both specifications and for both dependent variables. This would seem to be indicative of an increase in precision from weighting. (On the other hand, this increase in precision does not carry over to most other variables in the equation.) More importantly, the basis for a minimum-wage effect on employment is lessened in the weighted results (notwithstanding the statistically significant coefficients), even though the standard errors fall. In short, weighting substantially lowers the minimum-wage coefficient estimate in the employment equations (but not the earnings equations).

The difference in the weighted and unweighted coefficient estimates is somewhat surprising, as both should be consistent estimates of the true regression parameters. DuMouchel and Duncan (1983) note that a difference between weighted and unweighted estimates can reflect an omission of important factors from the equation. One possibility could be that the minimum-wage effect actually varies across counties, so that the weighted estimator better reflects the average effect in larger counties. For example, large-population counties tend to have higher average wages, and if the minimum-wage coefficient for employment is lower in high-wage counties, we would expect a lower coefficient estimate when we weight larger counties more heavily — so that in this case the omitted factor would be an interaction between average wages and minimum wages. The fact that these estimates differ suggests that we should consider a richer specification than used in Table 2, which we do below.

County-Specific Trends

Our models control for systematic differences in restaurant-and-bar employment determination across counties, but only for those differences that are stable over time. When using panels over a long-term period, this assumption of stable county effects may not be appropriate. One straightforward way to generalize this specification of county effects is to also allow for a systematic change in the county-specific effect over time, where the degree of change can differ across counties. This incorporation of unit-specific trends in the error term of the model has become increasingly common in studies using long panels. The inclusion of these trends helps to address the possibility that restaurant-and-bar employment is trending differently in states that increased their minimum wages compared with states that stuck with the federal minimum (and so witnessed a declining trend in the real minimum wage).

We modify our basic empirical model (equation 3) to include county-specific trends, as follows:

$$\log(Y_{ist}) = \varphi \log(MW_{st}) + \gamma X_{ist} + \mu_i + \lambda_i t + \tau_t + \varepsilon_{ist}, \tag{4}$$

where λ_i is a trend coefficient that varies across counties. Wooldridge (2002: 315–22) discusses two procedures for the estimation of this ‘random growth’

TABLE 3
Regression Estimates for Equations with County-Level Trends

Independent variable	*Employment*	*Earnings*
Minimum wage	–0.006	0.171**
	(0.033)	(0.035)
Population	0.277**	0.029
	(0.066)	(0.059)
Total employment	0.763**	0.207**
	(0.061)	(0.024)
Total average weekly earnings	–0.129**	0.133**
	(0.035)	(0.030)
Unemployment rate	0.001	–0.002**
	(0.002)	(0.001)
Enrolment rate	–0.083**	–0.049**
	(0.025)	(0.016)
R^2	0.99	0.97
p-value: Hausman test	0.0000**	0.0000**

Notes: See notes to Table 2. All regressions are weighted by the county's average population. The *p*-value reported is for a Hausman test of the null hypothesis that the probability limits of the coefficient estimates for the six continuous independent variables in each specification are the same in specifications with and without county-specific trends. Sample size in all regressions is 116,800.
**,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

model. First, it is possible to estimate the model using first differences, but this discussion is remitted until later. Second, an alternative approach analogous to the fixed-effects estimator is to directly control for the county-specific constants and trends in the estimation by sweeping out a county-specific linear trend for each variable in the model. This procedure entails estimating a simple linear trend model for each variable in the equation and using the residuals to estimate the parameters of interest. OLS estimation using these detrended variables is then appropriate (although the standard errors must be corrected to acknowledge the loss of 3,650 degrees of freedom occasioned by the estimation of separate trends in the error term for each county).

Table 3 reports estimates using the detrended data. The estimated elasticity of restaurant-and-bar employment to the minimum wage is still negative, but it is now very small and statistically insignificant.[2] The estimated earnings elasticity is also somewhat smaller, but the impact remains significant. As a result, the derived estimate of the labour-demand elasticity is quite small (–0.035). Employment in the restaurant-and-bar sector tends to exhibit a downward long-term trend in states that have increased their minimum wages *relative* to states that have not, biasing the fixed-effects estimates in Table 2 towards finding a negative employment effect of minimum wages. A similar pattern of results is obtained if we use state-level trends in place of the county trends. These results suggest that studies identifying employment effects by using variation in state minimum-wage laws must worry about the role of geographic-specific employment trends in their estimation.

