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

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Abstract

We use county-level data on employment and earnings in the restaurant-and-bar sector to evaluate the impact of minimum wage changes on low-wage labor markets. Our empirical approach is similar to the literature that has used state-level panel data to estimate minimum-wage impacts, with the difference that we focus on a particular sector rather than demographic group. Our estimated models are consistent with a simple competitive model of the restaurant-and-bar labor market in which supply-and-demand factors affect both the equilibrium outcome and the probability that a minimum wage will be binding in any given time period. Our evidence does not suggest that minimum wages reduce employment in the overall restaurant-and-bar sector, after controls for trends in sector employment at the county level are incorporated in the model. Employment in this sector appears to exhibit a downward long-term trend in states that have increased their minimum wages *relative* to states that have not, thereby predisposing fixed-effects estimates towards finding negative employment effects.

Does increasing the minimum wage lead to lower employment? At one time, the answer from economists was an emphatic yes. Theory pointed in this direction, as did the early round of statistical estimates from labor economists. But the conventional wisdom was challenged in a series of studies by Card (1992a, 1992b), Katz and Krueger (1992), and Card and Krueger (1994) that instead indicated minimal, even positive employment effects. Unlike the earlier research using time-series evidence, this new literature focused on employment changes accompanying isolated increases in the minimum wage, often exploiting geographic variation in the likely impact of these increases. These new findings did not go uncontested. For example, in updating the earlier time-series research to accommodate cross-state variation in minimum wages, Neumark and Wascher (1992) obtained results that were generally consistent with the prior received wisdom.

Although the "new" minimum-wage research largely used geographic variation to help identify employment effects, the underlying studies did so in quite different ways. Neumark and Wascher (1992) exploited a long panel of state-level observations on teenager and young adult employment to study the relationship with the state's minimum wage. This estimation approach allowed for a fixed state effect in employment outcomes, albeit one assumed not to vary over time. For their part, Card and Krueger (1994) studied employment among franchised restaurants in the fast-food sector in two states (New Jersey and Pennsylvania), with two observations per restaurant surrounding a 1992 increase in the minimum wage in New Jersey. The first-difference estimation technique employed by Card and Krueger also allowed for a state effect – and one that could in principle vary over time – but focused on a restricted geographic area.[1] As has been argued previously, this restriction in the geographic focus may have provided a natural experiment that statistically speaking is uninformative.

The major purpose of the present study is to combine the approaches of Neumark and Wascher (1992) and Card and Krueger (1994), so as to determine the sensitivity of the estimated minimum-wage effects to some of the modeling decisions made in these studies. Using county-level data on employment, we estimate panel-data models similar to those of Neumark and Wascher, being careful to consider the importance of the assumptions made about the error-correlation structure. For the most part, our estimation strategy is similar to theirs. The primary difference is that we focus on a particular sector (restaurants and bars) rather than a particular demographic group (teenagers). This sectoral focus is similar to that of Card and Krueger, though we are able to extend the geographic reach considerably. In general, our findings do not support the negative employment effects predicted for minimum wages. Our estimates are otherwise consistent with a competitive model, however, in suggesting a very small elasticity of labor demand in the restaurant-and-bar sector. And there is a further qualification: when we examine the fast-food part of the restaurant-and-bar sector does there is some indication of a negative employment effect in the wake of higher minimum wages.

I. Statistical Problems in the Minimum-Wage Literature

The empirical evidence concerning minimum-wage impacts has been surveyed on numerous occasions, both in respect of the initial aggregate time-series studies (for

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[1] The other studies by Card, Katz and/or Krueger also tended to use first-difference approaches over a short time series

example, Brown, Gilroy, and Kohen, 1982) and the state-based estimations of more recent vintage (both Brown, 1999, and Neumark and Wascher, 2006, provide useful summaries). The time-series evidence generally suggested minimum-wage impacts that were small and declining over time, while the later, and arguably preferable, evidence from studies making use of both time-series and cross-section variation produced no general consensus. Hence, the most recent literature has in part sought to reconcile the disparate findings of the initial cross-state studies.

There is a potential statistical complication in much of the research using cross-state variation in minimum wages that may have led to an overstatement of the precision of estimates generated in the literature. We refer to the problems of inference that arise when using "difference-in-difference" estimates, as documented by Bertrand, Duflo, and Mullainathan (2004) and Donald and Lang (2007). The former authors show that difference-in-difference estimates can be interpreted as estimates from a fixed-effects panel-data regression with policy-related independent variables that are often measured at a higher level of aggregation than the dependent variable. For example, in the Card and Krueger (1994) regression 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. Similar to Moulton (1990), Bertrand, Duflo and Mullainathan argue that the assumption that error terms are uncorrelated across restaurants in the same state/time-period can lead to severely biased inference if the actual correlation in these observations is nonzero.

When there is the potential for a high degree of potential correlation in the error terms within cross-sectional units over time, an increasingly common approach to statistical inference with panel data is to use “panel-corrected standard errors” (originally due to Liang and Zeger, 1986). Bertrand, Duflo and Mullainathan (2004) note that this is a strategy that can work relatively well, as long as the number of cross-sectional units (in this case, the number of states) is relatively large. A 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.

For their part, Donald and Lang (2007) raise an additional point concerning the estimation of policy impacts using natural experiments with a limited geographic range. Specifically, a required assumption in the approach of Card and Krueger (1994) is that the only possible reason for a difference in the average change in employment between New Jersey and Pennsylvania is the minimum-wage increase that occurred in New Jersey. It would seem more appropriate to assume that this difference in averages could also be affected by other (unobserved) changes between the two states.[2] If so, the Card-Krueger difference-in-difference estimate of the policy impact does not follow a well-defined distribution, even as the number of restaurants surveyed in each state approaches infinity.[3] The concerns over proper measurement of the dependent variable – a major

[2] For example, if changes in the macro economy affected restaurant employment differently in New Jersey and Pennsylvania, the implicit assumption of Card and Krueger would be incorrect.

