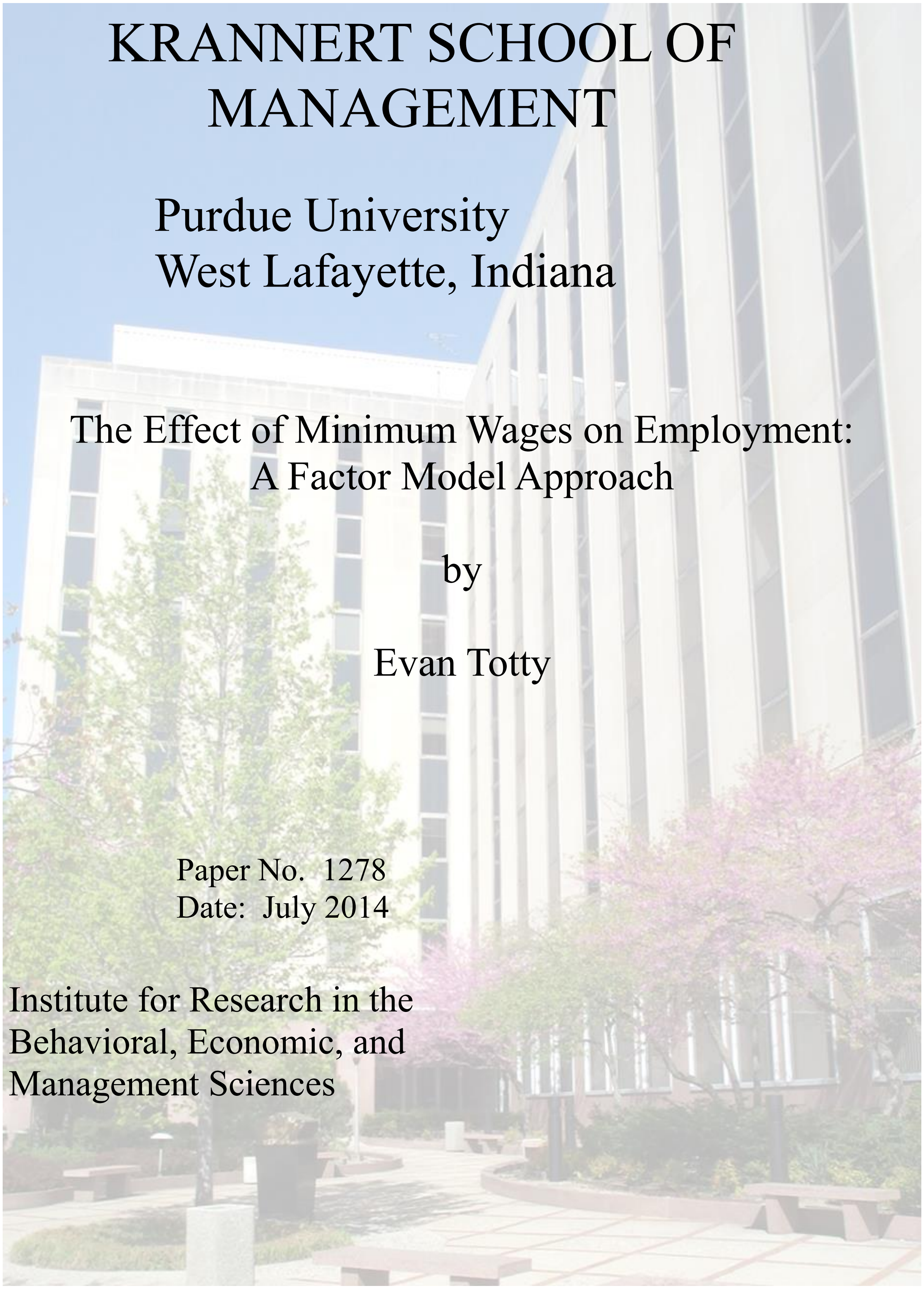

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The Effect of Minimum Wages on Employment: A Factor Model Approach

by

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Abstract

The goal of this paper is to resolve issues in the minimum wage-employment debate by using new factor model econometric methods to control for unobserved heterogeneity. Recent work has shown that traditional methods producing negative and statistically significant minimum wage-employment elasticities are sensitive to adding controls for unobserved heterogeneity, but these controls rely on assumptions that may not be supported by the data. The factor model results suggest that any negative employment effects that do exist are small. Furthermore, simulation results show that unobserved common factors can explain the different estimates across methodologies in the literature. A counterfactual experiment shows that the states that would be affected by a modest federal minimum wage increase are those that are most able to absorb minimum wage increases without experiencing decreased employment.

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1 Introduction

Understanding the effect of minimum wages on employment has long been of interest to economists, with empirical work on the subject dating back approximately 100 years (Obenauer and von der Nienburg (1915)). Despite this long history of attention, economists are still very much divided on this issue[1]. The last two decades, in particular, have produced an abundance of work on the subject, without providing a consensus. The empirical evidence in these studies differs depending on both the datasets used and the methodology[2]. The goal of this paper is to resolve the issues in the minimum wage-employment literature by using new panel data econometric methods that are robust to critiques from either side of the debate. Specifically, I use Pesaran's (2006) common correlated effects estimators and Bai's (2009) interactive fixed effect estimator, and I apply these estimators to two datasets and many specifications that have recently been used in the literature. The factor model methods used in this paper are well suited for a wide variety of empirical studies, although they have not yet received much use.

The evaluation of regional policies, such as minimum wage policies, can be difficult as outcomes are likely to be spatially correlated in addition to the more common issue of serial correlation. There is thus a need to control for this spatial dependence when evaluating regional policies. Dube et al. (2010) and Allegretto et al. (2011) raised this issue with respect to the minimum wage-employment literature. The traditional approach to estimating the minimum wage-employment elasticity with panel data has been to use ordinary least squares with state and year fixed effects, which has produced large and statistically significant

[1] In 2013, The University of Chicago based Institute of Global Markets asked 38 economists if they agreed with the following statement: "Raising the federal minimum wage to $9 per hour would make it noticeably harder for low-skilled workers to find employment." Thirty-four percent of the economists agreed, thirty-two percent disagreed, and twenty-four percent were uncertain.

[2] The theory is also ambiguous. The monopsony model is commonly used to explain how minimum wages could have no effect on employment and the competitive model is commonly used to predict a negative effect. However, the competitive model can also predict no effect by allowing for other channels of adjustment, such as higher prices, reductions in non-wage benefits, reductions in training, and labor substitution. The institutional model can also predict no effect of minimum wages on employment through costly monitoring of workers, efficiency wages, or a demand stimulus. For an overview of how minimum wages could have little or no effect on employment, see Schmitt (2013).

elasticities in the range of -.1 to -.3[3]. Dube et al. (2010) and Allegretto et al. (2011) add geographic controls, such as census division times period fixed effects, and state-specific linear time trends to address this issue of spatial heterogeneity. Dube et al. (2010) also employ a border discontinuity approach. Using these methods causes the negative effects found using the traditional approach to disappear[4]. However, Neumark et al. (2013) argue that the implicit assumption of these methods that geographically proximate places are better controls is not supported by the data. They also show that Allegretto et al.'s (2011) results are sensitive to extending the linear state-specific time trends to higher order polynomial trends. Neumark et al. (2013) claim that these controls throw out a great deal of valid identify information and conclude that neither the methods nor the results in in Dube et al. (2010) and Allegretto et al. (2011) are supported by the data[5].

This factor model setup provides a new way to control for spatial dependence in panel datasets. Factor models are unique not just because they facilitate the control of spatial dependence, but because they allow areas to be close in economic dimensions which depart from geographic proximity. This is the case, for instance, when two areas are affected by the same industry-specific shocks because of industry specialization, even if these two areas are not neighbors. These methods can therefore be seen as a more flexible way of controlling for spatial heterogeneity, as they do not impose any geographic relationship on the spatial dependence a priori. Neumark et al. (2013) argue in favor of the traditional state and year fixed effects approach, but they do propose the use of synthetic controls as a way to address this issue of unobserved heterogeneity while still letting the data speak. They

[3] A detailed history of the minimum wage-employment debate can be found in Brown (1999) and Neumark and Wascher (2008). Past studies on minimum wages and employment are usually either local case studies focusing on employment in a particular low-skill industry or national studies using panel data on teenage or restaurant employment. The national panel data studies typically find statistically significant negative employment effects with minimum wage-employment elasticities in the range of -.1 to -.3, while local case studies usually find no effect.

[4] The difference between the two papers is that Dube et al. (2010) analyze a national panel of restaurant employment, whereas Allegretto et al. (2011) use a national panel of teenage employment.

[5] Allegretto, Dube, and Reich respond to these criticisms in Allegretto et al. (2013). Specifically, they refute the interpretation of Neumark et al.'s (2013) evidence that questions the use of geographic controls and linear state-specific time trends and they provide new evidence that supports the use of local controls areas.

report significant negative effects, with teenage employment elasticities of -.15. Allegretto, Dube, and Reich applied their own implementation of the synthetic control approach in Allegretto et al. (2013) and found no significant effect of minimum wages on employment[6]. However, there are drawbacks to this pooled synthetic control approach. It leaves many details to the discretion of the researcher, such as choice of predictor variables and length of the pre- and post-intervention windows, allowing for multiple interpretations of what is an appropriate implementation. It also greatly reduces data availability, particularly when applied to minimum wage variation[7]. Furthermore, the matching of treated units with donor units relies only on observables, leaving no guarantee that treated units and their synthetic control units are also similar with respect to unobserved heterogeneity.

