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Minimum Wages and Teen Employment:

A Spatial Panel Approach

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Abstract:
The authors employ spatial econometric techniques and Annual Averages data from the U.S. Bureau of Labor Statistics for 1990-2004 to examine how changes in the minimum wage affect teen employment. Spatial econometric techniques account for the fact that employment is correlated across states. Such correlation may exist if a change in the minimum wage in a state affects employment not only in its own state but also in other, neighboring states. The authors show that state minimum wages negatively affect teen employment to a larger degree than is found in studies that do not account for this correlation. Their results show a combined direct and indirect effect of minimum wages on teen employment to be -2.1% for a 10% increase in the real effective minimum wage. Ignoring spatial correlation underestimates the magnitude of the effect of minimum wages on teen employment.

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Data and copies of the computer programs used to generate the results are available from Donald Lacombe. He can be reached at the address above.

Minimum Wages and Teen Employment: A Spatial Panel Approach

Existing panel data studies of the minimum wage do not account for the fact that employment is correlated across political boundaries. Such correlation may exist if a change in the effective minimum wage in a state (i.e., the maximum of the state and federal minimum wages) affects employment not only in its own state but also in other, neighboring states. For example, a minimum wage increase in one state may cause workers in a neighboring state without an increase to cross the border to look for a job. Thus, the overall effect of the minimum wage increase would include the reduction in employment in the neighboring state in addition to the reduction in the state that increased its minimum wage. The indirect effect of an increase in a state's minimum wage on employment in other states would not be captured by an analysis that did not account for spatial dependence. Another way that employment might be correlated across states is through geographic features such as rivers and other natural resources that cross state boundaries. "Employment centers" based on these geographic features might then cross state boundaries.

When observations are correlated across space, traditional econometric techniques that ignore this spatial dependence will produce incorrect estimates. Therefore, we estimate a Spatial Autoregressive (SAR) model using state-level panel data for teens aged 16-19 over the period 1990-2004 to show how real effective minimum wages affect teen employment and compare our estimates to those that do not account for spatial dependence.

Literature Review:

The literature on the effects of minimum wages on employment is voluminous. The most recent review of the literature is found in Neumark and Wascher (2007). They conclude that the bulk of the evidence shows negative effects of minimum wages on employment, even though some recent studies suggest that the employment effects are nonexistent or positive. They recommend panel studies over case studies for two reasons. First, it is difficult to discern a valid control group in a case study. Second, panel studies may incorporate both contemporaneous and lagged effects of minimum wages. Based on this recommendation we focus our discussion on panel data studies.

Neumark and Wascher (1992) used panel data for 1973-1989 to examine the effects of minimum wages on teen employment, including both state- and year- fixed effects to control for unmeasured economic conditions of state economies and business cycles. Their minimum wage variable was the maximum of the state and federal minimum wages multiplied by the coverage rate and divided by the average hourly wage. Dividing by the average wage was done to "better indicate how much the minimum wage cuts into the wage distribution (footnote 6, page 60)." So, in effect, their minimum wage measure was a relative minimum wage measure rather than a real one. They found that a 10% increase in their minimum wage measure led to a decline in the employment of teenagers of 1-2%.

Williams (1993) used state-year panel data for 1977-1989 to examine regional variation in the effects of federal minimum wage changes on teenage employment. He included region dummies and region dummies interacted with his minimum wage variable rather than state fixed effects and found negative, region-varying effects of minimum wages. Unlike Neumark and Wascher (1992), he estimated separate specifications using a relative minimum wage measure and a real minimum wage measure. Using his real minimum wage specification, he found that a 10% increase led to a 3.6%-6.8% decrease in teen employment.

Zavodny (2000) analyzed the effects of minimum wages on teens' employment and hours of work. She used both state- and individual-level data from the CPS Outgoing Rotation Groups for 1979-1993. She included both state- and year- fixed effects. Her results showed that minimum wages had a small negative effect on teen employment but no effect on hours of work. Like Williams (1993), she estimated specifications with relative and real effective minimum wages.

