Economic Inquiry

THE EFFECT OF MINIMUM WAGES ON EMPLOYMENT: A FACTOR MODEL APPROACH

EVAN TOTTY*

This paper uses factor model methods to resolve issues in the minimum wage-employment debate. Factor model methods provide a more flexible way of addressing concerns related to unobserved heterogeneity that are robust to critiques from either side of the debate. The factor model estimators produce minimum wage-employment elasticity estimates that are much smaller than the traditional ordinary least squares (OLS) results and are not statistically different from zero. These results hold for many specifications and datasets from the minimum wage-employment literature. A simulation shows that unobserved common factors can explain the different estimates seen across methodologies in the literature. (*JEL* C23, J21, K31)

I. 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 the effect of minimum wages. 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.[1] The goal of this paper is to resolve the issues in the minimum wage-employment literature by using panel data econometric methods that are robust to critiques from either side of the debate. Specifically, this study uses the common correlated effects estimators developed by Pesaran (2006) and the interactive fixed effects (IFE) estimator developed by Bai (2009). These estimators are

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Totty: Economist, U.S. Census Bureau, Washington, DC 20003, Phone 301-763-1151, Fax 765-494-1526, E-mail evan.scott.totty@gmail.com

1. The theory is also ambiguous. While the simple competitive model predicts a decrease in employment in response to a minimum wage hike, the monopsony model can predict no effect or even a small positive effect. Additionally, there are many other channels through which minimum wages could impact firms and employees that would mitigate the employment effect, such as labor–labor substitution, decreased costly labor turnover, reductions in nonwage benefits, improved organizational efficiency, increased worker effort, price increases, or reductions in profit (Hirsch, Kaufman, and Zelenska 2015; Simon and Kaestner 2004). Evidence on these other channels is sparse and mixed, but the most convincing evidence may support decreased labor turnover (Dube, Lester, and Reich 2016) and price increases (Aaronson, French, and MacDonald 2008; Harasztosi and Lindner 2015; Lemos 2008). See Manning (2016) for a discussion about how recent empirical studies on minimum wages and employment can be explained by theoretical models.

ABBREVIATIONS

CCE: Common Correlated Effects
CCEMG: Common Correlated Effects Mean Group
CCEP: Common Correlated Effects Pooled
CD: Cross Section Dependence
CPS: Current Population Survey
CPS ORG: CPS Outgoing Rotation Groups
DGP: Data Generating Process
IFE: Interactive Fixed Effects
IID: Independent and Identically Distributed
LEHD: Longitudinal Employer Household Dynamics
LMI: Labor Market Information
OLS: Ordinary Least Squares
QCEW: Quarterly Census of Employment of Wages
QWI: Quarterly Workforce Indicators

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applied to many datasets and 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.