The factor model approach therefore seems perfectly suited to address the methodological debate in the literature. It achieves Dube et al.'s (2010) and Allegretto et al.'s (2011) goal of controlling for spatial dependence without the use of geographic controls and time trends that Neumark et al. (2013) find problematic. The factor model approach also has several advantages relative to the more commonly used synthetic control approach: (1) It has a more straightforward implementation, leaving little up to the discretion of the researcher. (2) It can use all of the minimum wage variation in the data. (3) It explicitly models time-varying unobserved heterogeneity and controls for it during estimation. In fact, factor model estimators such as Bai's (2009) interactive fixed effects method have actually been shown to outperform the synthetic control approach (Gobillon and Magnac (2013)). Recent advances in the econometric literature also allow for consistent estimation of factor models when the factors are correlated with the explanatory variables, providing a solution to the possibility

[6]Allegretto et al. (2013) argue that Neumark et al.'s (2013) synthetic control approach is flawed due to an inappropriate matching variable, a contaminated sample (in which the minimum wage is rising in post-intervention and pre-intervention control periods), and very short pre- and post-intervention windows. They then report results that more properly apply the synthetic control approach and find results that confirm their previous findings.

[7]The synthetic control approach requires the availability of control states and the isolation of treatment with clearly defined pre- and post-treatment periods. This makes the use of federal minimum wage variation nearly impossible, as very few states are unaffected. State minimum wage variation is also often discarded because of a lack of long enough pre- and post-treatment windows without additional treatment. Allegretto et al. (2013) are able to use only 19 of 89 state minimum wage changes from 1997q4 to 2007q2.

of minimum wages being endogenous with respect to low-skill employment.

The factor model results suggest that any negative effects of minimum wages on employment are small. I first use traditional OLS state and year fixed effects methods and find minimum wage-employment elasticities of -.15 for both restaurant and teenage employment, in line with other estimates in the literature using these methods. I then use the factor model estimators from Pesaran (2006) and Bai (2009) and find minimum wage-employment elasticities of 0 to -.01 for restaurant employment and -.04 to -.10 for teenage employment. Furthermore, I show that these results are insensitive to adding flexible time trends and narrowing of the identifying information. While the results cannot rule out negative effects on teenage employment that are in the low end of the traditional -.1 to -.3 range, the results as a whole are suggestive that any negative effects of minimum wages on low-skill employment that do exist are small, and the lack of control for unobserved heterogeneity in the traditional OLS state and year fixed effects approach produces spurious negative results. Furthermore, analysis of what is being captured by the factor model shows obvious and interpretable time series and cross-section correlations.

I also use a simulation experiment to asses the relative ability of OLS and the factor model estimators to estimate the minimum wage-employment elasticity under the presence of various types of unobserved heterogeneity and perform a policy relevant counterfactual experiment. The simulation experiment shows that common factors in the true underlying DGP can cause the different estimates seen across methodologies. The counterfactual experiment shows that the states that would be affected by a higher federal minimum wage are states that are more able to absorb minimum wage increases without experiencing a decrease in employment.

The remainder of this paper is organized as follows: Section 2 describes how the variables are constructed and provides summary statistics for the data. Section 3 describes the factor models that the new panel data estimators make use of and then describes the estimators themselves. Section 4 presents the results for the minimum wage-employment elasticity and analyzes what the factor structure is capturing. Section 5 provides the simulation and counterfactual experiments. Section 6 concludes.

2 Data

This study uses the same datasets as Dube et al. (2010), Allegretto et al. (2011), and Neumark et al. (2013), updated to include more recent years. One dataset is a national panel of restaurant employment measured at the county level. The other is a national panel of teenage employment measured at the state level. Teenagers are traditionally the focus of panel studies on minimum wages and employment, but restaurants are also an appropriate group as restaurants are the most intensive user of minimum wage workers, the proportion of workers employed at or near the minimum wage is similar among restaurants and teenagers, and teenage minimum wage workers are often employed at restaurants (Dube et al. (2010)). Construction of the variables and summaries of the datasets are provided below. Each dataset is merged with a quarterly minimum wage variable which is always the higher of the federal and state minimum wage.

2.1 Restaurant Employment

Quarterly data on restaurant employment is constructed for the years 1990-2010 from the Quarterly Census of Employment and Wages (QCEW). The QCEW provides quarterly county-level payroll data by industry based on ES-202 filings that establishments submit for the purpose of calculating payroll taxes related to unemployment insurance. The county-quarter restaurant employment dependent variable is constructed from both Full Service Restaurants (NAICS 7221) and Limited Service Restaurants (NAICS 7222) and measures the total number of full service and limited service restaurant employees. The control variables are county-quarter total employment and county population. The total employment variable is constructed from the QCEW and the county population comes from the county-level

Census Bureau population data which is produced annually[8]. Data is available for the entire time frame of analysis for 1,371 counties[9]. Summary statistics for the dataset of analysis on restaurants are shown in Table 1.

2.2 Teenage Employment

Quarterly data on teenage employment is constructed for the years 1990-2013 from the Current Population Survey Outgoing Rotation Groups. State-quarter observations are constructed by aggregating the CPS-ORG individual level data up to the state-quarter level. The state-quarter teenage employment dependent variable is the fraction of teenagers (ages 16-19) that are employed. The control variables are the state-quarter relative size of the teenage population and state-quarter unemployment rate, also constructed from the CPS-ORG. Summary statistics for the dataset of analysis on teenagers are shown in Table 2.

3 Methodology

This section will first introduce the factor model setup that the new econometric methods make use of and discuss how the factor model setup relates to the question of the effect of minimum wages on employment. I will then briefly describe and discuss the new factor model estimation methods I will be using.

3.1 Factor Models

The factor model setup is based on models in which the error term is characterized by a multi-factor error structure. Specifically, the traditional error term in a regression equation is decomposed into time-specific "common factors" that can affect all cross-sectional units,

[8]The county-level Census Bureau population data is only available through 2010. Thus, the time frame of analysis for restaurant employment ends after 2010.

[9]For consistency with Dube et al. (2010) and Neumark et al. (2013), results are based on a balanced panel.

heterogeneous "factor loadings" that represent how each common factor affects each cross-sectional unit, and an idiosyncratic error term. This multi-factor error structure will be applied as an extension to the traditional approach of estimating the effect of minimum wages on employment.

Consider the traditional model for estimating the effect of minimum wages on employment as discussed in Section 1:

$$ln(E_{it}) = \beta ln(MW_{it}) + X_{it}\Gamma + \alpha_i + \delta_t + \varepsilon_{it} \tag{1}$$

where E_{it} is employment in county/state i in period t, MW_{it} is the higher of the federal and state minimum wage, X_{it} is a vector of control variables, α_i is a county/state fixed effect, and δ_t is a period fixed effect. Employment and the minimum wage are measured in logs so that β represents the minimum wage-employment elasticity. The contribution of this paper is to extend this model by adding a multi-factor structure to the error term. Specifically, the error term in the previous equation takes the form

$$\varepsilon_{it} = \lambda_i' f_t + u_{it} \tag{2}$$

where f_t is an (r x 1) vector of time-specific common factors that affect all cross-sectional units and λ_i is an (r x 1) vector of factor loadings that represents how each common factor affects that individual cross-section unit.

The idea of these common factors can be very intuitive. For example, skill-biased technological change could be a common factor affecting both low-skill employment and the minimum wage and could do so heterogeneously across counties and states. Previous work has shown that skill-biased technological change essentially increases competition for teenage jobs by creating job polarization, pushing adults out of middle-skill jobs and into low-skill jobs (Smith (2011)). Skill-biased technological change could also affect the minimum wage by causing income inequality to rise due to an increased demand for high-skill workers coupled with the increased supply of workers into low-skill jobs because of job polarization. This rising income inequality could then motivate legislators to raise the minimum wage. Furthermore, the effect of this skill-biased technological change could vary by state or even county, depending on the industrial specialization of the local labor market. This type of a common factor could be captured by the factor model setup described above but would cause negative omitted variable bias in the traditional OLS approach with state/county fixed effects and period fixed effects[10].

Applying this structure to the error term can be seen as a more flexible way of attempting to control for unobserved heterogeneity than previous methods used in the literature. The traditional state/county and year fixed effects approach can be rewritten as a special case of this factor model setup where $f_t = (1, \delta_t)'$ and $\lambda_i = (\alpha_i, 1)'$[11], as can the state-specific linear time trends and census division times period fixed effects approach ($f_t = (1, \delta_t, t, \delta_t)'$ and $\lambda_i = (\alpha_i, 1, \phi_i, \zeta_i)'$[12]). These previous methods assume that these controls fully capture the form of the unobserved heterogeneity, applying a fixed form a priori. The factor model approach allows the data to determine the nature of the unobserved shocks, allowing for an improved ability to control for unobserved heterogeneity if the fixed effects and time trends do not fully capture the true form of the unobserved heterogeneity. This is especially important with respect to spatial heterogeneity. The census division times period fixed effects and the border discontinuity approach assume, a priori, that more proximate places are better controls, while the traditional approach has no controls for spatial heterogeneity other than state fixed effects. The factor model approach allows for spatial heterogeneity, but places no geographic assumptions on the factor structure, allowing the data to determine the nature of

[10]The idea of unemployment being affected by common unobserved factors is not new. Bean (1994) and Blanchard and Wolfers (2000) discuss the role of common shocks together with heterogeneous effects of these common shocks across countries due to institutional differences when explaining the stylized facts about European unemployment. Smith and Zoega (2008) show that an unobserved common factor can explain up to 70% percent of unemployment variation across 21 OECD countries.