Keil, Robertson, and Symons (2001) used panel data on U.S. states and found that minimum wages negatively affected youth employment. They calculated a short-run negative effect of 3.7% and a long-run negative effect of 6.9%. They acknowledged the potential for spatial dependence in the error term but, rather than use spatial econometrics techniques that employ a weight matrix, they specified a general factor structure for the error process. However, such a procedure does not adequately address the issue of spatial dependence in either the dependent variable or the explanatory variables. For example, if teen employment is correlated across states, their analysis would ignore this and thus would produce a biased parameter estimate of the effect of a change in the minimum wage. An additional bias would occur because the parameter estimate would not represent the true marginal effect. Coefficient estimates from models that do account for spatial dependence in the dependent variable must be transformed in order to produce what LeSage and Pace (2009) refer to as effects estimates.[1] The effects estimates include own partial-derivative effects as well as cross-partial derivative effects, i.e. direct and indirect (spillover) effects.

Couch and Wittenburg (2001) examined the effect of minimum wages on teens' hours of work using monthly data from the CPS for 1979-1992 and found that estimated effects were larger when hours worked was analyzed than when employment was analyzed. While they included state fixed effects they did not include year fixed effects.

Since the Neumark and Wascher (2007) review, several other panel data studies have been published. Thompson (2009) used quarterly data for 1996-2000 for both counties and states to examine how federal minimum wage changes affected teen employment. He showed that using state-level observations masked differences across counties. There were no effects in some counties where the

[1] See LeSage and Pace (2009, Chapter 2) for additional details regarding the effects estimates.

minimum wage was not binding and large effects in other counties where the minimum wage was binding. He divided counties into two categories, high impact and low impact, and used difference-in-differences estimation. While he found no effects of the minimum wage in his state level analysis, in his county-level analyses he found that a 10% increase in the federal minimum wage led to a 2.6%-3.7% reduction in teen employment for all size counties and a 3.8-5.7% reduction for small counties.

Addison, Blackburn, and Cotti (2009) examined the effects of effective minimum wages on employment in certain particularly low-wage subsectors of the retail-trade sector. They used county-level data for 1990-2005 from the Quarterly Census of Employment and Wages (QCEW) and a panel regression framework that allowed for county-specific trends. Because of the level of their data, they included fixed effects for county and quarter. Unlike much of the literature, their results showed evidence of positive employment effects, which they justify by suggesting that monopsony, efficiency wages, or demand effects might be in play in these markets.

Sabia (2009) examined whether a negative relationship between minimum wages and teen employment could be found even if year effects were included. Some previous studies, such as Couch and Wittenburg (2001), had argued that inclusion of year effects wiped out minimum wage effects. Using monthly CPS data of a more recent vintage than earlier studies, he found that, regardless of whether year effects were included, a negative relationship remained. He estimated that employment was reduced 2%-3% and hours were reduced 4%-5% in response to a 10% increase in the minimum wage. In a related paper, Sabia (2009b) used monthly data from the 1979-2004 CPS to estimate the effects of minimum wage increases on retail employment and hours worked. He found that a 10% increase in the minimum wage was associated with a 1% decline in retail trade employment and usual weekly hours worked. He also found much larger effects for the least-skilled teenage employees in this sector.

Most recently, Allegretto, Dube, and Reich (2011) stated that previous studies that found disemployment effects of minimum wages did so because they did not include census division dummies and state-specific time trends. When they incorporated such controls they found either no effect or a positive effect of a minimum wage increase.

None of these studies, however, has adequately dealt with the issue of spatial dependence in the dependent variable.[2] When observations are correlated across space, traditional econometric techniques such as Ordinary Least Squares (OLS) can produce biased, inconsistent, or inefficient parameter estimates (LeSage and Pace, 2009). Spatial autocorrelation is formally defined by Anselin and Bera (1998, p. 241) to be

$$\operatorname{cov}\left(y_i, y_j\right) = E\left(y_i, y_j\right) - E\left(y_i\right)E\left(y_j\right) \;\; for\, i \neq j \tag{1}$$

where y_i and y_j are observations on a random variable at locations *i* and *j* in space, and the subscripts *i* and *j* can refer to states, counties, or any other geographic designation. Spatial econometric techniques must be used to estimate any model where there is spatial dependence in the dependent variable. A detailed explanation of the various spatial econometric models that can be estimated is provided in the Econometric Model section of the paper.