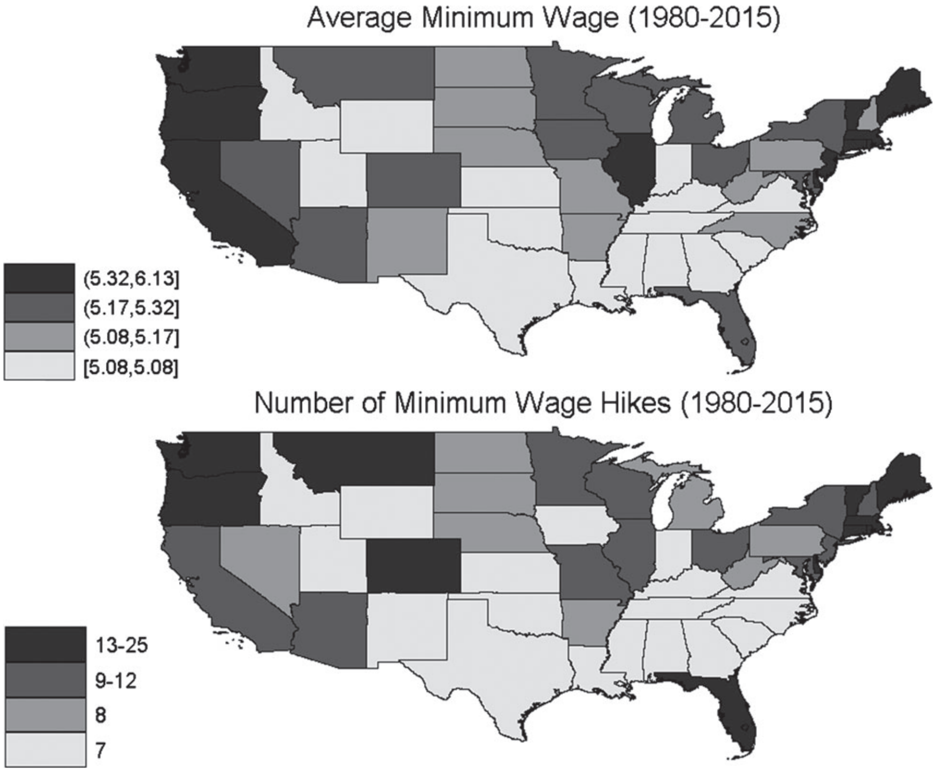
Minimum wage hikes are very common in the United States. There have been three instances of federal minimum wage hikes since 1990, each of which involved phasing in a higher minimum wage through two separate hikes in consecutive years. However, much of the minimum wage policy variation takes place at the state level: there has been at least one state-level minimum wage hike in each year since 1990. Additionally, state-level minimum wage hikes are becoming increasingly common. In 2016, for example, 17 states will increase their minimum wage. Several states have even begun indexing their minimum wage to adjust annually based on inflation. In total, 29 states currently have a minimum wage higher than the federal minimum wage. Recent campaigns among U.S. workers to increase the federal minimum wage from $7.25/hour to $15.00/hour have received a lot of attention. Not surprisingly, the merits of minimum wage hikes have been heavily debated by media members and politicians. However, minimum wages have also been heavily debated among economists in recent years. A 2015 poll by the Institute for Research on Global Markets asked 37 economists if they agreed with the following statement: "If the federal minimum wage is raised gradually to $15-per-hour by 2020, the employment rate for low-wage U.S. workers will be substantially lower than it would be under the status quo." Nine percent strongly agreed, 25% agreed, 37% were uncertain, and 29% disagreed.

Much of the reason why there is still an ongoing debate regarding the employment effects of minimum wage hikes is that, while the abundance of state-level minimum wage variation is useful for empirical studies, minimum wage hikes are, of course, not randomly distributed across space or time. Figure 1 shows the average minimum wage in each state from 1980 to 2015 and the total number of minimum wage hikes in each state during the same time period. Minimum wages are generally higher and raised more frequently in the Northeast, parts of the Midwest, and the West Coast. Because these regions of the United States differ along many dimensions other than just minimum wage policy, such as employment patterns, demographics, education levels, industrial compositions, and any number of unobservable variables, estimating an unbiased employment effect of minimum wage hikes using aggregate state-level employment data is challenging. As evidence of this, note that case studies which compare adjoining local areas with different minimum wages around the time of a policy change have tended to find no disemployment effects or even small positive effects (Card and Krueger 1994, 2000), while panel studies using data aggregated to the state or county level have tended to find relatively large disemployment effects (Neumark and Wascher 1992, 2007).[2] One potential reason for this inconsistency across methods could be that the panel studies are producing spurious estimates due to unobserved confounders in the aggregate data which are correlated with both employment and minimum wages.