[11]Equations 1-2 are rewritten here to embed the state/county and year fixed effects within the factor model setup for illustration purposes.

[12]In order to produce a state-specific time trend, $\phi_i = \gamma_s$ if $i \in$ state s. To produce a census division times period fixed effect, $\zeta_i = \xi_d$ if $i \in$ census division d.

the spatial dependence. Factor models are unique not just because they facilitate the control of spatial dependence, but because they allow areas to be close in economic dimensions which depart from geographic proximity. This is the case, for instance, when two areas are affected by the same industry-specific shocks because of industry specialization, even if these two areas are not neighbors.

Recent advances in the factor model literature make the use of these models very appealing. Specifically, new methods allow for consistent estimation when the common factors are correlated with the explanatory variables and under the presence of heteroskedasticity and serial correlation, in addition to the cross-sectional correlation implied by the factor structure itself. These advances therefore offer a solution to the potential issue of minimum wages being endogenous with respect to low-skill employment, which is pervasive throughout the literature[13]. That being said, the factor model approach cannot control for every possible threat to identification. While the factor model does add a lot of flexibility to the error term, it must assume that the factor loadings are time-invariant. The factor model approach therefore does not capture a situation in which states or counties have time-variant responses to common factors that vary differentially across states or counties. Nonetheless, these methods can control for a number of issues that are relevant to the topic of minimum wages and employment. Namely, they allow a more flexible form for the unobserved heterogeneity, they allow for spatial dependence in dimensions other than geographic proximity, and they can address the issue of endogeneity[14].

[13] Neumark et al. (2013) discuss the possibility that endogeneity of minimum wages with respect to low-skill employment could be causing negative bias in minimum wage-employment elasticity estimates. They claim that the evidence actually points to positive endogeneity bias, citing a study by Baskaya and Rubinstein (2011) that addresses the potential endogeneity of minimum wages by using an IV approach. However, the instrumental variable used by the authors seems questionable; Baskaya and Rubinstein (2011) IV for a state's minimum wage with the federal minimum wage multiplied by the probability that the federal minimum wage will be binding in that state. This IV seems questionable, as federal minimum wage variation seems likely to also be correlated with other sources of teenage employment change. Furthermore, Baskaya and Rubenstein (2011) do not explicitly test if minimum wages respond positively to teenage employment. Rather, they show that minimum wages respond positively to lagged overall employment. This is similar to what Reich (2009) finds, which Neumark et al. (2013) admit does not speak to the potential endogeneity of minimum wages with respect to teenage employment.

[14] The process by which minimum wages are raised can be a lengthy one, as there may be extensive legislative debate before approval and a number of years may pass between approval and implementation.

3.2 Estimation

Two methods for estimation will be used. The first method is Pesaran's (2006) common correlated effects estimators. This method does not attempt to estimate the common factors and factor loadings. Rather, the idea behind this method is to filter the explanatory variables by means of cross-sectional averages of the dependent and independent variables, such that asymptotically the effect of the unobserved common factors is eliminated. This estimator has the added benefit that it can be computed by ordinary least squares applied to regressions where the observed explanatory variables are augmented with cross-sectional averages of the dependent and independent variables. Pesaran (2006) proposes two versions of this method: the common correlated effects mean group (CCEMG) estimator, which assumes heterogeneous slope coefficients over cross-sectional units, and the common correlated effects pooled (CCEP) estimator, which assumes homogeneous slope coefficients. Standard errors are calculated using equations (58) and (69) in Pesaran (2006) for the CCEMG and CCEP estimators, respectively. See Pesaran (2006) for a more detailed description of these estimators.

The second method is Bai's (2009) interactive fixed effects (IFE) estimator. Bai's (2009) estimator does involve estimating the common factors and factor loadings. This is done by using principal component analysis[15]. Bai's (2009) method is based on the fact that, given the common factors and factor loadings, we can estimate the regression coefficients, and given the regression coefficients, we can estimate the factors and factor loadings using principal component analysis. However, the regression coefficients and factor structure are

For this reason, it is worth noting that the factor model presented above can be rewritten to incorporate lagged common factors. In this case, the error term in equation (1) takes the form $\varepsilon_{it} = \Lambda_i' F_t + u_{it}$ where $F_t = (f_t', f_{t-1}', ..., f_{t-s}')'$ is an $(r(s+1)$ x $1)$ vector of common factors, $\Lambda_i = (\lambda_{i0}', \lambda_{i1}',...,\lambda_{is}')'$ is an $(r(s+1)$ x $1)$ vector of factor loadings, and s represents the number of lagged factors. This setup makes these factor models even more intuitive, as both employment and minimum wage policies may be more likely to have a lagged response to unobserved factors, such as skill-biased technological change, than a contemporaneous response. Importantly, the estimation procedure described in the next section does not require the knowledge of the number of dynamic factors (Kapetanios et al. (2011)).

[15]Selection of the number of common factors, r, for the factor structure is based on the IC_{p1} criterion from Bai and Ng (2002).

both unknown in practice. Therefore, Bai (2009) proposes a procedure in which one iterates between estimating the regression coefficients and estimating the factor structure. This iteration continues until the change in the sum of squared residuals is below a specified threshold. A threshold of 10^{-9} is used in this paper. Bias-correction for serial correlation, cross-sectional correlation, and heteroskedasticity is performed using equations (23) and (24) in Bai (2009). Standard errors are calculated using Theorem 4 in Bai (2009). See Bai (2009) for a more detailed description of this estimator.

The relative merits of these three estimators are mostly unknown in the current state of the econometrics literature[16]. With respect to the two common correlated effects estimators, we would expect the CCEP version to perform better if minimum wages have homogeneous effects over cross-sectional units due to efficiency gains from pooling. Alternatively, the CCEMG version is better suited to handle a situation in which minimum wages effect employment differently in different states or counties, as the CCEMG estimator assumes heterogeneous effects over cross-sectional units. Intuitively, the latter may be more appealing due to spatial differences in industrial specialization or education which would affect the extent to which minimum wages are actually a binding constraint. The simulations in Pesaran (2006) favor the CCEP estimator for small to moderate sizes of N and T (sizes of 20, 30, 50, 100, and 200 were used for both N and T) and slightly favor CCEMG when N and T are relatively large. Recalling from Section 2 the N=1371, T=84 size of the restaurant employment dataset and N=51, T=96 size of the teenage employment dataset, the simulation results from Pesaran (2006) suggest favoring the CCEMG estimator for the restaurant employment dataset and CCEP for the teenage employment dataset.

Little is also known about the relative merits of the use of cross-sectional averages as proxies for the factors and the use of principal component analysis to estimate the factor structure. In both cases, consistent estimation requires that N be sufficiently large, as the

[16] These estimators have yet to receive much attention in empirical work. In a paper similar in spirit to this one, Kim and Oka (2014) use the IFE estimator to reconcile conflicting results in the literature on the effects of divorce law reform on divorce rates. The CCE estimators have seen more use, as they are easier to implement (Buch et al. (2009), Bond et al. (2010), Bertoli and Moraga (2013), Eberhardt et al. (2013)).

IFE estimator is $\sqrt{NT}$-consistent and the CCE estimators are $\sqrt{N}$-consistent. The relatively small cross-section dimension of the teenage employment dataset compared to the restaurant employment dataset means these methods may be more reliable for the latter. Chudik et al. (2011) show that Bai's (2009) IFE estimator performs similarly to Pesaran's (2006) CCE estimators in terms of bias and RMSE under the presence of various types of factor structures[17]. Westerlund and Urbain (2011) set out to address this issue of the relative merits of these two methods and show that Bai's (2009) principal component based method is more efficient, asymptotically, and therefore expect the IFE estimator to perform best. However, their simulations find that Pesaran's (2006) common correlated effects method performs the best.

4 Results

4.1 Minimum Wage-Employment Elasticity

As mentioned in Section 2, I use the same datasets that are used in Dube et al. (2010), Allegretto et al. (2011), and Neumark et al. (2013), updated to include more recent observations. The results are presented separately for restaurant and teenage employment in Table 3 and Table 4, respectively. In the tables, I first produce results using the methods from each of these three papers for the purpose of illustrating the different results in the literature and to show that updating the two datasets with more recent years does not change the conclusions when using their methods. Shaded regions represent specifications that were used in the paper by the corresponding authors. The primary specification is column 1, which is the traditional state and period fixed effects approach. Columns 2-6 add flexible time trends as a robustness check and because the common correlated effects estimators assume that the common factors are covariance stationary, which would be violated if there are time trends

[17]Chudik et al. (2011) find that tests based on Bai's IFE estimator are over-sized, likely due to a problem with the variance of the IFE estimator. I will address this issue in Section 4.

that are not controlled for.

The first row of Table 3 shows OLS estimates of the minimum wage-employment elasticity for each specification. The other rows show estimates from the corresponding factor model estimators. The first two columns of OLS results for the all county sample reproduce Dube et al.'s (2010) result that adding linear state-specific time trends to the OLS estimation removes the negative employment effects. When I extend these OLS estimates by adding up to a 5th-order polynomial state-specific time trend the estimates become a bit larger and significant, but the magnitudes remain small relative to the traditional specification. The contribution of the new estimators can be seen in the first column of the all-county sample of Table 3, which applies the factor model estimators to the traditional state and period fixed effects specification. The CCEP, CCEMG, and IFE estimates all produce very small negative employment effects, with elasticities in the 0 to -.01 range[18]. These estimates are smaller than the traditional -.1 to -.3 range and are smaller than the OLS estimate of -.151 for the traditional specification. Columns 2-6 extend these results by adding up to a 5th-order polynomial state-specific time trend. The CCEP, CCEMG, and IFE estimated elasticities are invariant to this flexible detrending, with elasticities remaining in the 0 to -.05 range.