[3] The result of Donald and Lang is that, in this case, the appropriate distribution is a t-distribution with S-2 degrees of freedom, where S is the number of states in the sample. In Card and Krueger this is 0 degrees of freedom. These issues are also relevant in our later analysis, although the use of 50 states mitigates these concerns to a great extent.

source of contention between Neumark and Wascher (2000) and Card and Krueger (2000) – become moot once this shortcoming of the natural experiment is acknowledged.

Differences in the level of aggregation between the dependent and independent variables would appear to be less important in the study by Neumark and Wascher (1992). Both the dependent and independent variables vary across states and time-periods, and the number of states used in the estimation is reasonably large. Neumark and Wascher do assume non-correlation in the error terms over time within states (after removing fixed effects), and a violation of this assumption would imply that their standard errors are inconsistent. Inference robust to this intrastate correlation can still be performed (and the results in Neumark and Wascher, 2007, still suggest a negative employment effect after correcting standard errors). Deere, Murphy, and Welch (1995) have also pointed to potential biases arising from cross-state variation in underlying trends when these trends are correlated with the minimum-wage measure. While their criticism was directed at the work of Card (1992a), it is also a concern for the type of empirical approach used in Neumark and Wascher (1992). In our case, we measure minimum-wage impacts over a 16-year period, and it would seem somewhat unlikely that the tendency for a state to be above or below the economy-wide average in employment would not vary over this period. As we show later, this becomes a particular concern when the evolution of the minimum-wage variable may be correlated with this state-level trend in employment.

Our models are estimated using county-level data from the Quarterly Census of Employment and Wages (QCEW). We are not the first to use these data in studying minimum wages. Kim and Taylor (1995) used the data for counties in California to study the 1988 increase in the California minimum wage, obtaining some evidence of a negative employment effect. Another case study that used the QCEW is Orazem and Mattila (2002), who report evidence of a disemployment effect from the 1990-91 federal minimum changes among counties in Iowa.[4] Both analyses are quite limited in their geographic focus, however, and are moreover susceptible to the criticisms of Betrand, Duflo, and Mullainathan (2004) if there are substantial state-level effects in employment. Both Neumark and Wascher (2000) and Card and Kruger (2000) also made use of the QCEW data in their discussion of the New Jersey/Pennsylvania experiment, but did not expand the analysis past the original limited focus.

A limited geographic focus is not a concern in the very recent analysis of Dube, Lester, and Reich (2007).[5] They make use of the QCEW data from 1990-2006 in the restaurant sector to generalize the case-study approach, while also allowing a comparison with the national panel studies. Their approach is based on comparisons of state-border counties (or counties within general metro areas that contain state borders), allowing for a county-pair effect that is specific to each time period. Variation in minimum wages between border counties then allows for the identification of minimum-wage effects. This identification is similar to that used in Card and Krueger (1994), but does not suffer from the inference problems of that study given the large number of border-county

[4] Both of these studies garner the identification of their minimum wage effects through the variation in average wages across counties. This identification strategy is doubtful if average wages affect employment holding constant the minimum-wage/average-wage ratio. We shall argue that there are both theoretical and empirical reasons to doubt this identification.

[5] We became aware of their study in the course of our own. Their approach is similar to ours in their use of a nationwide sampling frame in a county-level analysis of the QCEW data. Although there are several small differences between the two studies in sectors and method of examination, the main difference resides in how we control for county-level differences in employment associated with factors other than the minimum wage.

comparisons used in the estimation. Their results suggest little evidence of minimum-wage effects on employment once county-pair effects are controlled for in the model.

Our paper also makes use of a nationwide county-level sample from the QCEW, but our estimation approach is closer to Neumark and Wascher (1992) than to Card and Krueger (1994). A key extension of our analysis is to allow for county-specific trends in employment and earnings in the restaurant-and-bar sector. We also incorporate additional county-level factors that potentially affect employment and earnings. Estimation of models with these additional factors allows us to assess the extent to which our results are consistent with a competitive-model explanation of employment and earnings determination.

II. 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 labor markets that assumes the minimum wage exceeds the market-clearing wage. Discussions of the relevance of two-sector models in which part of the labor market is not covered by the minimum wage might also be included (see, for example, Brown, 1999), though the high coverage rates of minimum wage laws in recent years have generally led recent studies to discount the importance of such concerns. The fact that potential employees in the studied markets might earn above the minimum wage is often pointed out in interpreting the results of estimated models, where it is noted that the estimated employment elasticities with respect to minimum wages tend to understate the related labor-demand elasticities.

The following stylized model of low-wage labor markets explicitly takes into account the possibility that studied markets may have market-clearing wages above the minimum. The model starts by assuming constant-elasticity forms for labor supply and labor demand in a market. In particular, let labor demand be determined by

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

where E^d is the number of workers desired at wage *w*. The parameter β represents the labor-demand elasticity, while *X* is a positive-valued index of demand factors that shift the labor demand curve. Labor supply is determined by

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

where γ is the labor-supply elasticity and *Z* is a positive-valued index of supply factors.