Data:

We use state-year Annual Averages data from the U.S. Bureau of Labor Statistics (BLS) for the period 1990-2004. These data provide information on the labor force, employment, unemployment, and population by age group (BLS, 2006). Connecticut and Washington, D.C. are excluded due to missing information. Alaska and Hawaii also are excluded because these states are not bordered by other states and thus teen employment in these states cannot exhibit spatial dependence. Based on the

[2] Kalenkoski and Lacombe (2008) account for spatial correlation in a cross-sectional study of the effects of minimum wages on teen employment.

work of previous studies, we focus on teenagers aged 16-19, the group we expect would be most affected by a minimum wage increase.

Our dependent variable is the log of teen employment as a fraction of the teen population, a variable used by many studies. Our key independent variable is the log of the real effective minimum wage. We define this as the maximum of the federal and state minimum wages, calculated using federal minimum wage information from the BLS website and state information from the January issues of the BLS Monthly Labor Review, converted to 2004 constant dollars using the Consumer Price Index for Urban Consumers (CPI-U) (BLS, 2011). While many panel data studies do use an effective minimum wage, the maximum of the federal and state minimum wages, many simply divide this variable by the average adult wage to obtain a nominal relative wage rather than a real minimum wage. In this paper we use a real effective minimum wage for two reasons. First, we do not have an average hourly adult wage measure in our data that would enable us to construct the nominal relative minimum wage measure others in the literature have used. Second, a real minimum wage reflects the real cost of hiring. Williams (1993) provided theoretical justification and presented evidence for both types of minimum wage measures. In addition, Zavodny (2000) advocated for the real minimum wage measure for two reasons. First, she found that the relative measure was negatively associated with the average teen wage. Second, she stated the average adult wage was likely to be correlated with business cycle conditions that also affect teen employment and hours, thus rendering it endogenous.

Other panel data studies have included a measure of adult unemployment to control for general economic conditions. Therefore, we have included the state- and year- specific unemployment rate for individuals aged 20 and over as a regressor. Finally, some studies have included a measure of the size of the teen population relative to the general population. Therefore, we have included the percent of the population aged 16 to 19 as a regressor. However, it is not clear a priori that it is a relevant regressor and it turns out to be statistically insignificant in all specifications. Finally, a few other studies include a measure of school enrollment. However, this variable is potentially endogenous and it is not available in our data set. Therefore, we do not include this variable. In addition to these state- and year-varying regressors, we also include state- and year- fixed effects. Previous evidence from the literature and our own specification tests suggest that both state- and year- fixed effects should be included.

Econometric Model

A family of related spatial econometric models can be represented by the following:[3]

$$\begin{aligned} y_{it} &= \delta \sum_{j=1}^{N} w_{ij} y_{jt} + x_{it}\beta + \sum_{j=1}^{N} w_{ij} x_{ijt}\gamma + \mu_i + \lambda_t + u_{it} \\ u_{it} &= \rho \sum_{j=1}^{N} w_{ij} u_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

where i is an index for the cross-sectional dimension (i.e. the spatial units, or states in the U.S.), with $i = 1, \ldots, N$, and t is an index for the time dimension (i.e. the time periods), with $t = 1, \ldots, T$. y_{it} is an observation on the dependent variable at i and t, x_{it} is an $(1, K)$ row vector of observations on the explanatory variables, and β is a matching $(K,1)$ vector of fixed but unknown parameters. The terms μ_i and λ_t represent space- and time-period fixed effects, respectively.

The additional terms in the above equation are what make the panel model a spatial econometric one. In particular, the model may contain a spatially lagged dependent variable or a spatial autoregressive process in the error term. In addition, there may be spatially weighted explanatory variables in the model. An important aspect of any spatial econometric model is the spatial arrangement of the units in the sample. In practice, this is accomplished by specifying a spatial weights matrix, W, "which expresses for each observation (row) those locations (columns) that belong to its

[3] Through this section, we utilize the notation in Elhorst (2010a).

neighborhood set as nonzero elements (Anselin and Bera, p. 243)." The individual elements in the spatial weight matrix, w_{ij}, would equal "1" if observations i and j were "neighbors" (based on some metric) and "0" otherwise. Normally, a row stochastic weight matrix is used in a regression modeling context, which means that the rows of the spatial weight matrix sum to unity. This transformation of the spatial weight matrix provides for an intuitive explanation for the *Wy* and *Wu* terms. The *Wy* term can be thought of as a weighted average of the surrounding observations on the dependent variable, and *Wu* can be thought of as a weighted average of the surrounding error terms. Depending on the regression modeling context, both δ and ρ measure the extent of the spatial autocorrelation.