Next, I further extend the results for restaurant employment by looking only at contiguous counties on opposite sides of a state border. The OLS row of the contiguous county sample replicates Dube et al.'s (2010) result that adding linear state-specific time trends to the OLS estimation removes the negative employment effects. Neumark et al. (2013) exactly replicate this result, then present their case that time trends, census division times period fixed effects, and contiguous county analysis are not appropriate. The contribution of the factor model estimators is again seen in the first column, as the estimated elasticities are in the range of -.01 to -.03. These estimates are smaller than the OLS estimate of -.106 and are invariant to flexible time trends. Between the three factor model estimators, the six different

[18]The IFE estimators, while similar in magnitude to the CCEP and CCEMG estimators, have small standard errors. Tests based on IFE standard errors have been shown to be over-sized (Chudik et al. (2011)). I therefore performed the wild cluster bootstrap-t procedure from Cameron et al. (2008) to correct for this. The significance reported in the tables is based on the results of this procedure.

specifications, and the two different county samples, Table 3 provides 36 new estimates of the minimum wage-employment elasticity for restaurant employment. All 36 estimates fall in the .01 to -.05 range and 33 out of 36 fall in the 0 to -.03 range.

For teenage employment, Allegretto et al. (2011) and Neumark et al. (2013) use slightly different methods; Allegretto et al. (2011) first estimate linear probability models using individual-level data and then convert the coefficients into elasticities, whereas Neumark et al. (2013) aggregate the individual-level data up to the state-quarter level and use OLS. The first row of Table 4 shows probit estimates of the minimum wage-employment elasticity and the second row shows OLS estimates. The first two columns of the probit row replicate Allegretto et al.'s (2011) result that linear state-specific time trends remove the negative employment effect[19]. The OLS row replicates Neumark et al's (2013) result that large and significant negative employment effects return when the linear state-specific time trends are extended to a 3rd-order polynomial or higher, with elasticities larger than -.2.

Just as with the restaurant employment dataset, the factor model estimators report much smaller elasticities than their OLS counterparts. Looking first at column 1 of Table 4, the CCEP and CCEMG estimators produce elasticities of -.065 and -.040, respectively, while the IFE estimator produces an elasticity of -.104. These estimates are all smaller than or near the lower bound of the traditional -.1 to -.3 range and are smaller than the elasticity of -.151 from the OLS estimate of the traditional specification. Columns 2-6 show that the results are invariant to detrending by adding up to a 5th-order polynomial state-specific time trend. The factor model estimates show a little more variance across specifications for teenage employment than they did for restaurant employment, but the majority fall below the traditional -.1 to -.3 range and all of the estimates are smaller than their OLS counterparts in the OLS row[20]. Between the three factor model estimators and the six different specifications,

[19]The third row of the probit specification, in bold, represents the implied elasticity from the probit estimation, which includes controls for gender, race, age, education, and marital status. The implied minimum wage elasticity is calculated by dividing the probit coefficient by the group employment-to-population ratio.

[20]Recall from Section 3.2 that a possible explanation for the factor model estimates showing more variance for teenage employment than restaurant employment is the size of the two datasets. Precise estimation of the factors requires N to be sufficiently large. Because the restaurant employment dataset is measured at the

Table 4 provides 18 new estimates of the minimum wage-employment elasticity for teenage employment. The new results as a whole fall in the .02 to -.15 range, 15 of the 18 estimates fall in the -.01 to -.13 range, and 12 of the 18 are smaller than the traditional -.1 to -.3 range.

In summary, the factor model estimators used here show that any negative effects of minimum wages on restaurant employment are small, with minimum wage-employment elasticities in the 0 to -.05 range. OLS can only achieve this result with the use of time trends or geographic controls. For teenage employment, while the factor model elasticity estimates of 0 to -.15 cannot rule out negative effects on employment that are in the low end of the traditional -.1 to -.3 range, the results as a whole suggest that any negative employment effects of minimum wages that do exist are smaller than estimates using traditional OLS methods. These new methods are not subject to Neumark et al.'s (2013) criticisms of Dube et al.'s (2010) and Allegretto et al.'s (2011) methods of controlling for unobserved heterogeneity, as they do not rely on time trends or geographic controls. The CCEP, CCEMG, and IFE estimators produce elasticities that are considerably smaller that OLS estimates using the traditional state and period fixed effects specification that Neumark et al. (2013) argue in favor of. These results are also invariant to detrending and narrowing the identifying information, which is a significant contribution to settling the disagreement in the literature according to Neumark et al. (2013)[21].

4.2 Factor Analysis

The previous section showed that controlling for common factors is important for estimation and inference. In this section I focus on the factor structure itself and attempt to shed light on exactly what it is capturing by analyzing the estimated factor structure from Bai's

county level, it has a much larger cross-section dimension (N=1371) than the teenage employment dataset (N=51). This small cross-section dimension for teenage employment may be making consistent estimation difficult for the $\sqrt{N}$-consistent CCE estimators and the $\sqrt{NT}$-consistent IFE estimator.

[21]When discussing the use of new methods or specifications, Neumark et al. (2013) state that, "In particular, if these kinds of sensitivity analyses deliver robust results that are insensitive to detrending or to the narrowing of identifying information by restricting the set of control areas, then they can clearly bolster the evidence. (p. 47)"

(2009) IFE method. Direct economic interpretation of the estimated common factors is not guaranteed to be possible. Statistically, they are eigenvectors corresponding to the largest eigenvalues of the second moment matrix of the regression coefficient estimation residuals. Nevertheless, it may be useful for conceptual purposes to see if what the IFE estimator is capturing exhibits any cross-sectional or time-series patterns[22]. The number of factors, r, is estimated using the information criterion in Bai and Ng (2002). This procedure requires specification of the maximum number of factors allowed. A value of eight was chosen, and the information criterion selected r=8 for the restaurant employment dataset and r=2 for the teenage employment dataset. Given this value of r, Bai's (2009) IFE method is used to simultaneously estimate the factor structure and coefficients[23].

Table 5 shows summary statistics for the estimated restaurant and teenage employment common factors from the traditional specification in Table 3 (all-county sample) and Table 4 that included only state and period fixed effects. The first column shows the fraction of the total variance explained by factors 1 to p, where the total variance is the variance of the second moment matrix of the coefficient estimation residuals. This is given as the sum of the first p eigenvalues of the second moment matrix divided by the sum of all eigenvalues. Table 5 shows that much of the variance can be accounted for by a small number of factors. For restaurant employment, the first factor accounts for 57% of the variance explained by the 8 factors, and the first four factors account for 89%. In order to illustrate the persistence of each of the factors, column 2 reports the first-order autoregressive (AR(1)) coefficient for each factor. All of the factors are positively persistent, but there is heterogeneity, with some factors being highly persistent (the first factor has a persistence of .99) and others being weakly persistent (the third factor has a persistence of .30). For teenage employment, the first factor explains 52% of the variance and the first and second factors have AR(1)

[22]Estimation of the factor structure through principal components allows f_t to be serially correlated and λ_i to be cross-sectionally correlated, but does not require this to be the case. Additionally, whether or not f_t or λ_i has zero mean is not an assumption of principal components.

[23]The results for the minimum wage-employment elasticity in Section 4.1 were invariant to a wide range of values for r. These results are available upon request

coefficients of .41 and .35, respectively.

Figure 1 plots the eight restaurant employment common factors. The first four factors can be interpreted. The first factor is clearly a linear time trend and the second factor is a quadratic time trend. The third and fourth factors appear to be capturing seasonal effects with different time series patterns. Factors 5-8 do not exhibit any obvious, interpretable time series patterns. There are many explanations for what they could be capturing, including macroeconomic shocks or skill-biased technological change. Figure 2 plots the two teenage employment factors. These two factors do not exhibit any obvious time series trends. Just as with restaurant employment factors 5-8, these two teenage employment factors could be capturing many different things, including macroeconomic shocks or skill-biased technological change.

Finally, I can also plot the effect of the common factors on employment, for a single time period. Recalling equation (2), the IFE estimator estimates f_t, an (r x 1) vector of period-specific common factors, for each time period and λ_i, an (r x 1) vector of factor loadings, for each cross-sectional unit. Therefore, for a given time period, I can plot $\lambda_i' f_t$, a (1 x 1) estimate of the combined effect of the common factors on employment, for each cross-sectional unit. Figures 3-5 plot the combined effect of the restaurant employment common factors for the first two quarters of 1990 and the first quarter of 2010, respectively[24]. Three significant patterns are present in the figures. First, there are obvious spatial correlations in the effect of these common factors on employment. Looking first at Figure 3, which plots the effect of the common factors on employment for the first quarter of 1990, the Northeast, Midwest, and West Coast exhibit positive employment effects from the unobserved common factors. Much of the South and the entire state of Ohio exhibits negative employment effects. This pattern is intuitive, as we would expect differences in various labor market aspects such as industrial specialization or education to cause spatial correlation. The second pattern, visible in Figure 4, is that the effect of these common factors is fairly stable from one quarter to the

[24]Recall that the dependent variable in these regressions is in logs, so the maps represent the combined effect of the common factors on the natural log of a county's employment level.

next. This is once again intuitive, as the regional labor market differences that are causing heterogeneous effects of these common factors may be unlikely to change much in a span of three months. The third pattern is that, over a longer time span, the spatial correlations do change. This is seen in Figure 5, which plots the combined effect of the common factors for the first quarter of 2010. Now, much of the South and Northeast exhibit positive employment effects from the unobserved common factors, while parts of the Midwest and much of the West Coast show negative employment effects.