This challenge associated with minimum wage-employment studies using aggregate panel data has led to an abundance of new research on the topic in recent years; the recent debate in the minimum wage-employment literature has focused on how to generate credible estimates of employment effects when using aggregate state- or county-level panel data. A partial but representative summary of the recent literature is shown in Table 1. The traditional approach in early panel studies was to include two-way fixed effects (a fixed effect for each time period and a fixed effect for each state or county) in order to address the concerns about unobserved heterogeneity across areas and time periods (Neumark and Wascher 1992, 2007). This approach tends to find minimum wage-employment elasticity estimates in the range of −0.10 to −0.20, meaning that a 10% increase in the minimum wage causes a 1%–2% decrease in employment for low-skilled workers such as teenagers. However, the recent minimum wage-employment debate began when Dube, Lester, and Reich (2010) and Allegretto, Dube, and Reich (2011) argued that two-way fixed effects are not sufficient to fully address concerns about unobserved heterogeneity. They propose the use of state-specific time trends and Census division-by-period fixed effects in order to allow for even more heterogeneity. Dube, Lester, and Reich (2010) also use a border discontinuity approach for county-level analysis, which uses policy discontinuity at state borders to identify the effect of minimum wage hikes.

2. Studies based on firm-level personnel data, while much less common, have also found an increase in the employment of groups for which minimum wages are binding, although there may be substitution effects within that group (Giuliano 2013).

FIGURE 1
State Minimum Wages



Source: Based on data from Vaghul and Zipperer (2016).

This essentially embeds the case study approach into the panel setting by restricting the sample to all contiguous counties along state borders and adding contiguous county-pair fixed effects to the two-way fixed effects. Each of these approaches produces minimum wage-employment elasticity estimates that are much smaller than the traditional two-way fixed effects approach and not statistically different from zero. Addison, Blackburn, and Cotti (2009) and Addison, Blackburn, and Cotti (2012) also use geographic time trends and a border discontinuity approach to account for unobserved heterogeneity and find qualitatively similar results.

There are several potential issues associated with the use of state-specific time trends, Census division-by-period fixed effects, and the border discontinuity approach. Neumark, Salas, and Wascher (2014b) argue that the Census division-by-period fixed effects and border discontinuity approach throw out too much valid identifying information. This conclusion is reached based on the weights that a synthetic control approach places on same-division or border-county areas. They have also argued in a subsequent paper that Census division-by-period fixed effects and the border discontinuity approach may actually worsen policy endogeneity by changing the identifying variation from both state and federal variation, to only state variation, which is more likely to be endogenously determined (Neumark, Salas, and Wascher 2014a). Neumark, Salas, and Wascher (2014b) also argue that specifications with state-specific time trends may suffer from endpoint bias or the lack of flexible higher order state-specific time trends. They show that negative and statistically significant elasticity estimates return when they account for potential endpoint bias or allow for higher order state-specific time trends. Essentially, Neumark, Salas, and Wascher (2014b) argue in favor of the traditional two-way fixed effects specification over one that adds Census division-by-period fixed effects or state-specific time trends. Meer

TABLE 1
Partial Review of Recent Panel Studies

Study	Population	Approach	Elasticity	Conclusion
Neumark and Wascher (1992)	Teenagers	Traditional	−0.140**	Negative effect
Neumark and Wascher (2007)	Teenagers	Traditional	−0.136*	Negative effect
Sabia (2009)	Retail	Traditional	−0.106***	Negative effect
ABC (2009)	Retail	County-specific linear trends	0.225**	Positive effect
DLR (2010)	Restaurants	Census division-by-period fixed effects	−0.023	No effect
		CDxP FE & state-specific linear trends	0.054	No effect
		Contiguous county pairs	0.016	No effect
ADR (2011)	Teenagers	Census division-by-period fixed effects	−0.036	No effect
		State-specific linear trends	−0.034	No effect
		CDxP FE & state-specific linear trends	0.047	No effect
NSW (2014a, 2014b)	Restaurants	Synthetic controls	−0.063***	Negative effect
	Teenagers	State-specific 5th-order polynomial trend	−0.185**	Negative effect
		Synthetic controls	−0.145**	Negative effect
ADRZ (2013, 2015)	Teenagers	Synthetic controls	−0.036	No effect
		Double-selection post-LASSO	−0.012	No effect

Notes: The elasticity result is taken directly from the results reported in each study. For Neumark and Wascher (2007), this elasticity is constructed using the employment-population ratio in Table 1 and the employment coefficient in Table 2, specification 1. The "traditional" approach refers to using two-way fixed effects for time and location, with no additional controls for regional heterogeneity or selection of states experiencing minimum wage hikes. ABC = Addison, Blackburn, and Cotti (2009), DLR = Dube, Lester, and Reich (2010), ADR = Allegretto, Dube, and Reich (2011), NSW = Neumark, Salas, and Wascher, ADRZ = Allegretto, Dube, Reich, and Zipperer. The synthetic control approach in NSW pools all synthetic and real data together and then estimates the two-way fixed effects specification with a fixed effect for each set of synthetic and real observations.