One concern with these results stems from the possibility that the relative downward employment trend in states with above-federal minimum wages is itself caused by the higher minimum wages. Higher minimum wages may not immediately impact restaurant-and-bar employment, but they may lower its growth in a county in subsequent years. In results not reported here, we did examine the potential for lagged effects of minimum wages on employment, finding little such evidence. To focus on the particular nature of the relative trends, however, we decided to examine the evolution of restaurant-and-bar employment (as a share of total employment) more closely. Specifically, we separated counties in states that raised their state minimum at any time above the federal minimum from those other counties that did not (i.e. were always at the federal level). The restaurant-and-bar employment share was actually very similar in these two sets of counties over the 1990–2005 interval, being 8.6 per cent in states that raised their minimum at any time and 8.9 per cent in states that always stayed at the federal minimum. Both groups of counties also experienced an increase in their restaurant-and-bar employment share over this period, although it remains the case that the share was increasing less rapidly in those states raising their minimum. However, for counties in this latter group, the rate of increase in employment actually rose after the state minimum was increased (albeit at a smaller rate than for counties in states sticking with the federal minimum). The reasons for this difference in underlying trends are not obvious — it may have something to do with regional differences in preferences for eating out. In any case, it is obvious that the idea that raising the minimum wage might have caused a slowdown in the simple rate of restaurant-and-bar employment growth in these counties is not supported, as the evidence suggests that employment actually grew faster after the increase than before.

Having addressed the raw trends in employment, we next consider a potential shift in the regression model's employment trend more directly. To this end, we re-estimated the models in Table 3 incorporating a new variable that allows the trend effect to shift when a county's minimum wage is above the federal minimum. This was accomplished by including the variable $(\log(MW_{st}) - \log(\text{federal } MW_t) * \text{subtrend}_{st}$ in the regression, where 'subtrend' is a variable that measures the current number of contiguous quarters that the state's minimum has exceeded the federal minimum. This additional variable allows for a spline in the trend, based on the number of quarters at an above-federal minimum *and* the size of the difference between the state and federal minima. In the employment equation, the coefficient estimate for the interaction term was negative, which is consistent with higher minimum wages reducing the trend in employment. That said, the estimated effect is very small and statistically insignificant — the coefficient (standard error) is –0.0007(0.0008) — while the minimum-wage coefficient itself remains statistically insignificant. The interaction term was also statistically insignificant in the earnings equation. In short, on this evidence there is little to suggest that our controlling for county-specific trends is somehow masking an influence of the state minimum wage causing lower growth in employment.

Returning therefore to the estimates in Table 3, why is it obvious that the results with county-specific trends are to be preferred to the simpler fixed-effects results? Fortunately, the fixed-effects specification is nested within the specification that includes trend effects, so that it is possible to test whether or not the omission of county-level trends in the model leads to an inconsistency in the estimation of the effects of the primary independent variables in the model. We use a Hausman test to investigate the difference in the probability limits of the coefficient estimates between the specifications. The *p*-values for this test are provided in Table 3, and the results allow us to reject the possibility that the coefficients are the same.[3] In other words, the data suggest that the specifications incorporating county-level trends are preferable to those that omit them. We also note that minimum-wage coefficient estimates using ordinary least squares with county-level trends are very similar to the weighted estimates with trends reported in Table 3. As noted above, a difference in weighted and unweighted estimates suggests a possible misspecification, so in this case the differences shown earlier in Table 2 may be reflecting the omission of county-specific trends. It is clear that the specifications with trends are to be preferred, and our primary inference in this article is based on results that use this source of identification.