Section 4.1 showed that controlling for these common factors is important for estimation and inference of the effect of minimum wages on employment. This section has shown that much of the variance in the data can be explained by a small number of factors, that many of these factors have interpretable time series patterns, and that there are spatial correlations in the effect of these factors on employment. The emergence of these interpretable patterns in the factor structure, despite the fact that the principal components estimation does not require any such time series or spatial correlation, supports the assertion in Dube et al. (2010) and Allegretto et al. (2011) that these correlations should be accounted for. The difference between their methods and those used in this paper is that the factor model estimators allow the data to determine what the unobserved time series and cross-section correlations are, rather than imposing a specific form a priori.

5 Simulation and Counterfactual Experiments

5.1 Simulations

In this section, I assess the relative ability of OLS and the factor model estimators to estimate the minimum wage-employment elasticity under various assumptions about the unobserved heterogeneity. Specifically, I analyze the performance of each of the estimators used in Section 4 with and without the presence of common factors in the data-generating process. Of particular interest is the performance of the factor model estimators without the presence of factors in the DGP and the performance of the OLS estimator with the presence of common factors in the DGP. The simulations are performed for both restaurant and teenage employment.

The first simulation analyzes the performance of the OLS, CCEP, CCEMG, and IFE estimators with only state/county and period fixed effects representing the unobserved heterogeneity in the DGP. This DGP uses OLS results as the true value of the coefficients, with independent and identically distributed (IID) normal errors. For the restaurant employment DGP, these coefficients come from the OLS estimates of the traditional specification in the all-county sample of Table 3 and the error variance is computed using the residuals from this specification. For the teenage employment DGP, the true value of the coefficients and the error variance come from the OLS estimates of the traditional specification in Table 4. The simulation is performed for 1,000 repetitions for each dataset[25].

The results of this simulation are shown in Table 6. Columns (1) and (4) report the median of each of the estimators for restaurant and teenage employment, respectively, and columns (2)-(3) and (5)-(6) report the 95% confidence interval. The true value of the coefficient for the minimum wage-employment elasticity in the DGP is shown in the first row of the table. All four estimators perform well without the presence of factors in the DGP, with median estimates near the true value. The factor model estimators also perform well in terms of the confidence intervals, with only the CCEMG estimate of the restaurant employment dataset showing a significantly larger confidence interval. There are two important results from this simulation: First, the factor model estimators perform well even without the presence of factors in the DGP. Second, the pattern of results in this simulation does not match the pattern of results in the results section; the OLS estimator produces very different results than the CCEP, CCEMG, and IFE estimators in the results section, but very similar results in simulations with only state and period fixed effects representing the unobserved

[25] The DGP is $y_{it} = \hat{\beta} ln(MW_{it}) + X_{it}\hat{\Gamma} + \hat{\alpha}_i + \hat{\delta}_t + v_{it}$, where the covariates are the same variables presented earlier, the parameters are from the OLS results reported in Tables 3 and 4, and v_{it} is an idiosyncratic error term whose variance is determined by the variance of the OLS residuals. State/county and period fixed effects are included in the OLS, CCEP, CCEMG, and IFE estimation for this simulation.

heterogeneity in the DGP.

The second simulation analyzes the performance of the OLS, CCEP, CCEMG, and IFE estimators with state/county and period fixed effects and common factors representing the unobserved heterogeneity in the DGP. This DGP uses the coefficients, common factors, and factor loadings from the IFE estimation, with independent and identically distributed (IID) normal errors. For the restaurant employment DGP, the true value of the coefficients comes from the IFE estimation of the traditional specification in the all-county sample of Table 3 and the error variance is computed using the residuals from this specification. For the teenage employment DGP, the true value of the coefficients and the error variance come from the IFE estimation of the traditional specification in Table 4. The simulation is performed for 1,000 repetitions for each dataset[26].

The results of this simulation are shown in Table 7. For restaurant employment, the CCEP, CCEMG, and IFE estimators all perform well. The OLS estimator, however, shows negative bias. In fact, the true value of the coefficient for the minimum wage-employment elasticity is not even in the OLS 95% confidence interval. For teenage employment, the OLS estimator once again shows clear negative bias, with the 95% confidence interval not containing the true value of the minimum wage-employment elasticity coefficient. The CCEP and CCEMG estimator show some bias for the teenage dataset. This is likely due to the small cross-section dimension of the teenage dataset, as discussed in Section 3.2. Two important results emerge from this simulation: First, OLS shows significant negative bias. Second, the pattern of results from this simulation matches the pattern of results seen in Table 3 and 4; the OLS estimates of the minimum wage-employment elasticity are much larger in magnitude than the factor model estimates both in Table 3 and 4 and in simulations with common factors included in the DGP.

In summary, the simulation results show that the CCEP, CCEMG, and IFE estimators

[26]The DGP is $y_{it} = \hat{\beta} ln(MW_{it}) + X_{it}\hat{\Gamma} + \hat{\alpha}_i + \hat{\delta}_t + \hat{\lambda}_i' \hat{f}_t + v_{it}$, where the covariates are the same variables presented earlier, the parameters are from the IFE estimation reported in Tables 3 and 4, and v_{it} is an idiosyncratic error term whose variance is determined by the variance of the IFE residuals. State/county and period fixed effects are included in the OLS, CCEP, CCEMG, and IFE estimation for this simulation.

all perform well with only state/county and period fixed effects representing the unobserved heterogeneity in the DGP. The OLS estimator, however, exhibits negative bias when there are common factors in the DGP. These results suggest that the presence of common factors in the true underlying DGP could cause the different estimates of the minimum wage-employment elasticity across methodologies seen in Table 3 and 4.

5.2 Counterfactuals

This section provides a simple counterfactual experiment designed to assess what impact a further increase in the federal minimum wage would have on employment. The common correlated effects mean group (CCEMG) estimator, described in Section 3, allows for an interesting counterfactual experiment because it estimates a different parameter value for each cross-sectional unit. Thus, while the actual CCEMG estimator reports the average of these individual slope parameters, the individual parameters can be used to assess the differential impact that an increase in the federal minimum wage would have across the United States. The Fair Minimum Wage Act of 2013 proposed that the federal minimum wage be increased to \$10.10 via three consecutive \$0.95 raises. Therefore, for this experiment I analyze what effect a \$0.95 raise in the federal minimum wage would have had on employment in the last quarter of each of the two datasets[27]. This is done by comparing the fitted level of employment in that quarter, based on the CCEMG individual parameters, to the predicted level of employment had the federal minimum wage been \$8.20 rather than \$7.25[28].

Table 6 shows the results of this counterfactual experiment by dataset. The table reports

[27]This simple counterfactual obviously ignores many relevant issues, such as changes in the overall state of the economy since the last quarter of the dataset and the possibility of lead or lag effects. However, the main purpose of this counterfactual is to illustrate the heterogeneous effects of the increase among the states that would actually be affected.

[28]Specifically, using the notation from equations (1) and (2), I first calculated the fitted value of log employment, $\hat{ln(E_{it})} = \hat{\beta}_i ln(MW_{it}) + X_{it}\hat{\Gamma}_i + \hat{\alpha}_i + \hat{\delta}_t$, and exponentiated to get the fitted level of employment. Note that the parameters are indexed by i because I am using the individual parameters from the CCEMG estimation of the traditional state and period fixed effects approach. Then, I replaced the minimum wage with a counterfactual minimum wage which is the higher of the state minimum wage and \$8.20 to get the new fitted level of employment, $\hat{ln(E_{it}^{count.})} = \hat{\beta}_i ln(MW_{it}^{count.}) + X_{it}\hat{\Gamma}_i + \hat{\alpha}_i + \hat{\delta}_t$, and exponentiated to get the counterfactual level of employment.

the mean effect, median effect, standard deviation, largest positive effect, and largest negative effect. Column 1 shows the results for restaurant employment, measured in number of employees. Increasing the minimum wage by $0.95 increased county-level restaurant employment by an average of 41.30 employees, while the median effect was exactly zero[29]. The extreme effects were an increase in restaurant employment of 14,181 employees and a decrease in restaurant employment of 2,964. The results for teenage employment, measured as the fraction of teenagers employed, are shown in column 2 and are similar to the restaurant employment results. A $0.95 increase in the federal minimum wage increased the state-level fraction of teenagers employed by an average of .0052 with a median effect of zero. The extreme effects were an increase in the fraction of teenagers employed of .1990 and a decrease in the fraction of teenagers employed of .0459.

This simple conterfactual shows that there is considerable heterogeneity in the effect of minimum wages on employment across different regions. From a policy perspective, this heterogeneity is important because not all states will be directly impacted by a higher federal minimum wage. Recall from column 1 of Table 3 and Table 4 that the CCEMG estimate of the minimum wage-employment elasticity, which averages the individual cross-sectional slope parameters, was -.013 and -.040 for restaurant and teenage employment, respectively. Therefore, a positive mean effect of a federal minimum wage increase on restaurant and teenage employment in the counterfactual experiment means that states where an increase in the federal minimum wage was actually binding were states that are more capable of absorbing minimum wage increases without experiencing a decrease in employment. This also means that states where minimum wages are harmful to employment are the states that tend to have higher minimum wages, while states that do not experience negative employment effects of minimum wages tend to have lower minimum wages. This results seems counterintuitive and is perhaps related to the fact that the determination of state minimum wages is often as much of a political debate as it is an economic debate.