Given (2), special cases can be obtained by restricting parameters. For example, setting both $\rho = 0$ and $\gamma = 0$, we obtain a model that exhibits spatial dependence only in the dependent variable. This model is the spatial autoregressive (SAR) model. The spatial error model (SEM) arises when the restrictions $\delta = 0$ and $\gamma = 0$ are in effect, resulting in spatial dependence in the error term alone. Placing the restriction $\rho = 0$ results in the spatial Durbin model (SDM). The SDM allows for a spatially lagged dependent variable as well as spatially lagged independent variables. The SAR model is used when one believes that there may be possible spatial autocorrelation in the dependent variable. In our particular application, it may be that teens may cross state lines to obtain employment in a higher-wage state or that there are "employment centers" that draw employees from surrounding states, perhaps due to geographic features, such as valuable natural resources, that cross state boundaries, drawing employment into a particular region. It is important to note that the inclusion of the *Wy* term on the right hand side of the above equation introduces simultaneity bias and therefore the use of OLS as an estimation strategy will produce biased and inconsistent parameter estimates (Anselin 1988, pp. 57-59). Therefore maximum likelihood estimation is used to estimate the parameters in the SAR model.[4]

[4] Details regarding maximum likelihood estimation of spatial econometric models are contained in Anselin (1988) and LeSage and Pace (2009).

The SEM is utilized when one believes that there may be variables that are omitted from the model that are spatially correlated but that are uncorrelated with the included regressors. The conditions under which this spatial residual autocorrelation arises are nicely illustrated in a housing context by Dubin (1998, p. 304), “Housing prices are a prime example: clearly the location of the house will have an effect on its selling price. If the location of the house influences its price, then the possibility arises that nearby houses will be affected by the same location factors. Any error in measuring these factors will cause their error terms to be correlated." In the SEM, the OLS estimator is unbiased, but inefficient. SEM can also be efficiently estimated via maximum likelihood.

LeSage and Pace (2009) point out that SDM should be used when one believes that there are omitted variables in the model that are spatially correlated and these spatially correlated omitted variables are correlated with an included explanatory variable in the model. If these two conditions hold, the SDM is the most appropriate model. In our context, a potential omitted variable may be a measure of the education-level of a state’s population. It may be correlated with the included adult unemployment rate. As indicated by (2), all three of these models may include space- and time-fixed effects. In our case we have state- and year-fixed effects. To determine whether such fixed effects are jointly significant, standard Likelihood Ratio (LR) tests can be performed (Elhorst, 2010b). Additionally, a test can be performed to determine whether the SDM simplifies to the SAR model. The null hypothesis to be tested is $H_o : \gamma = 0$ (Elhorst 2010a), i.e., that the spatially weighted explanatory variables are not spatially correlated. Further details regarding the estimation and use of spatial panel data models are contained in Elhorst (2010a) and Elhorst (2010b).

Results

Table 2 presents results from a standard fixed effects model that does not account for spatial dependence. To determine whether state- and year- fixed effects should be included, we perform two

LR tests, one for the inclusion of state fixed effects and one for year fixed effects. The null hypothesis for the state fixed effects is $H_o: \mu_1, \mu_2, \ldots, \mu_n = 0$ and the results indicate that this null hypothesis should be rejected (LR: 1301.40, df 47, p-value 0.0000). The null hypothesis for the year fixed effects is $H_o: \lambda_1, \lambda_2, \ldots, \lambda_t = 0$ and the results indicate that this hypothesis also should be rejected (LR: 438.48, df 15, p-value 0.0000). Therefore, both state- and year- fixed effects are included in our models.