Models with Interactions

In Section 3, we noted that a simple demand-and-supply model should lead to a coefficient for the log of the minimum wage that is a function of the probability that the minimum wage is effective in that labour market. Although our results in Tables 2 and 3 do help tie our data analysis to previous research on minimum-wage effects, we have yet to account for the possibility that changes in observable factors could affect the likelihood that the minimum wage is binding in a given labour market. We therefore assume that the probability that the minimum wage is effective — *p* in equation (1) — is a linear function of the minimum wage and our demand and supply factors, namely,

$$p_{\text{ist}} = \alpha_0 + \alpha_1 \log(\text{MW}_{\text{st}}) + \alpha_2 \text{X}_{\text{ist}}. \tag{5}$$

Our expectation is that higher minimum wages would make it more likely that the minimum wage is effective (so $\alpha_1 > 0$). Shifts in labour demand and supply should also influence whether the competitive wage is above the minimum; for example, we would expect higher average wages across all industries to increase the competitive wage in the restaurant-and-bar sector, and so decrease *p*. We can estimate the employment equation by extending equation (4) as follows

$$\log(\text{Y}_{\text{ist}}) = p\beta \log(\text{MW}_{\text{st}}) + \gamma \text{X}_{\text{ist}} + \mu_{\text{i}} + \lambda_{\text{i}}\text{t} + \tau_{\text{t}} + \varepsilon_{\text{ist}},$$

which, after substituting equation (5), yields

TABLE 4
Regression Estimates with Minimum Wage Interactions

Independent variable	*Without county-specific trends (a)*		*With county-specific trends (b)*	
	Employment	*Earnings*	*Employment*	*Earnings*
Minimum wage	2.555**	−0.254	0.524	−0.476
	(0.949)	(0.695)	(0.394)	(0.350)
Population	0.383**	0.017	0.189*	0.292**
	(0.148)	(0.098)	(0.111)	(0.077)
Total employment	0.562**	0.048	0.892**	0.196**
	(0.142)	(0.087)	(0.108)	(0.052)
Total average weekly earnings	−0.750**	0.410**	−0.201	0.407**
	(0.212)	(0.161)	(0.171)	(0.153)
Unemployment rate	−0.036**	−0.019**	−0.015	−0.030**
	(0.014)	(0.007)	(0.013)	(0.006)
Enrolment rate	0.139	0.008	−0.209	−0.178
	(0.241)	(0.182)	(0.256)	(0.155)
Minimum wage squared	−0.762**	0.120	−0.139	0.184*
	(0.270)	(0.194)	(0.106)	(0.095)
Minimum wage interactions				
County population	−0.026	−0.046	0.056	0.002
	(0.058)	(0.049)	(0.043)	(0.030)
Total employment	0.020	0.065	−0.071	0.009
	(0.068)	(0.050)	(0.046)	(0.029)
Total average weekly earnings	0.339**	−0.121	0.043	−0.153**
	(0.113)	(0.077)	(0.095)	(0.076)
Unemployment rate	0.020**	0.012**	0.009	0.016**
	(0.008)	(0.004)	(0.007)	(0.003)
Enrolment rate	−0.126	−0.035	0.073	0.074
	(0.125)	(0.099)	(0.139)	(0.087)
R^2	0.99	0.96	0.99	0.97

Notes: See notes to Table 3. All minimum wage interactions were created by multiplying the minimum wage by the deviation of each control variable from its own mean. Sample size in all regressions is 116,800.
**,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

$$\log(\mathrm{Y_{ist}}) = \alpha_0\beta\log(\mathrm{MW_{st}}) + \alpha_1\beta\log(\mathrm{MW_{st}})^2 + \alpha_2\beta\log(\mathrm{MW_{st}})\mathrm{X_{ist}} + \gamma\mathrm{X_{ist}} + \mu_\mathrm{i} + \lambda_\mathrm{i}\mathrm{t} + \tau_\mathrm{t} + \varepsilon_\mathrm{ist}. \tag{6}$$

Equation (6) can be estimated by adding controls for the squared minimum-wage variable, along with interactions of the log minimum wage with X. A similar equation would hold for the log-earnings model (although the labour-demand elasticity β would not now appear). These types of minimum-wage interactions do not seem to have been considered in the previous literature.