Significance levels are as follows: *10%, **5%, ***1%.

and West (2015) also show that if the effect of a minimum wage hike is to change the growth rate of employment, rather than a level change, then specifications with state-specific time trends will be biased toward zero.

Synthetic controls have also been used in the literature as an alternative way to address the concerns about unobserved heterogeneity discussed above. Unsatisfied with state-specific time trends, Census division-by-period fixed effects, and the border discontinuity approach, Neumark, Salas, and Wascher (2014b) proposed a synthetic control-style matching estimator as an alternative way to address the concerns about unobserved confounders influencing the aggregate panel data. Their synthetic control approach produces large negatively elasticity estimates. However, Allegretto et al. (2013) have shown that a synthetic control approach that more closely follows the approach outlined in Abadie, Diamond, and Hainmueller (2010), with cleaner identification of treatment vs controls groups and longer pre- and post-treatment windows, produces small elasticity estimates that are not statistically different from zero. The two camps have continued to debate the Census division-by-period fixed effects, state-specific time trends, border discontinuity approach, and synthetic controls in follow-up work (Allegretto et al. 2013, 2017; Neumark, Salas, and Wascher 2014a). Allegretto et al. (2017) also use the double-selection post-LASSO approach advanced by Belloni, Chernozhukov, and Hansen (2014) as a way of letting the data determine which, if any, additional controls should be included beyond the traditional two-way fixed effects. This procedure selects Census division-by-period fixed effects from one Census division and 29 state-specific linear time trends (no higher order trends) and produces small elasticity estimates that are not statistically different from zero. Clearly, more work is needed to address the methodological issues inherent to this topic in order to achieve a consensus in the literature.

The contribution of this paper is to bring a different econometric approach to the data. The factor model estimators advanced by Pesaran (2006) and Bai (2009) are well-suited to address the issues described above: the methods in these papers allow for consistent estimation of regression parameters under the presence of multiple unobserved common factors influencing large panel data. The unobserved common factors are allowed to be correlated with the independent variables of interest, which makes the estimators very useful for studies with aggregate panel data, as both the dependent and independent variables are likely to be influenced by unobservable confounders. The intuition for the estimators in Pesaran (2006) and Bai (2009) is to use either cross section averages of all the variables or principal components to proxy for the unobserved common factors in the data, so that they can be controlled for directly. Essentially, the factor model estimators apply a very flexible structure to the error term of a given specification which embeds many other structures, including, for example, state-specific time trends and Census division-by-period fixed effects.

By using the factor model estimators, rather than ordinary least squares (OLS), to estimate the traditional two-way fixed effects specification, it is possible to control for unobservable heterogeneity without having to make specific assumptions about the form of the unobserved heterogeneity. Importantly, the factor model estimators have been shown to perform well even when there are no unobserved common factors in the error term (Bai 2009; Kim and Oka 2014; Pesaran and Tosetti 2011). This means that using the factor model estimators will produce estimates similar to OLS if the two-way fixed effects specification is correct, but will produce estimates more similar to Dube, Lester, and Reich (2010) and Allegretto, Dube, and Reich (2011) if there are time trends or regional heterogeneity that is unaccounted for. Therefore, the factor model estimators both address the concerns associated with each camp in the recent minimum wage-employment debate and have specific advantages over each of the other approaches used in the literature.