If the minimum wage ($w_{\min}$) is not binding in this market, the equilibrium wage and employment levels will be

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

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 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, observed employment can be written

$$E^o = dE_{\min} + (1-d)E^* = dw_{\min}^{\beta} X + (1-d)X^{\frac{\gamma}{\gamma-\beta}} Z^{\frac{-\beta}{\gamma-\beta}} \qquad (1)$$

Alternatively, given that *d* is an indicator function, 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

$$E(\log(E^o \mid w_{\min}, X, Z)) = p\beta\log(w_{\min}) + \frac{\gamma - p\beta}{\gamma-\beta}\log(X) - \frac{\beta - p\beta}{\gamma-\beta}\log(Z)\,, \quad (2)$$

where $p = E(d \mid w_{\min}, X, Z)$ is the probability that the labor market has an effective minimum wage.[6]

One implication of equation (2) is the justification of an empirical reduced-form regression that relates the log of employment (in a low-wage labor market) to the log of the minimum-wage and to a set of demand and supply factors.[7] Another implication is that the coefficient on the log of the minimum wage equation identifies the labor-demand elasticity, if corrected by dividing the estimated coefficient by an estimate of the percentage of the labor market that actually receives the minimum wage (this type of

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[6] One caveat in the derivation of equation (2) should be noted. It would be preferable to interpret *d* in equation (1) as the percentage of the labor market in which the minimum wage is effective, allowing for the possibility that minimum-wage firms coexist with above-minimum firms in the same industry and labor market. With this interpretation, the derivation of equation (1) follows as before, but the derivation of equation (2) becomes more complicated. We would either need to take the log of equation (1), which does not simplify, or we would need separate data on the log of employment in minimum-wage and above-minimum wage firms in the market to use in estimating equation (2). A direct estimation of equation (1) is made quite difficult in our case by the large number of fixed effects we wish to control for in our empirical models.

[7] This justification for including supply factors in an employment/minimum-wage equation was noted by Neumark and Wascher (1994) in their argument that enrollment rates should be in their employment equations.

correction is noted in Brown, 1999). Alternatively, an equation for the average wage in the labor market could be estimated. Using a logic similar to that for deriving equation (2), the reduced-form log-wage equation is

$$E(\log(w) \mid w_{\min}, X, Z) = p\log(w_{\min}) + (1-p)\frac{1}{\gamma-\beta}\log(X/Z), \tag{3}$$

from which an estimate of p is readily obtainable. Dividing the minimum-wage coefficient in the employment equation by this estimate would then provide an estimate of the labor-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. One way to incorporate this influence is to model p as an explicit function of observables. This function should include any factors that would lead to a higher likelihood of the minimum wage being effective in the market. A simple strategy is to model this probability as a linear function of these characteristics. Arguably, any factor that would shift supply or demand would belong in this function, as

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

In practice, we specify

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

Substituting in equation (2) 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.[8]

An alternative approach that allows the minimum wage to explicitly affect the proportion affected is to consider the impact of discrete changes in the minimum wage. For example, suppose that in our model we have an increase in the log minimum wage equal to $\Delta\log(w_{\min})$. Let d_1 indicate that the minimum wage was effective in the market both before and after the change, d_2 that is was not effective in either case, and d_3 that it became effective only after the increase. Then the change in employment is equal to

$$\Delta\log(E^o) = d_1\beta\Delta\log(w_{\min}) + d_2 0 + d_3\left(\beta\Delta\log(w_{\min}) + \beta\log(w_{\min}^{init}) - \frac{\beta}{\gamma-\beta}\log(XZ)\right)$$

$$= (d_1 + d_3)\beta\Delta\log(w_{\min}) + d_3\beta\left(\log(w_{\min}^{init}) - \frac{1}{\gamma-\beta}\log(XZ)\right). \qquad (4)$$

If measures of the "proportion affected" $(\mathrm{d}_1 + \mathrm{d}_3)$ are available for individual markets, this equation could be used to identify the labor-demand elasticity by incorporating this proportion as a variable in the equation. (Even if all markets experienced the same minimum-wage change, the labor-demand elasticity would be identified from the variation in the proportion affected.) This type of approach has been used in several papers by Card, and Card and Kruger (as discussed in Card and Krueger, 1995), although their estimated equations do not exactly follow the structure of equation

[8] The fact that $p\beta$ appears as part of the coefficient for all three variables in equation (2) suggests that additional information is potentially available by imposing this restriction in estimating interactions between all variables in the model. However, any such identification would rely on the assumption that the model is correctly specified; that is, in the absence of minimum-wage laws, there would have been no interactions between the regressors determining employment.

(4).[9] In our case, data on the proportion affected is not available. Although it may be possible to model the probability of the market being affected by the minimum wage increase (in a manner similar to the modeling of *p* discussed above), we did not pursue that strategy here.

An estimation of the model in equations (2) and (3) requires data that allow a focus on an industry or group of workers likely to be affected by the minimum wage. We also need information on local labor market conditions that might be related to the probability that the minimum wage is effective for that industry or group. In the next section, we discuss our approach to estimation using U.S. data on county-level employment in the restaurant-and-bar sector.

III. Data and Statistical Approach

Previous research on minimum-wage impacts has generally chosen one of two strategies. One is to use aggregated data on employment for a particular group of workers (most commonly, teenagers), where the aggregation is generally at the state or national level. A second approach has been to focus on a single sector of the economy – most commonly, fast food restaurants – and to examine employment changes surrounding a limited number of minimum-wage changes in a small number of geographic areas. Our approach is similar to the latter in focusing on a particular sector, but similar to the former in considering variation in the minimum wage across a large number of geographic areas.

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

[9] In cases where $\Delta \log(w_{\min})$ is not identical across markets, these authors do not include this variable in the equation, nor do they include the initial value of the minimum wage.

QCEW reports quarterly county-level payroll data on private employment and earnings for narrowly defined industries. These data are collected from paperwork employers file in conjunction with the unemployment insurance program. All firms with workers subject to state and federal unemployment insurance laws are represented in the data, which (according to the BLS) covers 99.7 percent of all wage and salary civilian employment. The industry of all firms in the data is coded according to the North American Industrial Coding System (NAICS), and aggregations of the data by county, industry, and quarter are available to users, beginning with the initial data collection for the first quarter of 1990.