Estimates of the models incorporating interactions are presented in Table 4. In these models, the interactions are formed by multiplying the log of the minimum wage by the other variables deviated from their sample means. This procedure implies that the non-interacted minimum-wage coefficient estimates can be treated as estimates when the other controls are equal to their means. Models with and without county-specific trends are included in Table 4. The sensitivity of the results to incorporating these trends leads us to base our inferences on the last two columns of the table.

Estimates of the employment equation suggest that adding the interactions and squared terms does not provide clear evidence favouring their inclusion, as their coefficient estimates are not individually statistically significant. Nevertheless, we are able to reject the hypothesis that jointly the interactions have no impact on the dependent variable (p-value = 0.003). And there is stronger evidence to suggest that the addition of these terms is relevant in the log-earnings equation. The county-wide average earnings interaction has a statistically significantly negative coefficient estimate, suggesting that higher-wage counties will tend to have a lower probability of the minimum wage being effective. The results also support an increasing impact of the unemployment rate on this probability, as we would expect. The squared minimum-wage variable has a statistically significantly positive coefficient estimate, suggesting that higher minimum wages also increase p. Although the other interactions are not statistically significant, it is less obvious that shifts in these other factors should have such a clear impact on the competitive wage. For its part, the estimated minimum-wage impact on log earnings has a similar magnitude to earlier tables; for example, the elasticity of earnings with respect to the minimum wage at a minimum wage of $6 is estimated to be 0.183.[4]

The fact that there are expected nonlinear and interaction effects in the earnings equation but not the employment equation may seem a weakness of the results, but this is in fact consistent with a very low labour-demand elasticity in the industry. Given that the minimum-wage interaction coefficients in the employment equation are all multiplied by this elasticity, it becomes difficult to obtain precise estimates when this elasticity is small. We see the model as consistent with the theoretical model discussed in Section 3, but with a small labour-demand elasticity which leads to the minimum-wage effect showing up mostly in earnings.

6. Alternative estimators and samples

First-Difference Estimates

Most of the minimum-wage research that has used long state-level panels on teenagers or young adults has employed fixed-effects estimators to control for systematic state effects. By comparison, research based on 'natural experiments', or a single change in the federal minimum wage, has used first-difference estimators to remove state effects. Either method is arguably appropriate given the specification in equation (3), as first-differencing also removes the state effect from that equation. Indeed, county-specific trends can easily be handled with a first-difference estimator, as the first difference of equation (4) gives

TABLE 5
Minimum-Wage Coefficient Estimates from Differenced Regressions for Employment and Earnings

Independent variable	*First difference (a)*		*Four-period difference (b)*	
	Employment	*Earnings*	*Employment*	*Earnings*
Minimum wage	0.043 (0.186)	–0.039 (0.125)	–0.016 (0.017)	0.141** (0.031)
R^2	0.45	0.33	0.19	0.14

Notes: See notes to Table 3. These regressions also include the other variables in the specifications used in Table 3. Sample size in panel (a) regressions is 114,975. The sample size in panel (b) regressions is 109,500.
**,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

$$\Delta \log(\mathrm{Y}_{\mathrm{ist}}) = \varphi \Delta \log(\mathrm{MW}_{\mathrm{st}}) + \gamma \Delta \mathrm{X}_{\mathrm{ist}} + \lambda_{\mathrm{i}} + \Delta \tau_{\mathrm{t}} + \Delta \varepsilon_{\mathrm{ist}}.$$

In other words, an estimation of the first-difference equation using a fixed-effects estimator (with both county and quarter effects) should remove both fixed and trend effects at the county level from the model. The appropriate manner of modelling p is not as clear in this model, so we chose to estimate a first-difference model comparable to the models presented in Table 3.