[29]Some states have a state minimum wage above $8.20 and are therefore unaffected in this counterfactual.

6 Conclusion

Despite the fact that empirical studies on minimum wages and employment date back at least 100 years, there is no consensus among economists about the effect that minimum wages have on low-skill employment. Results vary depending on both the methodologies and the datasets used. The current state of the debate is focused on the methodology used for national panel studies. Specifically, the concern is how to control for spatial and time series correlation. Dube et al. (2010) and Allegretto et al. (2011) have shown that negative effects of minimum wages on employment found using the traditional OLS state and year fixed effects methods are sensitive to the inclusion of geographic controls, linear state-specific time trends, and border discontinuity designs. However, Neumark et al. (2013) call these controls into question and conclude that neither the methods nor the results in Dube et al. (2010) and Allegretto et al. (2011) are supported by the data. My contribution is the use of new econometric methods from Pesaran (2006) and Bai (2009) in order to resolve the methodological issues in the literature. These methods are robust to critiques from either side of the debate, as they allow me to control for spatial and time series correlation without the use of the time trends and geographic controls that Neumark et al. (2013) find problematic.

The factor model estimators are unique because they allow the data to determine the nature of the spatial and time series correlation, rather than imposing a specific form a priori, and because they allow areas to be close in economic dimensions other than geographic proximity. This is the case, for instance, when two areas are affected by the same industry-specific shocks because of industry specialization, even if these two areas are not neighbors. Analysis of the factor structure that Bai's (2009) IFE method estimates shows interpretable serial correlation in the common factors and obvious spatial correlation in the effect of these common factors on employment. The factor model estimators also provide a solution to the potential issue of minimum wages being endogenous with respect to low-skill employment. The ability of the factor model estimators to control for these correlations, as well as endogeneity, allows for improved estimation and inference.

I first estimate minimum wage-employment elasticities using traditional OLS state and year fixed effects methods and find estimates of -.15 for both restaurant and teenage employment, in line with the previous literature using these traditional methods. I then apply the factor model estimators from Pesaran (2006) and Bai (2009) and find minimum wage-employment elasticities in the range of 0 to -.01 for restaurant employment and -.04 to -.10 for teenage employment. I further show that these results are invariant to robustness checks that include flexible time trends and narrowing of identifying information.

Simulation results show that OLS and factor model estimators perform similarly with only state and year fixed effects representing unobserved heterogeneity in the DGP, while OLS estimates of the minimum wage-employment elasticity were significantly negatively biased in simulations with common factors in the DGP. The latter pattern is very similar to the pattern of results seen earlier in the paper, with the factor model estimators producing elasticities much closer to zero than OLS. Thus, the presence of common factors in the true underlying DGP could cause the different estimates of the minimum wage-employment elasticity seen across different methodologies. A counterfactual experiment shows that the average effect across counties and states of a modest increase in the federal minimum would be near zero. This is because the states for which a modestly higher federal minimum wage would actually be binding are states that are more able to absorb a minimum wage increase without experiencing a decrease in employment.

While the factor model approach does not constitute a panacea, it does address the issues in the current state of the minimum wage-employment literature. The emergence of interpretable patterns from the factor structure that Bai's (2009) IFE method estimates, despite the fact that it does not require there to be any such time series or spatial correlation, supports the assertion in Dube et al. (2010) and Allegretto et al. (2011) that these correlations should be accounted for. The difference between their methods and those used in this paper is that the factor model estimators allow the data to determine the nature of the serial and spatial correlations. Neumark et al. (2013) also argue for this idea of letting the data speak, claiming that the use of geographic controls and linear time trends throws out a great deal of valid identifying information. They propose the use of synthetic controls to accomplish this and report significant negative effects, although Allegretto et al. (2013) have followed up with their own implementation of the synthetic control approach finding no significant effects of minimum wages on employment. The factor model approach has many advantages relative to pooled synthetic controls. These advantages include a more straightforward implementation, the ability to use all minimum wage variation in the data, explicit modeling of and control for time-varying unobserved heterogeneity, and the ability to address the issue of minimum wages being endogenous with respect to low-skill employment. These factor model methods are well suited for a wide variety of empirical studies and should receive more attention in future work.

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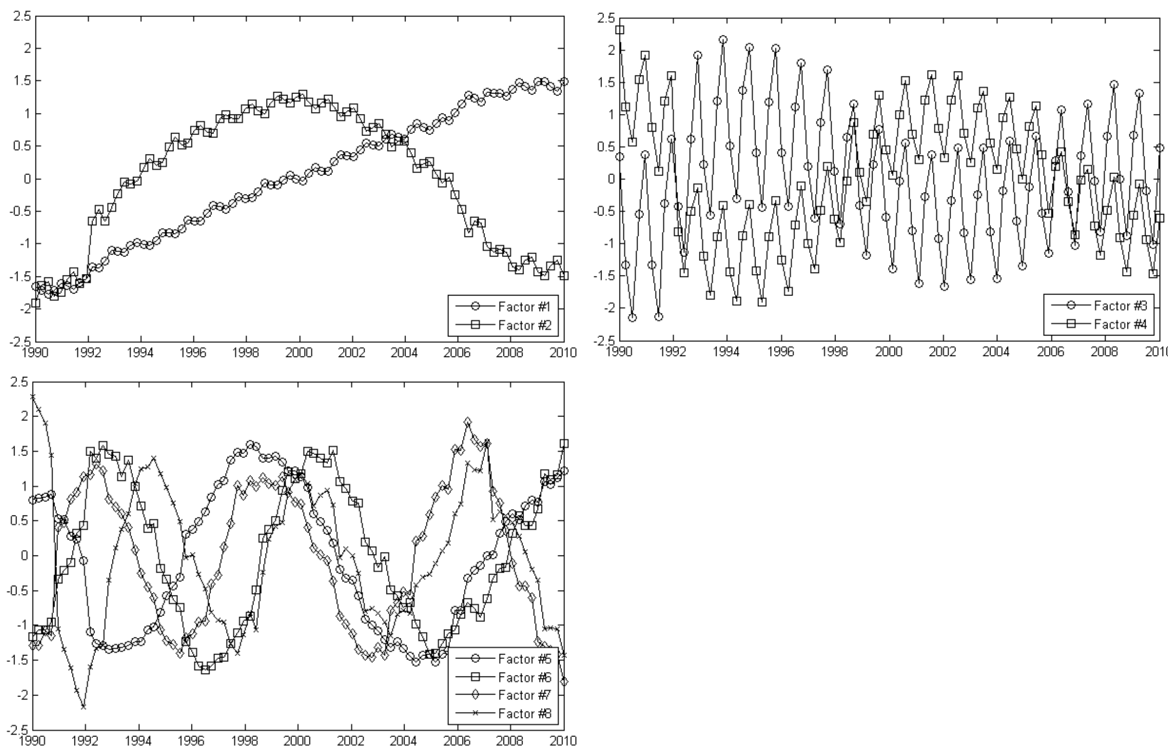
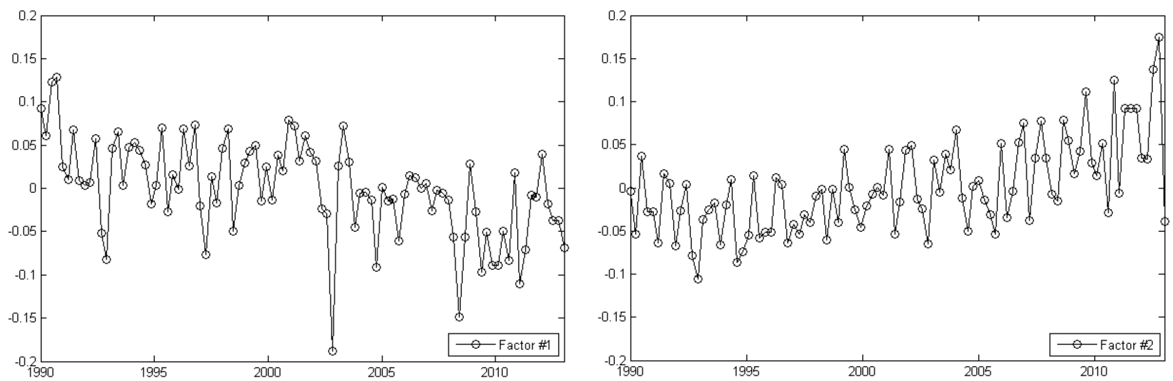
Figure 1: Plots of the Restaurant Employment Common Factors