The data found within the QCEW survey have many advantages over other employment surveys. It provides census (rather than sample) observations of employment and earnings for detailed industrial specifications within a large number of narrowly defined geographic regions. The county level of aggregation provides a reasonable approximation of a labor 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 blemish. 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 earnings per worker.[10] Even so, the QCEW provides accurate and comprehensive measures of employment and earnings in highly disaggregated markets, and represents a new data source that has been underutilized in research examining minimum-wage impacts on employment.

As noted in the previous section, we wish to supplement data on employment and earnings from QCEW with additional measures that might reflect supply-and-demand factors in low-wage labor markets in a particular county. Our basic econometric model is

$$\log(Y_{ist}) = \varphi \log(MW_{st}) + \gamma X_{ist} + \mu_i + \tau_t + \varepsilon_{ist} \quad (5)$$

where Y_{ist} denotes either industry employment or earnings in county *i* and state *s* during period *t*, MW_{st} is the natural log of the real minimum wage, X_{ist} is a vector of supply and demand factors, μ_i and τ_t are fixed county and time effects, and ε_{ist} is the idiosyncratic error term. The county effect should control for any fixed aspects of the county that might affect the labor market, including any persistent differences in institutional, economic, or demographic characteristics of counties that might affect employment or earnings. The quarter effect should control for any national-level macroeconomic effects. Controls included in X, then, are intended to reflect how a county's labor 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 (NAICS sector number 722) in the years 1990-2005. This sector includes traditional full-service restaurants, fast food restaurants, cafeterias, and stand-

[10] This measure includes most wage-like compensation, including tips, bonuses, stock options, and employer contributions to retirement plans.

alone bars. The BLS does censor sector-specific observations on employment and earnings if the number of establishments in the county is below a certain level.[11] We perform most of 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.[12] Focusing on just the general restaurant-and-bar sector, we have a balanced panel of 1,825 counties, providing 116,800 quarterly observations – or roughly 58 percent of the potential sample of 3,143 counties in the United States. We also wish to estimate models for sub-sectors of the restaurant-and-bar sector, although as we increase the level of industrial disaggregation the rate of censoring also increases slightly.

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 labor-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 fifteen 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 four separate federal minimum wage increases.

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[11] BLS withholds publication of data when necessary to protect the identity and data of cooperating employers, as there are industry/county combinations where the QCEW data would include a very small number of employers. These data are suppressed in the QCEW public-use data for that industry/county, but may be included in the data at less detailed levels of aggregation (for example, in a more general definition of industry for that county).

[12] Most counties either have valid observations for all 64 quarters, or have no valid observations for any of the 64 quarters. There are 634 counties with valid observations for part but not all of the time period; we discuss estimation incorporating this set of counties in section V.

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 may influence employment or earnings and change across the sample over time. In attempting to measure county-specific, time-varying supply and demand factors that might influence employment and earnings, the depth of the QCEW survey is again useful. As the QCEW survey provides observations at all NAICS aggregation levels, data on total county employment and average weekly earnings for all industries combined is also available. The inclusion of total county employment and earnings helps to control for the county-level status of the labor market. In particular, the average earnings variable may reflect the tendency for supply-and-demand factors to lead to high wages in general in that county, suggesting that the competitive wage in the restaurant-and-bar industry is also likely to be higher.

Other measures that may be relevant to outcome indicators in low-wage labor markets were obtained from sources other than the QCEW. We view the population of the county as a factor that could directly affect both labor supply and demand. To incorporate this factor, we obtained population estimates from the U.S. Census Bureau's Population Estimates Program. Unemployment rates for prime-age males are often included in models of minimum-wage effects. Unemployment rates at the county level are available from the Local Area Unemployment Survey (LAUS), though the best we could do was assemble unemployment measures for all workers, not just for prime-age men.[13]

A final control variable is a measure of school enrollment at the state level, taken from the Current Population Survey (CPS). This variable comprises the percentage of individuals aged 16-24 years enrolled in school. It is based on answers to the CPS question: "Last week, were you enrolled in a high school, college, or university?" The enrollment rate is generally thought to reflect supply factors, a higher percentage of young individuals not in school serving to increase the supply of a part of the workforce that is heavily associated with the restaurant-and-bar sector (see Neumark and Wascher, 1994). It can also reflect demand factors, as students (especially college students) may be less likely to eat at restaurants. The inclusion of this variable in minimum-wage models has been controversial, as it is argued that the enrollment choice may itself be a function of the decision to work (see Card, Katz and Krueger, 1994).[14] To some extent, the reverse causality issues surrounding the enrollment rate are lessened by using a higher level of aggregation in calculating the enrollment rate. Although we fail to capture specific enrollment-rate effects at the county level (for example, the location of a large university in the county), we do measure the extent to which the desire for higher levels

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[13] It is possible to get unemployment rates for prime-age men at the state level from the Current Population Survey. We prefer a county-specific measure, and so did not use this in our primary analysis. However, estimates using the CPS variable in place of the county-specific measure yielded very similar conclusions. Results are available from the authors on request.

[14] Card, Katz, and Krueger also criticized the particular enrollment measure used by Neumark and Wascher (1992), and found that their results were sensitive to the choice of enrollment measure. We use the Card, Katz and Krueger's preferred measure, namely, one that allows individuals to be both employed and enrolled at the same time.

of educational attainment are characteristic of that state (which could be determined, for example, by state-level tuition and scholarship policies for college enrollment).

Our specification differs from those used in many recent minimum-wage studies in that our dependent variable is the log of employment, rather than an employment rate. If an employment rate were to be used, two possible measures suggest themselves. One would be the percentage of all employed workers in the restaurant-and-bar sector, the other the percentage of the population in that sector, and the choice between the two was not obvious. In any case, by including both the log of total employment and the log of total population as independent variables, our model can be thought of as an unrestricted version of a regression model that uses the log of either employment rate as the dependent variable.