The minimum-wage coefficients from our first-difference estimates are presented in Table 5. The estimated elasticity of restaurant-and-bar employment with respect to the minimum wage is positive but small and statistically insignificant. The minimum-wage coefficient is estimated much less precisely using the first-difference estimator, providing a very wide confidence interval for the estimated elasticity. This factor leads us to base our primary inference on our detrended results, discussed above. Another worrisome aspect of the first-difference results is the negative but statistically insignificant coefficient estimate in the earnings equation (although once again estimated with a very wide confidence interval).

In estimating a given empirical model, first-difference estimates are likely sensitive to only short-run effects of minimum wages, while our detrended model is more likely to be sensitive to long-run reactions (see Baker *et al.* 1999). We estimated our detrended model with one or two lags of the minimum wage but found results similar to our non-lagged results. To examine the possibility that a quarterly change is too short to capture a long-run minimum-wage effect, we also estimated models using a four-period difference in all variables.[5] Presented in the final two columns of Table 5, these results provide estimates that are in general similar to the detrended estimates (of Table 3). Although studies that use quarterly differences to estimate minimum-wage coefficients may be missing some of the impact, the evidence here suggests that a longer-run difference can provide evidence similar to a model estimated using non-differenced data that have been detrended.

State Minimum Changes versus Federal Minimum Changes

A concern sometimes expressed in the literature is that responses to increases in the minimum wage may differ according to whether the change is a state initiative rather than a federal mandate. Bazen and Le Gallo (2009) estimate first-difference models that allow for this possibility and find negative employment effects for federally legislated changes alone. This result is consistent with the argument that state minimum wages are increased primarily when negative employment effects are less likely, leading to an upward bias in the usual state-panel estimates. One limitation of these authors' results is that they do not have year effects in their models that identify separate federal and state minimum-wage impacts. Indeed, when year effects are accounted for there is no evidence of a minimum-wage impact. We performed a similar estimation with our first-difference model, interacting the change in the minimum with a dummy variable indicating whether or not the change was due to a federal increase rather than a state increase (this allows year effects to be maintained in the model). However, we did not find evidence of a statistically significant interaction.

A related concern is that the states that never choose to be above the federal minimum may have systematically different minimum-wage effects on employment than those fixing state minima above the federal. For example, states where the minimum wage is likely to be effective may need to worry more about disemployment effects, and so may choose to stay at the federal minimum. A simple way to check for this possibility is to re-estimate the model using data from only those states that raised their state minimum over the federal minimum at some time during the period under study. If states that raise their own minimum wages are those who see little reason to expect employment decreases, then we should expect to see even less evidence of minimum-wage effects in this case.

Table 6 reports detrended estimates using this sub-sample. Rather than finding less evidence of a negative wage impact in these states compared with the full-sample results in Table 3, we actually find a statistically significant negative employment effect within this set of states (the impact on earnings is positive, as before). As a higher state minimum may be indicative of a minimum wage that is more likely to be effective, we also estimated the interactive model of Table 4 using this sub-sample. If a higher minimum increases the probability that the minimum wage is binding, we should expect to see a positive coefficient on the squared minimum-wage variable in the average earnings equations. The results are consistent with this expectation. The average wage across all industries also has the expected negative impact in the earnings equations, suggesting that the minimum wage is less effective when the average wage increases. Not only are these results as anticipated, they are also similar to those for the full sample reported in Table 4. That said, the results for the employment equation are not so easy to interpret. Thus, although the coefficient for the level of the minimum wage is negative, we do not obtain the expected negative sign on the squared minimum-wage

TABLE 6
Regression Estimates Using the Sample of Counties in States that Raised their Minimum Wages Above the Federal Minimum at Some Point during 1990–2005

Independent variable	*Non-interacted*		*Interacted*	
	Employment	*Earnings*	*Employment*	*Earnings*
Minimum wage	–0.090**	0.159**	–0.951	–0.462
	(0.026)	(0.030)	(0.555)	(0.321)
Minimum wage squared			0.240	0.174*
			(0.145)	(0.083)
Minimum wage interactions				
Population			0.093	0.034
			(0.163)	(0.040)
Total employment			–0.100	–0.017
			(0.077)	(0.043)
Total average weekly earnings			0.093	–0.159
			(0.163)	(0.097)
Unemployment rate			0.006	0.014**
			(0.007)	(0.004)
Enrolment rate			0.108	0.040
			(0.184)	(0.096)
R^2	0.99	0.98	0.99	0.98