Minimum wage-employment elasticity estimates based on the factor model estimators are significantly different than estimates based on OLS. Using the same datasets from the papers discussed above, OLS estimates based on the two-way fixed effects specification replicate the −0.10 to −0.20 elasticity estimates from the literature. The factor model estimators produce elasticity estimates that are much smaller than OLS and not statistically different from zero; restaurant elasticity estimates are in the range of −0.01 to −0.03 while teenage elasticity estimates are in the range of −0.03 to −0.07. These small elasticity estimates are robust to different data sources and different assumptions about the number of common factors in the data.

Analysis of the factor structure estimated from the data suggests that the common factors are capturing time trends, among other things, and also suggests the presence of time-varying regional heterogeneity in the effect of the common factors, which could roughly be approximated by a Census division-by-period fixed effect. However, the factor structure also captures factors that appear to be unrelated to time trends and shows some neighboring or same-Census division counties that appear to be very dissimilar in the effects they experience from common factors. Thus, while analysis of the factor structure does lend support for preferring specifications with state-specific time trends and/or Census division-by-period fixed effects, as in Dube, Lester, and Reich (2010) and Allegretto, Dube, and Reich (2011), over ones without them, it also supports the broad points in Neumark, Salas, and Wascher (2014a, 2014b) that time trends may not always be appropriate and that proximate places do not always make ideal control groups.

Finally, simulations at the end of the paper show two key findings. First, the pattern of results discussed above, in which OLS produces relatively large negative elasticity estimates and the factor model estimators produce estimates close to zero, cannot be reproduced from the data if the two-way fixed effects specification is correct. Second, the OLS estimate of the minimum wage-employment elasticity produced from the two-way fixed effects specification is negatively biased by the common factors present in the data.

The remainder of the paper is organized as follows: Section II describes the factor model setup of which the Pesaran (2006) and Bai (2009) estimators make use and describes the estimators themselves. Section III describes how the variables are constructed and provides summary statistics. Section IV discusses the results. Section V discusses the simulations. Section VI concludes.

II. EMPIRICAL APPROACH

A. *Multi-Factor Error Structure*

The factor model setup is based on a model 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 section units, heterogeneous "factor loadings" that represent how a common factor affects a particular cross section unit, and an idiosyncratic error term. In the analysis below, the factor structure will be applied to the traditional two-way fixed effects specification, which is the most saturated specification on which the literature has been able to agree. Factor model estimators from Pesaran (2006) and Bai (2009) will then be used for estimation.

The traditional specification for estimating the effect of minimum wages on employment, originating from Neumark and Wascher (1992), is given by

$$ln\left(E_{it}\right) = \beta ln\left(MW_{it}\right) + \Gamma X_{it} + \alpha_i + \delta_t + \epsilon_{it}. \tag{1}$$

Depending on the dataset used in the analysis below, E_{it} is either a count of the number of restaurant/teenage employees in county i and period t or the fraction of teenagers employed in state i and period t. MW_{it} is the higher of the federal and state minimum wage in state or county i and period t. Employment and the minimum wage are measured in logs so that β represents the minimum wage-employment elasticity.[3] The term X_{it} is a vector of control variables defined in Section III that are intended to proxy for supply and demand forces on employment. Unit and period fixed effects are represented by α_i and δ_t, respectively. Several studies have estimated this two-way fixed effects specification with OLS and no additional controls for unobserved heterogeneity and found large negative effects of minimum wages on employment (Neumark and Wascher 1992, 2007; Sabia 2009). The identification assumption is that minimum wage variation is uncorrelated with the error term ϵ_{it}, conditional on the two-way fixed effects and other controls.[4]

The difference with the factor model approach is that it allows for the presence of cross section dependence remaining in the error term ϵ_{it}. Cross section dependence is the tendency of outcomes, or residuals in this case, to be correlated across areas. This dependence could be spatial, caused by similarity in geographic characteristics. However, unlike spatial econometric methods, factor models also allow this dependence to depart from geographic proximity, which could occur if two areas experience the same industry-specific shock because of industry specialization, even if they are not neighbors. Cross section dependence is problematic for inference (Andrews 2005), but will also cause bias if unobserved common factors are correlated with the regressors. The factor model approach facilitates the control of cross section dependence through time-specific common factors that can have heterogeneous effects over areas:

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

where f_t is an $(r \times 1)$ vector of unobserved time-specific common factors and λ_i is an $(r \times 1)$ vector of factor loadings that capture unit-specific effects of the common shocks. These common factors may be thought of as omitted variables. As discussed below, the factor model estimators from Pesaran (2006) and Bai (2009) allow these unobserved common factors to be correlated with the regressors. Therefore, the identification assumption is no longer that minimum wage variation is uncorrelated with ϵ_{it}, but that it is uncorrelated with u_{it}. That is, minimum wage variation is uncorrelated with the error term, conditional on the two-way fixed effects, other controls, and the common factors and factor loadings.[5]

It is possible to think of examples of omitted variables that could cause bias in the OLS estimate of β from Equation (1) in either direction, but could also be captured by the factor structure in Equation (2). Neumark, Salas, and Wascher (2014b) argued that minimum wages may be more likely to be raised when labor markets are tight, citing Baskaya and Rubinstein (2011). This would suggest that minimum wage hikes are associated with positive employment shocks, which would cause positive endogeneity bias in the OLS estimate of β from Equation (1). These types of general macroeconomic shocks could be captured by the factor model structure; a common factor could represent a macroeconomic trend and the factor loadings represent how the macroeconomic trend affects each county/state, which would vary depending on characteristics of the area such as demographics and industrial composition. Alternatively, technological change could produce negative endogeneity bias. Smith (2011) studied teenage employment rates from 1980 to 2009 and showed that job polarization due to technological change pushes middle-skill adults into low-skill jobs traditionally held by teenagers, thus lowering teenage employment. Allegretto et al. (2013) showed that between 1990 and 2007, high minimum wage states experienced greater

3. This specification imposes a linear relationship on the size of the minimum wage hike and the size of the employment change: doubling the size of the minimum wage hike will double the employment effect. In reality, the relationship may not be linear. Firms may be more able to absorb small minimum wage hikes without changing employment than large minimum wage hikes. The reason why this specification is used is that it has been the common approach in the recent literature and because there is relatively little variation in the size of minimum wage hikes during the time frame of analysis in this paper: most minimum wage hikes from 1990 to 2013 were in the range of 5%–15%.

4. More formally, $E(\epsilon_{it}|ln(MW_{it}), X_{it}, \alpha_i, \delta_t) = 0$.

5. More formally, $E\left(u_{it}|ln\left(MW_{it}\right), X_{it}, \alpha_i, \delta_t, \lambda_i' f_t\right) = 0$.

job polarization, on average, than low minimum wage states. Combining these results suggests that high minimum wage states have experienced greater job polarization, which puts downward pressure on teenage employment. This would cause negative endogeneity bias in the OLS estimate of β from Equation (1), but could be captured by the factor structure; a common factor could track skill-biased technological change at the country level, while the factor loadings capture the heterogeneous effects of technological change across areas, which would vary according to characteristics such as education level and industrial composition.[6]

B. Factor Model Estimators

There are two commonly used approaches for estimating regression equations with a multifactor error structure, each of which will be used in the analysis below. The first method is the common correlated effects approach from Pesaran (2006). This method does not attempt to estimate the common factors and factor loadings directly. Rather, Pesaran shows that, in a large N and large T setting, cross sectional averages of the dependent and independent variables can be used as proxies for the common factors. This estimator has the added benefit that it can be computed by OLS applied to regressions where the observed explanatory variables are augmented with cross sectional averages of the dependent and independent variables. Pesaran proposes two versions of this method: the common correlated effects mean group (CCEMG) estimator and the common correlated effects pooled (CCEP) estimator. The CCEMG estimator allows minimum wages to have heterogeneous effects over areas by estimating a separate regression coefficient for each cross section unit. The individual slope coefficients can then be averaged to obtain a single mean group estimate. The CCEP estimator is a generalized version of the standard fixed effects estimator that estimates a single pooled regression coefficient but still allows the common factors to have heterogeneous effects over areas. Standard errors are calculated using Equations (58) and (69) in Pesaran (2006) for the CCEMG and CCEP estimators, respectively. The variance of the CCEMG estimator is estimated non-parametrically as the variance of the individual slope coefficients. The variance of the CCEP estimator takes on the common sandwich estimator form and is also based on the variance of the individual slope coefficients. Confidence intervals and significance reported in the results section are based on bootstrapped t-statistics using the *wild cluster bootstrap-t* procedure from Cameron, Gelbach, and Miller (2008), clustered at the state level.