Detailed summary statistics for all variables included in our models are given in Table 1. Average employment in the restaurant-and-bar sector is 3,883 workers, which is about eight percent of average total private employment. Average weekly earnings in restaurants and bars also fall substantially below the overall average earnings (31 percent of the average), although average earnings in restaurants and bars is a higher percentage (33 percent) of total earnings in counties with a state minimum above the average. In counties in our sample where the state minimum was above the federal minimum at any time over the period studied, the excess averaged $0.90 above the federal value. These counties also had both higher unemployment rates and enrollment rates. 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 percent of states are in the above-federal-minimum category but less than ten percent of our county/quarter observations come from these states. This substantial difference in size led us to consider weighted least squares estimation of our models, as discussed in the next section.

Finally, a few statistical issues arise in estimating our models. The inclusion of fixed county effects and fixed time effects does not rule out correlation in the idiosyncratic error term (ε) within counties over time, or across counties at a point in time. Ignoring this correlation can lead to severe biases in the standard errors, especially when the level of aggregation varies across the variables included in the model (see Moulton, 1990; Bertrand, Duflo, and Mullainathan, 2004). This is a particular concern in our case, as most variables are measured at the county level but minimum wages vary only at the state level. In our reported estimates, all standard errors are calculated allowing for any type of correlation structure among the error terms for a given state.[15] This approach to calculating standard errors is also robust to heteroskedasticity in ε , even when using weighted least squares estimates. Although use of "clustered" standard errors has become commonplace in panel-data analysis, it has generally not been addressed in previous minimum wage studies.

Second, we use a logarithmic specification for each of our dependent variables. Blackburn (2007) argues that estimated models that utilize the logarithm of a variable as the dependent variable will only provide consistent estimates of percentage effects on the underlying variable if the error term is distributed independently of the regressors. For

[15] As our data are county level, another approach would be to cluster at that level. Although this would allow for a general time-series structure in the errors for a given county, it would not allow for the possibility that counties in the same state could have correlated errors at a point in time.

example, if the variance of the error terms is related to the value of the regressors, estimates of the logarithmic model will likely be inconsistent as estimates of percentage effects. We examined the potential for heteroskedasticity in our data by using the residuals to estimate skedastic functions in which the variance is allowed to vary linearly with all of the regressors in our model. The results did not suggest an important influence of the minimum wage on this variance, suggesting the use of logarithmic dependent variables is not likely a cause for concern when interpreting our regression estimates.

IV. Estimation Results

A. Basic Models

As a first examination of the correlation 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 the log of employment, and the log of average weekly earnings, both for the restaurant-and-bar sector. 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 labor demand in this sector is roughly -0.9.[16] The estimated coefficient for the minimum-wage variable is of a magnitude similar to that reported in

[16] 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 (2) and (3).

most analyses using state-level panel data (see, in particular, Neumark and Wascher, 2006).[17]

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 labor demand elasticity of around -1. Not surprisingly, increases in total employment and county population tend to be associated with increases in restaurant-and-bar employment. They also both have small positive effects on average earnings in restaurant and bars. Counties with higher average earnings in general also appear to have higher sectoral earnings but lower employment. This result is consistent with an inward shift of the labor supply schedule in this particular labor market. There is little evidence of an enrollment-rate effect on employment, although this variable has a negative coefficient estimate in the average earnings equation. This result could reflect higher enrollment rates increasing supply (with restaurant-and-bar employment conducive to school attendance and work) while decreasing demand. Unemployment rates do not appear to be an important factor in either equation.

Although estimated at the county level, these results are quite consistent with most of the earlier state-level studies. As much of this early research has used standard errors appropriate only under ideal regression assumptions, our findings suggest that these results can be considered robust to inference that allows for heteroskedasticity and general intra-state correlation in the error terms.

[17] On the other hand, these studies primarily looked at teenagers, a higher percentage of whom work at the minimum wage than is the case for overall employment in the restaurant-and-bar sector. Given this difference, our basic estimates are perhaps larger in magnitude than traditionally observed in the literature.

B. Weighted Estimation

Our ordinary least squares estimators implicitly provide 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 would be that the error variance is related to population, suggesting that a correction 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 (WLS) 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 is not suggested for 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).[18]

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; 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.[19] The fact that these estimates differ suggests that we should consider a richer specification than used in Table 2. In the next subsection, we incorporate county-specific trends in our estimation and find this to be very important to our estimation results.

C. County-Specific Trends

Our models control for systematic differences in restaurant-and-bar employment determination across counties, but only 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

[18] Some of the other coefficient estimates are also affected by the weighting; for example, the enrollment rate is now also statistically significant in the employment equation.
[19] In this case, the omitted factor would be an interaction between average wages and minimum wages.

the error term of the model has become increasingly common in studies using long panels.[20] The inclusion of these trends helps to address the possibility that restaurant-and-bar employment growth is trending differently in states that increased their minimum wages compared to states that stayed at the federal minimum (and so witnessed a declining trend in the real minimum wage).

We modify our basic empirical model (equation 5) to include county-specific trends, that is

$$\log(Y_{ist}) = \varphi \log(MW_{st}) + \gamma X_{ist} + \mu_i + \lambda_i t + \tau_t + \varepsilon_{ist}\ , \qquad (6)$$

where λ_i is a trend coefficient that varies across counties. Wooldridge (2002, pp. 315-322) discusses two procedures for the estimation of this model.[21] It is possible to estimate the model using first differences, but we will save this discussion until later. Instead, an 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 entails estimating a simple linear trend model for each variable in the equation, and using the residuals from these trend models to estimate the parameters of interest.[22] 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). Table 3 reports estimates using detrended data.

[20] Dube, Lester, and Reich (2007) incorporate state-level trends in their county-level analysis of minimum wages, assuming that all counties in the same state follow the same trend.

[21] This is often referred to as a “random growth model” when a logarithmic dependent variable is used.

[22] This detrending process is essentially the extension of the de-meaning process used to estimate fixed-effects models.