Notes: See notes to Table 4. Regressions include the same additional controls as in the Table 3 and Table 4 regressions, respectively. The sample size in all regressions is equal to 33,024.
**,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

variable. Nevertheless, neither the squared minimum-wage coefficient nor the other interactions are statistically significant in the employment equation. We take these results as indicative of a tendency for minimum-wage effects to vary across geographic areas in a way that for this set of states is not adequately captured in our interactions. In fact, the possibility of this type of variation in minimum-wage effects has not been considered previously in the economic literature but may be deserving of a closer scrutiny.

Separate Estimates for Fast Food and Traditional Service Restaurants

Up to this point, our estimates have used employment across all establishments in the Food Service and Drinking Places sector of the QCEW. It is possible to disaggregate these sectors, as the NAICS coding system distinguishes four sub-sectors of the industry. Separate estimation for two of the sub-sectors was not pursued, given the large number of censored counties that occur in the (Alcoholic Beverage) Drinking Places sub-sector and the Special Food Services sub-sector (comprising caterers and mobile food services). However, we have re-estimated our models separately for the remaining two sub-sectors: Full-Service Restaurants (NAICS Code 7221) and Limited-Service Eating Places (NAICS Code 7222), subject to the caveats entered in Section 4.

One reason for examining Limited-Service Eating Places separately is that this sub-sector provides a more direct link to the previous minimum-wage studies that have focused on fast-food restaurants. We did not isolate this industry initially, as our estimate of the average weekly wage within the limited-service sub-sector was not substantially different — specifically, 7.5 per cent less — from the full-service sub-sector. But there are a number of reasons to anticipate that minimum-wage effects could differ across full-service and limited-service sub-sectors, even if they share a similar probability of being affected by minimum-wage increases. If labour costs are a greater share of total costs in limited-service restaurants, the labour-demand elasticity could be larger (in absolute magnitude) in that sector. Empirical evidence has shown that limited-service restaurants raise their output prices significantly more than full-service restaurants after a minimum-wage increase (e.g. see Aaronson *et al.* 2008). On the other hand, this could be because of a more inelastic product demand in the limited-service sector. Hence, the relative size of the labour demand elasticities in these two sub-sectors is not transparent. A final issue is that our average weekly wage estimates do not reflect possible differences in average hours worked per week; if average hours are lower in full-service restaurants, it may be that there is actually a greater probability of the minimum wage being effective in limited-service restaurants (as the average hourly wage would be lower). Unfortunately, information on hourly wages within these two sub-sectors is not available from US Census sources, as the Census industry codes do not distinguish between limited-service and full-service restaurants.

Estimates of our employment and earnings equations by sub-sector are provided in Table 7. These weighted estimates incorporate county-specific trends to ensure comparability with the weighted estimates in Table 3. These estimates provide a marginally statistically significant negative effect of minimum wages on employment in the limited-service sub-sector (implying a labour-demand elasticity of –0.33), while the estimated effect in the full-service sub-sector is positive and statistically significant. The estimated impact on earnings is also larger in the limited-service sub-sector, consistent with the speculation that minimum wages are more likely to be binding in limited-service restaurants.

TABLE 7
Minimum-Wage Coefficient Estimates for Sub-Sectors of the Restaurant-and-Bar Sector

Independent variable	*Limited-service restaurants*		*Full-service restaurants*	
	Employment	*Earnings*	*Employment*	*Earnings*
Minimum wage	–0.083*	0.252**	0.148**	0.137**
	(0.049)	(0.070)	(0.066)	(0.030)
R^2	0.99	0.91	0.99	0.95
Sample size	115,008		105,088	

Notes: See notes to Table 3. These regressions also include the other variables in the specifications used in Table 3.
**,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

7. Summary and discussion

We have used county-level data on employment and earnings in the US restaurant-and-bar sector to consider the impact of minimum-wage changes on wage and employment outcomes in low-wage labour markets. The analytical framework of our empirical model is similar to the literature that has used state-level panels to estimate minimum-wage impacts, but our focus is on a sector that has primarily been analysed using datasets with insufficient geographic variation to reliably identify minimum-wage effects. Our estimates are consistent with a simple competitive model of the restaurant-and-bar labour market in which supply-and-demand factors also affect the probability that a minimum wage will be binding in any given time period.