In this model with state- and year-fixed effects but no controls for spatial dependence, the results indicate a negative and statistically significant relationship between the real effective minimum wage and teen employment. Specifically, a 10% increase in the effective real minimum wage is associated with a 1.8% decrease in teen employment. This estimate lies comfortably in the range of estimates surveyed by Neumark and Wascher (2007). The unemployment rate of individuals aged 20 and over also is associated negatively with teen employment, with a 10% increase in the unemployment rate associated with a 1.3% decline in teen employment. The final explanatory variable, the percentage of the population between the ages of 16 and 19, is insignificant at any reasonable level.

Table 3 presents a SAR model that includes both state and year fixed effects. LeSage and Pace (2009) note that the SDM is the only model that produces unbiased coefficient estimates under all of the possible data generating processes implied by equation (2) above. However, as noted in Elhorst (2010a) the hypothesis $H_o: \gamma = 0$ can be tested to determine if the SDM can be simplified to the SAR model. The results of our LR test (LR: 1.4665, p-value 0.9617) indicates that we cannot reject the null hypothesis. Therefore, the SDM can be simplified to the SAR model. The spatial weight matrix, W, that we use is a 5-nearest-neighbors weight matrix for the states in our sample.[5]

In terms of overall model fit, we have two different measures from which to choose. The first is the R^2, which in this model is equal to 0.9208 due to the fixed effects soaking up most of the variation.

[5] LeSage and Pace (2010) note that the configuration of the spatial weight matrix matters very little when the proper effects estimates are calculated.

Because of this nature of fixed effects, Elhorst (2010a, p. 23) recommends an alternative goodness-of-fit measure based on the squared correlation coefficient between actual and fitted values. In our model this measure is 0.0891. The difference between the two measures indicates how much of the variation in the dependent variable is explained by the fixed effects. It appears that the fixed effects portion of the model explains approximately 83% of the variation in the dependent variable.[6]

The results from this SAR model indicate that there is a modest level of spatial autocorrelation in the dependent variable, with the δ parameter equal to 0.1860 and significant at the 1% level. This result is important for two reasons. First, it confirms our usage of the SAR model as the appropriate model. Second, this quantity is very important in terms of calculating the proper marginal effects. LeSage and Pace (2009) show that the marginal effect of a change in an explanatory variable is calculated using the following formula:

$$\begin{aligned} \partial y_i / \partial x_{ir} &= S_r\left(W\right)_{ii} \\ \partial y_i / \partial x_{jr} &= S_r\left(W\right)_{ij} \end{aligned} \tag{3}$$

where $S_r\left(W\right)=\left(I_n-\delta W\right)^{-1}\beta_r$, i is the subscript representing location i, j is the subscript denoting location j, r represents the r[th] explanatory variable, and β_r is the coefficient on the r[th] explanatory variable. The upper quantity in equation (3) shows how a change in an explanatory variable at location i affects the dependent variable at location i, a quantity known as the direct effect. The lower quantity in equation (3) shows how a change in an explanatory variable at location j affects the dependent variable at location i, where $i \neq j$. This is known as the indirect, or spillover effect. It should be noted that the quantity $S_r\left(W\right)$ produces a matrix of effects estimates. LeSage and Pace (2009) recommend that one calculate scalar summaries of these measures to get an average effect. The average direct effect is the

[6] Elhorst (2010a, p. 23) notes that that variation explained by the fixed effects can be quite substantial.

average of the diagonal elements of the $S_r(W)$ matrix, the average indirect effect is the average of the off-diagonal elements of the $S_r(W)$ matrix, and the average total effects are the sum of the two. Statistical inference regarding these effects estimates and how they are calculated are contained in LeSage and Pace (2009).

Our primary focus is the direct, indirect, and total effects of the real effective minimum wage on employment. The direct effect of a change in a state's real effective minimum wage measures how a change in a particular state's minimum wage affects teen employment in that same state. According to the results in Table 3, the direct effect is -0.1726 and it is significant at the 5% level. This means that as a state increases its own real effective minimum wage by 10%, teen employment in that same state decreases by 1.726%, a result in line with previous studies that did not utilize spatial econometric techniques.[7] A major advantage of the spatial econometric techniques that we use in this study is their ability to quantify spatial spillovers in the form of the indirect effects. The indirect effect estimate is -0.039, although it is just shy of being statistically significant at conventional levels, with a p-value of 0.1177. The negative sign indicates that as a state increases its real effective minimum wage, teen employment in adjacent states (as defined by our W matrix) decreases as well. One possible explanation for the effect is that as a state increases its real effective minimum wage, it becomes more attractive to workers in neighboring states who decide to queue for jobs in the state that raised its minimum wage. Consequently, teen employment in the neighbor state will decrease.