After controlling for local trends, the estimated elasticity of restaurant-and-bar employment to the minimum wage is negative, but very small and statistically insignificant. The estimated earnings elasticity is also somewhat smaller after detrending, but the impact is still significant. As a result, the derived estimate of the labor-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.[23] These results suggest that studies identifying employment effects by using variation in state minimum-wage laws need to worry about the role of spatial trends in their estimation.

D. Models with Interactions

In section II, 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 labor market. Our results in Tables 2 and 3 help tie our data analysis to previous research on minimum-wage effects, but they do not account for the possibility that changes in observable factors could affect the likelihood that the minimum wage is binding in a given labor market. To account for this possibility, we assume that the probability the minimum-wage is effective – p in equation (2) – is a linear function of the minimum wage, and of our demand and supply factors, namely,

$$p_{ist} = \alpha_0 + \alpha_1 \log(MW_{st}) + \alpha_2 X_{ist} \quad . \qquad (7)$$

[23] Unweighted estimates of the detrended model (not reported) are similar to the weighted estimates in Table 3, suggesting that the misspecification that may have led to differences in the Table 2 results is indeed handled by the inclusion of the county-specific trends.

Our expectation is that higher minimum wages would make it more likely that the minimum wage has an effect (so $\alpha_1<0$). Shifts in labor 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 restaurant and bars, and so decrease *p*. We can estimate the employment equation by extending equation (6)

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

which after substituting equation (7) provides

$$\log(Y_{ist}) = \alpha_0 \beta\log(MW_{st}) + \alpha_1\beta \log(MW_{st})^2 + \alpha_2\beta \log(MW_{st})X_{ist} + \\ + \gamma X_{ist} + \mu_i + \lambda_i t + \tau_t + \varepsilon_{ist} \ . \qquad (8)$$

Equation (8) 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 labor-demand elasticity β would not now appear). It would be possible to estimate the parameters by requiring that the α's be the same in the employment and earnings equations, although we do not impose this restriction in our estimates.[24]

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 times the other variables deviated from their sample means. This 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

[24] Minimum-wage interactions do not appear to have been considered in the previous literature. The one exception is the use (in many studies) of the ratio of the minimum wage to the average wage, which in our framework can be interpreted as assuming *p* is inversely proportional to the average wage.

included in the table. The sensitivity of the results to incorporating these trends leads us to base our inferences on the last two columns of Table 4.

Estimates of the employment equation suggest that adding the interactions and squared terms does not provide explicit evidence that their inclusion is necessary, as the interaction coefficient estimates (and the squared-log-minimum-wage coefficient estimate) are not individually statistically significant. That said, we are able to reject the hypothesis that jointly the interactions have no impact on our estimates (p-value=.003). On the other hand, there is a stronger evidence to suggest that the addition of these variables is relevant in the log-earnings equation. The countywide average earnings variable 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 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.[25]

The evidence that there are 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 labor-demand elasticity in the industry. Given that the

[25] This is the estimated elasticity when the values of the other supply-and-demand factors are at their sample means.

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 II, but with a small labor-demand elasticity leading to the minimum wage effect showing up mostly in earnings.

V. Alternative Estimators and Samples

A. 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, have used first-difference estimators to remove state effects. Either method is arguably appropriate given the specification in equation (5), 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 (6) gives

$$\Delta\log(Y_{ist}) = \varphi\Delta \log(MW_{st}) + \gamma\Delta X_{ist} + \lambda_i + \Delta\tau_t + \Delta\varepsilon_{ist} \quad ,$$

so that 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 modeling *p* is not as clear in this model (see the discussion surrounding equation (4) in section II), so we chose to estimate a first-difference model comparable to the models presented in Table 3.

Our basic 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 is small and statistically insignificant. The minimum-wage coefficient is estimated much less precisely with 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 the same empirical model, the first-difference estimates are likely sensitive to only short-run effects of minimum wages, while the detrended model is more likely to be sensitive to long-run reactions. 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.[26] Presented in the final two columns of Table 5, these results provides estimates that are in general similar to the detrended estimates (of Table 3), especially for the minimum-wage coefficients. Although studies that use quarterly differences to estimate minimum-wage coefficients may be missing some of the impact, the evidence

[26] 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.

here suggests a longer-run difference can provides evidence similar to a model estimated using non-differenced data that have been detrended.

B. State Minimum Changes vs. Federal Minimum Changes

A concern sometimes mentioned in the literature centers on the possibility that responses to increases in the minimum wage may differ if the change is due to a state initiative rather than a federally-mandated increase. The fact that state-panel minimum-wage models are generally identified only from state minimum increases formed the basis of the critique of Burkhauser, Couch, and Wittenburg (2000), leading them to estimate models that omitted year effects.[27] Neumark and Wascher (2006) cite a working paper by Bazen and Le Gallo (2006) as estimating first-difference models that allow changes in the minimum wage due to state law to have different effects than changes due to a federally-legislated change, with evidence of negative employment effects only for federally-legislated changes.[28] This would be 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.

We examined this issue in a manner that still allows us to use non-first-differenced data. Burkhauser, Couch, and Wittenburg (2000) are correct in arguing that that the traditional state-panel estimates are identified only if there are some states with minimum wages above the federal. The minimum-wage coefficient is largely identified

[27] We re-estimated our Table 2 specification for the employment equation excluding quarterly effects, and did not find evidence of employment effects for the minimum wage variable. This result suggests that the negative effects generated in their paper by ignoring time effects may be specific to the time frame studied.