In our estimated models, a control for local-level trends has an important influence on the estimated minimum-wage coefficients. Employment in the restaurant-and-bar sector appears to exhibit a downward long-term trend in states that have increased their minimum wages *relative* to states that have not, thereby biasing fixed-effects estimates towards obtaining negative employment effects. Our findings imply that studies seeking to identify employment effects by using variation in state minimum-wage laws need to be greatly concerned about the neglect of geographic-specific employment trends in their estimation. After making this correction, we fail to find statistically significant evidence that increasing the minimum wage reduces restaurant-and-bar employment. One possible explanation may be the existence of a very low-labour demand elasticity in this sector, one that leads to statistical difficulty in uncovering any employment decline. It could also be that minimum-wage changes affect product demand in this sector, which would also mitigate any minimum-wage impacts in equilibrium. The results generated for two separate sub-sectors of the industry are intriguing in this regard: our finding of no disemployment in the overall sector seems to be the sum of a small negative effect in the limited-service sector and a small positive effect in the full-service sector. This difference in effects could be due to differential impacts of minimum wages on costs in the two sub-sectors, but it might also reflect relative product-demand shifts as higher wages lead to full-service restaurants being more attractive than their limited-service counterparts.

With a few exceptions, minimum-wage case studies have focused on the restaurant sector. The obvious justification for this focus is the relatively large percentage of workers who are paid at the federal minimum in that sector. The sector's high labour-turnover rate also suggests that adjustments of employment to changes in costs can be fairly rapid. Yet there are a number of weaknesses attaching to this restricted focus. Restaurants may show lower labour-demand elasticities than establishments in other sectors that can be more mobile in their choice of location. (Production in the restaurant sector needs to be geographically close to the consumer, but this is not true in other sectors such as manufacturing.) There may also be a level of product differentiation in the restaurant sector that allows a significant pass-through of higher labour costs into product prices. Accordingly, the case-study emphasis on this sector may not offer the best environment for uncovering negative employment effects. In a concurrent project, we have therefore examined minimum-wage impacts in other disaggregated low-wage sectors at the county level (Addison *et al*. 2009). This study also fails in general to uncover adverse employment effects of increases in the minimum wage.

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Notes

1. Standard errors fall considerably in the absence of clustering, so that our results are also statistically significant if the need for clustering is ignored.
2. This change in statistical significance is not due to a decrease in the precision of the minimum-wage coefficient estimates, as could happen if the removal of county-level trends eliminated a large share of the relevant variation in the minimum-wage variable. In fact, detrending actually leads to a smaller standard error of the minimum-wage estimate in the employment equation, which in turn suggests that there is sufficient residual variation in the policy variable to estimate the effect with a reasonable degree of precision.
3. This test focuses on the coefficients for the six continuous variables only. A standard Hausman test is not appropriate, as the potential correlation in error terms (recognized in the use of clustered standard errors) implies that the fixed-effects estimator is not efficient under the null. Instead, we use a variance estimator (for the difference in coefficient estimates) that allows the two sets of coefficient estimates to be correlated (see Cameron and Trivedi 2005: 271–3 for details).
4. This is the estimated elasticity when other supply-and-demand factors are at their sample means. Given that interactions are defined using deviations from means, the elasticity is the first derivative of the quadratic function evaluated at a \$6 minimum, which becomes $-0.476 + 2(0.184)\log(6) = -0.183$.
5. In particular, we formed differences as the value of the variable in the current quarter minus its value in the same quarter of the previous year. This approach is likely to create a moving-average process in the error term of the estimated equation, but this does not bias the coefficient estimates and is handled by clustering at the state level in calculating our standard errors.

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