The final effect estimate requiring discussion is the total effect, which is the sum of the direct effect and the indirect effect. Arguably, this is the most important quantity that needs interpretation in that the total effect measures how changes in the real effective minimum wage affects total teen employment, taking into account both own-state and spillover effects. The point estimate for the total

[7] Technically, the regression coefficient from the non-spatial panel data model cannot be directly compared with its spatial counterpart because the latter contains feedback effects. See LeSage and Pace (2009) for details.

effect of a change in the real effective minimum wage is -0.2112 and is statistically significant at the 5% level. The total effect estimate shows that, as the real effective minimum wage increases by 10%, teen employment decreases by 2.11%, an effect greater than the consensus result. Thus, it appears that controlling for spatial dependence matters. Not doing so may lead to an underestimate of the negative effect of minimum wages on teen employment.

Conclusion

Previous studies of the minimum wage have neglected the issue of spatial dependence. This has potentially led to biased, inconsistent, and inefficient parameter estimates. The advantages of using spatial econometric techniques in a panel data setting are, firstly, that spatial dependence can be modeled and controlled for and, secondly, that spatial spillovers can be accounted for to produce more accurate estimates of the quantities of interest. Using a panel data set covering the period 1990-2004, we examine how changes in the real effective minimum wage affect teen employment. Estimation of the standard panel data model with state- and year- fixed effects but no controls for spatial dependence suggests that, as the real effective minimum wage increases by 10%, teen employment decreases by 1.78%, a finding that is consistent with estimates from other studies. Controlling for spatial dependence through estimation of a SAR model indicates that a 10% increase in the real effective minimum wage results in a 2.11% decrease in teen employment, a larger estimate because it includes both direct and indirect effects. Thus, studies that ignore spatial dependence may underestimate the negative effect of minimum wages on teen employment.

Table 1: Means and Standard Deviations (N = 705)

Variable	Mean	Standard Deviation
Teen employment/population ratio	0.4578	0.0872
Real effective minimum wage	3.8837	0.1969
Unemployment rate of adults aged 20 and over	4.5664	1.3327
Percent of the population aged 16 to 19	0.0760	0.0092

Table 2: Non-spatial Fixed Effects Model (N = 705)

Dependent Variable: Natural log of teen employment to population ratio		
Explanatory Variables		
Natural log of the real effective minimum wage	-0.179 (0.0846)	**
Natural log of the unemployment rate of adults aged 20 and over	-0.13 (0.0167)	***
Natural log of the percent of the population aged 16 to 19	0.008 (.0.363)	
Adjusted R^2	0.084	

Fixed effects are not shown. Standard errors are in parentheses below the estimated coefficients. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 1% level.

Table 3: Spatial Autoregressive Model (SAR) Results (N=705)

Dependent Variable: Natural log of teen employment to population ratio			
Explanatory Variables	**Direct Effect**	**Indirect Effect**	**Total Effect**
Natural log of the real effective minimum wage	-0.173 ** (-0.348,-0.004)	-0.039 (-0.010,-0.0008)	-0.211 ** (-0.415,-0.005)
Natural log of the unemployment rate of adults aged 20 and over	-0.128 *** (-0.164,-0.092)	-0.029 *** (-0.051,-0.010)	-0.157 *** (-0.204,-0.111)
Natural log of the percent of the population aged 16 to 19	0.009 (-0.063,0.081)	0.002 (-0.017,0.022)	0.011 (-0.080,0.103)
ρ = 0.1859 (t-stat: 3.37 p-value: 0.000757)			
Adjusted R^2: 0.9208, $Corr^2$: 0.0891			

Fixed effects are not shown. Lower and upper 95% confidence intervals for the effects estimates are underneath the estimates within parentheses. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 1% level. Estimates are bias-corrected using the procedure of Lee and Yu (2010).

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