[28] We did a similar estimation with our first-difference model, interacting the change in the minimum with a dummy variable for whether or not the change was due to a federal increase rather than a state increase. However, we did not find evidence of a statistically significant interaction.

by the comparison of employment in states with state minima above the federal with those at the federal minimum, in any given year. But this does not imply that all of the variation in the minimum wage is due solely to state-level changes; for example, federal increases will tend to lower the variation across states in a given year. Our concern, therefore, is that the states that never choose to be above the federal minimum may have systematically different minimum wage effects on employment than those who fix 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 quick way to check for this possibility is to re-estimate the model using data from only those states that ever raised their state minimum over the federal minimum during the period under study. These detrended estimates are reported in Table 6, and actually provide more evidence of a negative employment effect from minimum wages than the comparable full-sample estimates from Table 3. This estimate is still statistically insignificant, but it does suggest that worries about the selectivity in state-minimum increases do not seem to be relevant in our data.

C. Using the Unbalanced-Panel Observations

Our estimates are calculated using only counties with a sufficient number of establishments in the restaurant-and-bar industry to avoid censoring in the QCEW public use files. This limits problems associated with counties entering and leaving the sample because of the number of establishments rising above and falling below the censoring threshold. To consider the sensitivity of our results to this strategy, we estimated models that also included counties with missing information for at least one (but not all) of the quarters. The weighted results for employment and earnings are presented in the first and second columns of Table 7, and suggest similar conclusions to the comparable balanced-panel estimates reported earlier in Table 3.

These unbalanced-panel estimates suffer from a potential bias if the minimum wage affects the probability that employment is censored in the QCEW because it lowers the number of establishments in the county below the censoring threshold. To explore whether this type of bias might be important, we estimated linear-probability models for the probability that a county is censored in a given quarter. The estimated equation is analogous to equation (6), with a dummy variable for being censored serving as the dependent variable. The estimates are calculated using only the sample of counties with partial information on restaurant-and-bar employment over the 64 quarters. These estimates are reported in the final column of Table 7. As can be seen, they fail to provide a clear indication that minimum wages have an impact on the probability of being censored in the QCEW.

D. 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).

One reason for examining Limited-Service Eating Places separately is that this sub-sector provides a better 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 from that in 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 labor costs are a greater share of total costs in limited-service restaurants, then the labor-demand elasticity could be larger (in magnitude) in that sector. On the other hand, the product-demand elasticity is likely larger in the full-service sector, suggesting the labor-demand elasticity should be greater there as well. Increases in the minimum wage could also have differential affects on product demand in the two sub-sectors. Finally, 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).[29]

Estimates of our employment and earnings equations by sub-sector are provided in Table 8. These weighted estimates incorporate county-specific trends, and so should be comparable to the weighted estimates in Table 3. These estimates provide a

[29] Information on hourly wages within these two sub-sectors is not available from U.S. Census sources, as the Census industry codes do not distinguish between limited-service and full-service restaurants.

marginally statistically significant negative effect of minimum wages on employment in the limited-service sub-sector (implying a labor-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 effective in limited-service rather than full-service restaurants.

VI. Summary and Discussion

In the present treatment, we have used county-level data on employment and earnings in the restaurant-and-bar sector to consider the impact of minimum wage changes on wage and employment outcomes in low-wage labor 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 analyzed using data sets with insufficient geographic variation to reliably identify minimum-wage effects. We find our estimates to be consistent with a simple competitive model of the restaurant-and-bar labor market in which supply-and-demand factors also affect the probability that a minimum wage will be effective if 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 finding a negative employment effect of minimum wages. 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 role of spatial 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. This may be the result of a very low-labor 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 separate sub-sectors of the industry are intriguing in this regard. Our finding that there is no evidence for 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.[30] 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 high labor-turnover rate characteristic of that sector also suggests that adjustments of employment to changes in costs can be fairly rapid. Yet there are a number of weaknesses attached to this restricted focus. At a county level, restaurants may tend to have lower labor-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

[30] The two sub-sectors are roughly equal in total employment in any given quarter.

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 labor costs into product prices. Accordingly, the case-study emphasis on the restaurant sector may not offer the best environment for uncovering negative employment effects. In the future, we intend to examine minimum-wage impacts in other disaggregated low-wage sectors at the county level.

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Table 1	**Descriptive Statistics for the County Sample: 1990-2005**		
	Mean (Standard Deviation)		
Variable	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)	3,515 (9,132)	7,322 (18,811)
Restaurant-and-Bar Average Weekly Earnings	167 (44)	163 (40)	195 (56)
Total Private Employment	50,712 (151,268)	45,751 (133,523)	97,619 (263,347)
Total Private Average Weekly Earnings	536 (135)	529 (128)	591 (172)
Population (annual)	135,949 (365,589)	122,507 (312,190)	263,128 (682,043)
Unemployment Rate (all industries)	5.86 (2.71)	5.81 (2.71)	6.41 (2.61)
Real Minimum Wage	5.66 (0.44)	5.57 (0.30)	6.47 (0.65)
Enrollment Rate (State-level)	0.46 (0.11)	0.46 (0.11)	0.49 (0.11)
Sample Size	116,800	105,642	11,158

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

Table 2	**Regression Estimates of Employment and Earnings Equations for the Restaurant-and-Bar Sector**							
	Ordinary Least Squares (a)				*Weighted Least Squares (b)*			
Independent Variable	*Employment*	*Earnings*	*Employment*	*Earnings*	*Employment*	*Earnings*	*Employment*	*Earnings*
Minimum Wage	-0.198** (0.084)	0.229** (0.040)	-0.230** (0.079)	0.223** (0.031)	-0.115* (0.067)	0.215** (0.024)	-0.098** (0.039)	0.201** (0.021)
Population			0.474** (0.077)	0.072** (0.024)			0.329** (0.099)	-0.057 (0.038)
Total Employment			0.518** (0.044)	0.106** (0.017)			0.591** (0.052)	0.156** (0.025)
Total Average Weekly Earnings			-0.311** (0.046)	0.158** (0.014)			-0.138** (0.048)	0.194** (0.032)
Unemployment Rate			0.000 (0.001)	0.000 (0.001)			-0.001 (0.002)	0.001 (0.001)
Enrollment Rate			-0.027 (0.049)	-0.073** (0.021)			-0.086** (0.042)	-0.054** (0.021)