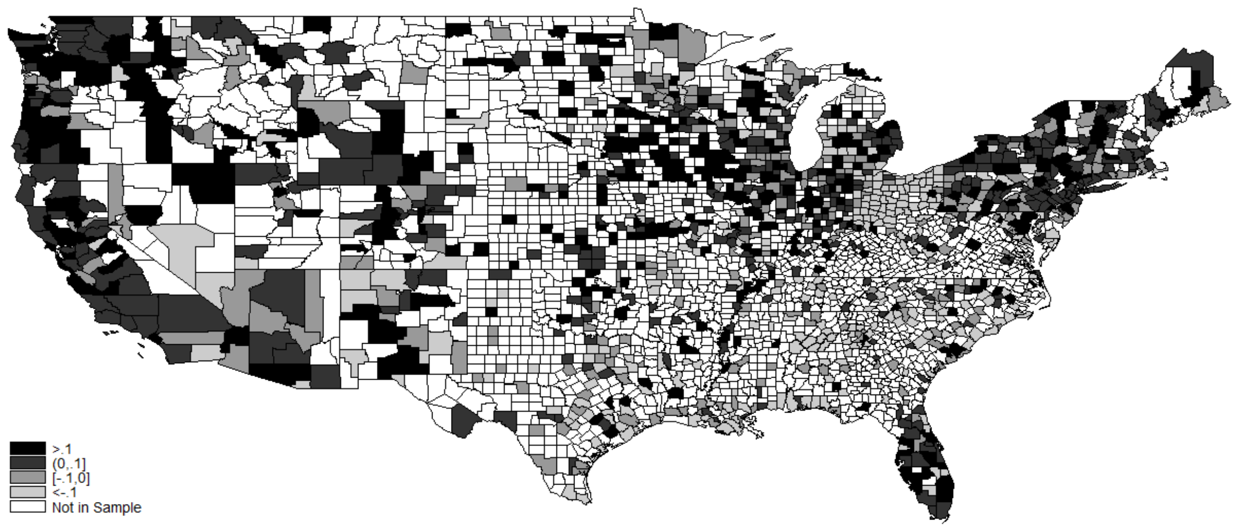
This figure plots the eight common factors for restaurant employment estimated from Bai's (2009) interactive fixed effects method, which simultaneously estimates the coefficients and factor structure shown in equations (1)-(2). Statistically, the common factors are eigenvectors corresponding to the largest eigenvalues of the second moment matrix of the regression coefficient estimation residuals. The number of factors is selected according to the information criterion in Bai and Ng (2002). Results are based on the traditional state and period fixed effects specification of Table 3 (all-county sample).

Figure 2: Plots of the Teenage Employment Common Factors



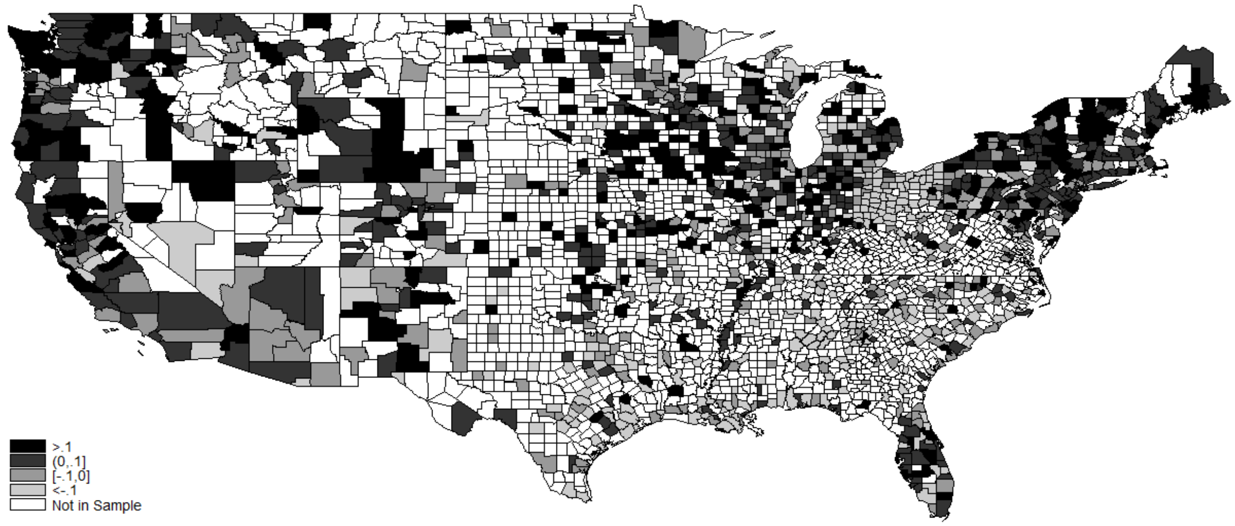
This figure plots the two common factors for teenage employment estimated from Bai's (2009) interactive fixed effects method, which simultaneously estimates the coefficients and factor structure shown in equations (1)-(2). Statistically, the common factors are eigenvectors corresponding to the largest eigenvalues of the second moment matrix of the regression coefficient estimation residuals. The number of factors is selected according to the information criterion in Bai and Ng (2002). Results are based on the traditional state and period fixed effects specification of Table 4.

Figure 3: Combined Effect of Restaurant Employment Common Factors on Log Employment - 1990q1



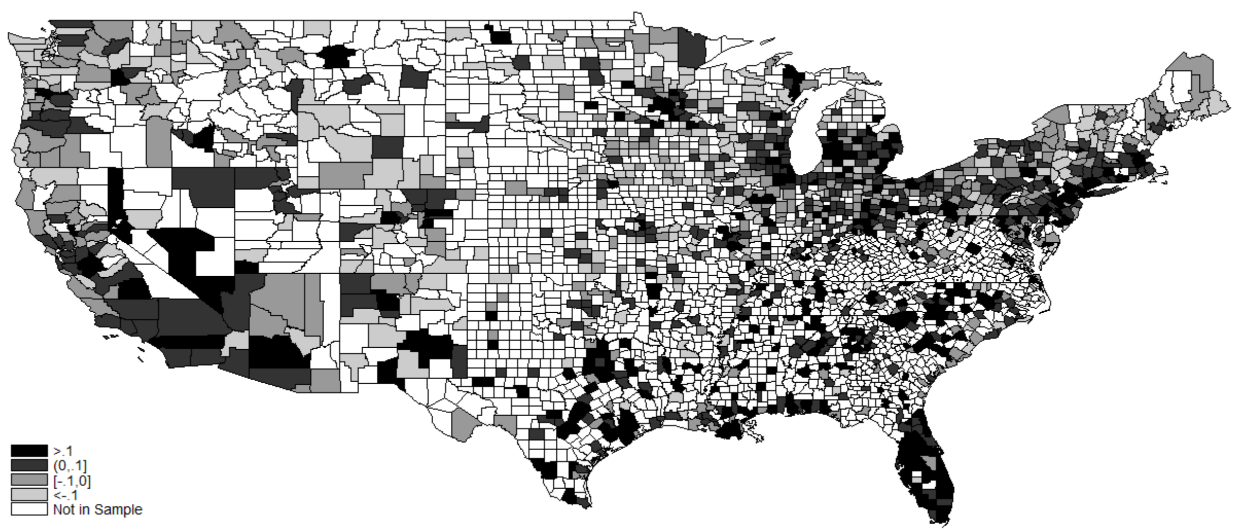
This figure plots $\lambda_i' f_t$ for the specified period, which is the factor structure given in equation (2). This represents the combined effect of the estimated unobserved common factors on log employment in the given county. The factor structure is estimated from Bai's (2009) interactive fixed effects method, which simultaneously estimates the coefficients and factor structure shown in equations (1)-(2). f_t is an (r x 1) vector of time-specific common factors that affect all cross-sectional units and λ_i is an (r x 1) vector of factor loadings that represents how each common factor affects that individual cross-section unit. Results are based on the traditional state and period fixed effects specification of Table 3 (all-county sample). Only counties with observations for each quarter are included in the analysis, following Dube et al. (2010).

Figure 4: Combined Effect of Restaurant Employment Common Factors on Log Employment - 1990q2



See note for Figure 3.

Figure 5: Combined Effect of Restaurant Employment Common Factors on Log Employment - 2010q1



See note for Figure 3.

Table 1: Summary Statistics - Restaurant Employment Dataset, 1990-2010

	Mean (1)	Standard Deviation (2)
Restaurant Employment	4,766	11,144
Total Employment	70,959	181,564
Population	180,971	422,618
Minimum Wage	\$5.49	\$1.22
Periods	84	
Number of Counties	1,371	

Summary statistics are based on a balanced panel. Restaurant and total employment data are from the Quarterly Census of Employment and Wages. County population data is from the county-level Census Bureau population data. The minimum wage is always the higher of the federal and state minimum wage and is reported in nominal dollars. See section 2.1 for more details.

Table 2: Summary Statistics - Teenage Employment Dataset, Ages 16-19, 1990-2013

	Mean (1)	Standard Deviation (2)
Fraction of Teenagers Employed	0.41	0.12
Unemployment Rate	5.68	2.14
Relative Size of Teenage Population	0.09	0.01
Minimum Wage	\$5.58	\$1.26
Periods	96	
N	51	

Teenage employment, the unemployment rate, and the relative size of the youth population are constructed by aggregating Current Population Survey Outgoing Rotation Groups up to the state-quarter level. The minimum wage is always the higher of the federal and state minimum wage and is reported in nominal dollars. See section 2.2 for more details.