Note: Each column of estimates is from a separate regression. All dependent variable and independent variables are in logarithmic form, with the exceptions of the unemployment rate and enrollment rate. The standard errors in parentheses are corrected to allow for possible non-independence of observations within a county. All regressions included fixed-effects for county and quarter. Regressions in panel (b) are weighted by the average population in their respective county. **,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

Table 3	**Regression Estimates for Equations with County-Level Trends**		
Independent Variable	*Employment*		*Earnings*
Minimum Wage	-0.006 (0.033)		0.171** (0.035)
Population	0.277** (0.066)		0.029 (0.059)
Total Employment	0.763** (0.061)		0.207** (0.024)
Total Average Weekly Earnings	-0.129** (0.035)		0.133** (0.030)
Unemployment Rate	0.001 (0.002)		-0.002** (0.001)
Enrollment Rate	-0.083** (0.025)		-0.049** (0.016)

See Notes to Table 2. All regressions are weighted by the county's average population. **,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

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** (0.949)	-0.254 (0.695)	0.524 (0.394)	-0.476 (0.350)
Population	0.383** (0.148)	0.017 (0.098)	0.189* (0.111)	0.292** (0.077)
Total Employment	0.562** (0.142)	0.048 (0.087)	0.892** (0.108)	0.196** (0.052)
Total Average Weekly Earnings	-0.750** (0.212)	0.410** (0.161)	-0.201 (0.171)	0.407** (0.153)
Unemployment Rate	-0.036** (0.014)	-0.019** (0.007)	-0.015 (0.013)	-0.030** (0.006)
Enrollment Rate	0.139 (0.241)	0.008 (0.182)	-0.209 (0.256)	-0.178 (0.155)
Minimum Wage Squared	-0.762** (0.270)	0.120 (0.194)	-0.139 (0.106)	0.184* (0.095)
<u>Minimum Wage Interactions</u>				
County Population	-0.026 (0.058)	-0.046 (0.049)	0.056 (0.043)	0.002 (0.030)
Total Employment	0.020 (0.068)	0.065 (0.050)	-0.071 (0.046)	0.009 (0.029)
Total Average Weekly Earnings	0.339** (0.113)	-0.121 (0.077)	0.043 (0.095)	-0.153** (0.076)
Unemployment Rate	0.020** (0.008)	0.012** (0.004)	0.009 (0.007)	0.016** (0.003)
Enrollment Rate	-0.126 (0.125)	-0.035 (0.099)	0.073 (0.139)	0.074 (0.087)

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. **,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

Table 5 **Estimates of 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)
Population	0.454** (0.176)	0.601** (0.216)	0.393** (0.053)	0.327** (0.061)
Total Employment	0.929** (0.149)	0.284** (0.041)	0.567** (0.021)	0.009 (0.031)
Total Average Weekly Earnings	-0.062 (0.052)	0.081** (0.031)	-0.127** (0.027)	0.112** (0.034)
Unemployment Rate	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	-0.002** (0.001)
Enrollment Rate	-0.049** (0.025)	-0.018 (0.017)	-0.009 (0.017)	0.002 (0.007)

See Notes to Table 3. **,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

Table 6	**Regression Estimates Using the Sample of Counties with State-Law Variation.**		
Independent Variable	*Employment*		*Earnings*
Minimum Wage	-0.034 (0.021)		0.150** (0.026)
Population	0.150 (0.155)		0.303** (0.135)
Total Employment	0.729** (0.145)		0.250** (0.035)
Total Average Weekly Earnings	-0.070** (0.027)		0.099** (0.026)
Unemployment Rate	0.005** (0.002)		-0.003 (0.002)
Enrollment Rate	-0.116** (0.034)		-0.073** (0.024)

See Notes to Table 3. The sample size in each regression is equal to 11,158. **,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

Table 7	**Regression Estimates using the Unbalanced Sample**		
Independent Variable	*Employment*	*Earnings*	*Dummy for Being Uncensored*
Minimum Wage	-0.002 (0.033)	0.175** (0.036)	0.265 (0.261)
Population	0.351** (0.062)	0.280** (0.055)	1.384** (0.665)
Total Employment	0.747** (0.061)	0.195** (0.023)	0.009 (0.025)
Total Average Weekly Earnings	-0.136** (0.033)	0.139** (0.028)	-0.017 (0.032)
Unemployment Rate	0.001 (0.001)	-0.002** (0.001)	0.031 (0.021)
Enrollment Rate	-0.083** (0.025)	-0.051** (0.015)	-0.023 (0.050)

See Notes to Table 3. The dependent variables are in logarithmic form, except for the uncensored dummy. The sample size in the first two columns is 157,205, while the sample size in the last column is 72,806. **,* denote statistical significance at the 0.05 and 0.10 levels, respectively.

Table 8 **Regression 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* (0.049)	0.252** (0.070)	0.148** (0.066)	0.137** (0.030)
Population	0.236** (0.092)	0.318** (0.078)	0.375** (0.123)	0.193** (0.068)
Total Employment	0.657** (0.067)	0.208** (0.029)	0.776** (0.070)	0.225** (0.031)
Total Average Weekly Earnings	-0.151** (0.033)	0.135** (0.030)	-0.102** (0.043)	0.089** (0.026)
Unemployment Rate	0.004 (0.003)	-0.003** (0.001)	-0.002 (0.003)	-0.002** (0.001)
Enrollment Rate	-0.104** (0.031)	-0.069** (0.016)	-0.098** (0.028)	-0.062** (0.015)
Sample Size	115,008		105,088	

See Notes to Table 3. **,* denote statistical significance at the 0.05 and 0.10 levels, respectively.