Table 3: Minimum Wage-Employment Elasticity - Restaurant Employment

	Traditional (1)	Linear Trend (2)	Quadratic Trend (3)	3rd Order Polynomial (4)	4th Order Polynomial (5)	5th Order Polynomial (6)
			All Counties			
OLS (DLR)	-.151*	.005	-.022	-.057***	-.042***	-.034**
	(.079)	(.024)	(.020)	(.020)	(.015)	(.016)
CCEP	.005	.016	-.015	-.050***	-.027*	-.020
	(.015)	(.014)	(.014)	(.013)	(.014)	(.013)
CCEMG	-.013	-.004	-.024	-.031*	-.029*	-.012
	(.017)	(.018)	(.017)	(.017)	(.016)	(.015)
IFE	-.006	-.008	-.016	-.006	.003	.001
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)
			Contiguous Counties			
OLS (DLR/NSW)	-.106	.010	-.016	-.038	-.020	-.013
	(.065)	(.021)	(.028)	(.030)	(.022)	(.021)
CCEP	-.011	.001	-.009	-.040*	-.019	-.012
	(.023)	(.022)	(.021)	(.021)	(.021)	(.019)
CCEMG	-.025	-.010	-.032	-.043*	-.038	-.019
	(.032)	(.032)	(.031)	(.030)	(.026)	(.026)
IFE	-.007	-.008	-.012	-.002	-.003	-.009
	(.011)	(.011)	(.010)	(.010)	(.010)	(.010)

Shaded regions represent specifications that were estimated in papers by the corresponding authors (DLR=Dube et al. (2010), NSW=Neumark et al. (2013)). All specifications include county and period fixed effects, as well as controls for county population and total employment. All trends are state-specific trends. CCEP, CCEMG, and IFE stand for Pesaran's (2006) common correlated effects pooled (CCEP) and mean group (CCEMG) estimators and Bai's (2009) interactive fixed effects estimator. See Section 3 for more details. OLS standard errors are clustered at the state level. CCEP, CCEMG, and IFE standard errors are calculated following Pesaran (2006) and Bai (2009). Significance reported for the IFE estimator is based on the results of a wild cluster bootstrap-t procedure. See footnote 18 for more details. Significance levels are as follows: *10 percent, **5 percent, ***1 percent.

When Dube et al. (2010) include linear trends they also include census division times period dummies for the all county sample and county-pair times period dummies for the contiguous county sample. This specification is replicated in the table. With only a linear trend the effect is -.039 (.018) and -.044 (.031) for the all and contiguous county samples, respectively.

Neumark et al. (2013) identically replicate the results from Dube et al. (2010) for the contiguous county sample.

Table 4: Minimum Wage-Employment Elasticity - Teenage Employment

	Traditional (1)	Linear Trend (2)	Quadratic Trend (3)	3rd Order Polynomial (4)	4th Order Polynomial (5)	5th Order Polynomial (6)
Probit (ADR)	-.034*	-.009	-.003	-.033	-.024	-.037
	(.018)	(.018)	(.022)	(.022)	(.027)	(.029)
	-.105*	**-.028**	**-.010**	**-.099**	**-.074**	**-.113**
OLS (NSW)	-.151**	-.010	-.048	-.209**	-.219**	-.229**
	(.061)	(.098)	(.102)	(.092)	(.085)	(.092)
CCEP	-.065	-.043	.009	-.090	-.018	-.065
	(.064)	(.067)	(.059)	(.087)	(.089)	(.080)
CCEMG	-.040	-.025	.029	-.129	-.088	-.106
	(.089)	(.089)	(.081)	(.102)	(.108)	(.104)
IFE	-.104	-.049	-.038	-.138	-.124*	-.151**
	(.040)	(.047)	(.048)	(.057)	(.064)	(.068)

Shaded regions represent specifications that were estimated in papers by the corresponding authors (ADR=Allegretto et al. (2011), NSW=Neumark et al. (2013)). All specifications include state and period fixed effects. All trends are state-specific trends. CCEP, CCEMG, and IFE stand for Pesaran's (2006) common correlated effects pooled (CCEP) and mean group (CCEMG) estimators and Bai's (2009) interactive fixed effects estimator. See Section 3 for more details. Probit and OLS standard errors are clustered at the state level. CCEP, CCEMG, and IFE standard errors are calculated following Pesaran (2006) and Bai (2009). Significance reported for the IFE estimator is based on the results of a wild cluster bootstrap-t procedure. See footnote 18 for more details. Significance levels are as follows: *10 percent, **5 percent, ***1 percent.

Following Allegretto et al. (2011), the probit row estimates the effect of minimum wages on employment by using individual-level data and estimating linear probability models with a dichotomous dependent variable indicating if the individual is employed. Additional controls for the state-quarter unemployment rate and group relative population are included, as well as individual controls for gender, race, age, education, and marital status. The first two rows report the coefficients and standard errors from these models. The third row reports the implied minimum wage elasticity, calculated by dividing the coefficient by the group employment-to-population ratio.

Following Neumark et al. (2013), the effect of minimum wages on employment is calculated by aggregating individual-level data up to the state-quarter level and using OLS. The dependent variable is the natural log of the state-quarter teenage employment-to-population ratio. Additional controls for the state-quarter natural log unemployment rate and the state-quarter natural log relative teenage population size are included.

The CCEP, CCEMG, and IFE estimates use individual-level data aggregated to the state-quarter level, as in Neumark et al. (2013), and use the same control variables as Neumark et al. (2013).

Table 5: Summary Statistics for Restaurant and Teenage Employment Factors

Factor #p	R_p^2 (1)	AR1($\hat{f}_{pt}$) (2)
	Restaurant Employment	
1	0.5684	0.9941
2	0.7408	0.9752
3	0.8189	0.3006
4	0.8900	0.6705
5	0.9318	0.9823
6	0.9593	0.9673
7	0.9810	0.9565
8	1	0.8881
	Teenage Employment	
1	0.5172	0.4060
2	1	0.3499

This table shows summary statistics for the eight common factors for restaurant employment and two common factors for teenage employment estimated from Bai's (2009) interactive fixed effects method, which simultaneously estimates the coefficients and factor structure shown in equations (1)-(2). Statistically, the common factors are eigenvectors corresponding to the largest eigenvalues of the second moment matrix of the regression coefficient estimation residuals. The number of factors is selected according to the information criterion in Bai and Ng (2002). Results are based on the traditional state and period fixed effects specification of Table 3 (all-county sample) and Table 4. R_p^2 is the relative importance of each factor, calculated as the fraction of the total variance of the data explained by factors 1 to p. This is given as the sum of the first p largest eigenvalues of the sample second moment matrix divided by the sum of all eigenvalues. AR1($\hat{f}_{pt}$) is the first order autocorrelation coefficient for the given factor.

Table 6: Minimum Wage-Employment Elasticity Simulation Results - No Factors in DGP

	Restaurant Employment			Teenage Employment		
	Median (1)	2.5% (2)	97.5% (3)	Median (4)	2.5% (5)	97.5% (6)
True value	***-.1516***			***-.1510***		
OLS	**-.1523**	-.2644	-.0338	**-.1515**	-.2005	-.1038
CCEP	**-.1501**	-.3191	.0207	**-.1517**	-.2086	-.0888
CCEMG	**-.1517**	-.3978	.0993	**-.1533**	-.2214	-.0774
IFE	**-.1521**	-.2937	-.0223	**-.1513**	-.2065	-.0933

This table reports simulation results for the case without common factors in the data generating process. The DGP is $y_{it} = \hat{\beta} ln(MW_{it}) + X_{it}\hat{\Gamma} + \hat{\alpha}_i + \hat{\delta}_t + v_{it}$, where the covariates are the same variables presented earlier, the parameters are from the OLS results for the traditional state and period fixed effects specification reported in Table 3 (all-county sample) and Table 4, and v_{it} is an idiosyncratic error term whose variance is determined by the variance of the OLS residuals. The number of repetitions is 1,000.

Table 7: Minimum Wage-Employment Elasticity Simulation Results - Factors in DGP

	Restaurant Employment			Teenage Employment		
	Median (1)	2.5% (2)	97.5% (3)	Median (4)	2.5% (5)	97.5% (6)
True value	***-.0060***			***-.1037***		
OLS	**-.1509**	-.1839	-.1150	**-.1652**	-.2111	-.1172
CCEP	**.0062**	-.0405	.0599	**-.1401**	-.1979	-.0806
CCEMG	**-.0172**	-.0878	.0537	**-.1183**	-.1912	-.0418
IFE	**-.0230**	-.0875	.0425	**-.1035**	-.1523	-.0548

This table reports simulation results for the case with common factors in the data generating process. The DGP is $y_{it} = \hat{\beta} ln(MW_{it}) + X_{it}\hat{\Gamma} + \hat{\alpha}_i + \hat{\delta}_t + \hat{\lambda}_i' \hat{f}_t + v_{it}$, where the covariates are the same variables presented earlier, the parameters are from the IFE results for the traditional state and period fixed effects specification reported in Table 3 (all-county sample) and Table 4, and v_{it} is an idiosyncratic error term whose variance is determined by the variance of the IFE residuals. The number of repetitions is 1,000.

Table 8: Summary Statistics for Counterfactual Minimum Wage Experiment

	Restaurant Employment (Number of Employees) (1)	Teenage Employment (Fraction of Teenagers Employed) (2)
Mean Effect	41.3030	.0052
Median	0	0
Standard Deviation	559.63	.0376
Min	-2,964	-.0459
Max	14,181	.1990

This table shows summary statistics for a simple counterfactual to assess the affect of an increase in the federal minimum wage on employment. The counterfactual shows the impact that a \$0.95 increase in the federal minimum wage would have had on employment in the last quarter of each dataset. I first calculated the fitted value of log employment, $ln(\hat{E_{it}}) = \hat{\beta}_i ln(MW_{it}) + X_{it}\hat{\Gamma}_i + \hat{\alpha}_i + \hat{\delta}_t$, and exponentiated to get the predicted level of employment. Note, the parameters are indexed by i because I use the CCEMG individual cross-section unit parameters. Then, I replaced the minimum wage with a counterfactual minimum wage which is the higher of the state minimum wage and \$8.20 to get the new fitted level of employment, $ln(\hat{E_{it}^{count.}}) = \hat{\beta}_i ln(MW_{it}^{count.}) + X_{it}\hat{\Gamma}_i + \hat{\alpha}_i + \hat{\delta}_t$, and exponentiated to get the counterfactual level of employment. See Section 5.2 for more details.