The second method is the interactive fixed effects (IFE) approach from Bai (2009), which does involve directly estimating the common factors and factor loadings. This is done by jointly estimating the regression coefficients and the factor structure in an iterative process. The IFE approach is based on the fact that, given the common factors and factor loadings, the regression coefficients can be estimated using OLS after subtracting the factor structure from the data, and given the regression coefficients, the factors and factor loadings can be estimated by performing principal component analysis on the regression residuals.[7] However, the regression coefficients and factor structure are both unknown in practice. Therefore, Bai proposes an iterative procedure in which, given an initial guess of either the regression coefficients or the common factors and factor loadings, one iterates between estimating one, given the other, until the percent change in the sum of squared residuals falls below a pre-specified threshold.[8] A threshold of 10^{-9} is used in this paper. Bias-correction for serial correlation, cross sectional correlation, and heteroskedasticity is performed using

6. It is worth noting that the factor structure shown above can be rewritten to incorporate lagged common factors. This is appealing in the context of the minimum wage-employment application, given that it is reasonable to assume that both employment and minimum wages may be slow in responding to economic conditions due to social norms against laying off workers and the delay between when minimum wage hikes are approved and actually implemented. In this sense, it is intuitive to think that employment and minimum wages may have a lagged response to common factors. The factor model can be rewritten to incorporate lagged responses by rewriting a dynamic factor model as a static factor model, with the error term in Equation (1) now taking the form $\epsilon_{it} = \Lambda_i' F_t + u_{it}$, where $F_t = \left(f_t', f_{t-1}', ..., f_{t-s}'\right)'$ is an $(r(s+1) \text{ x } 1)$ vector of common factors, $\Lambda_i = (\lambda_{i0}', \lambda_{i1}', \ldots, \lambda_{is}')'$ is an $(r(s+1) \text{ x } 1)$ vector of factor loadings, and s represents the number of lagged factors.

7. Because the IFE estimator actually estimates the factor structure, the number of common factors, r, must be prespecified. One approach is to use the information criteria from Bai and Ng (2002), which estimates the number of strong factors in the data. Alternatively, IFE results could be provided for different numbers of common factors. Moon and Weidner (2015) showed that the IFE estimator still performs well if the number of common factors is over-estimated, but can suffer if too few factors are included.

8. Bai (2009) suggests initiating the iteration two different ways: (1) with the OLS estimates of the regression

Equations (23) and (24) in Bai (2009). Standard errors are calculated using Theorem 4 in Bai (2009). The variance of the IFE estimator takes on the standard sandwich estimator form, based on the square of the residuals. Confidence intervals and significance reported in the results section are based on bootstrapped t-statistics using the *wild cluster bootstrap-t* procedure from Cameron, Gelbach, and Miller (2008), clustered at the state level.

The Appendix gives more details on the factor model approach, including its advantages and limitations and its relative merits compared to the other approaches in the minimum wage literature. Most importantly, the CCE and IFE estimators have been shown to perform well even when there are no common factors in the error term (Bai 2009; Kim and Oka 2014; Pesaran and Tosetti 2011); they are essentially equivalent to OLS when the OLS estimator and factor model estimators are applied to the "correct" specification. This allows them to serve as a middle ground between the two-way fixed effects approach and approaches that include additional controls.[9]

III. DATA

A. Data Sources

Following the recent minimum wage-employment literature, two different low-skill groups are analyzed in this study: restaurant workers and teenagers. Restaurant workers and teenagers are the two most commonly studied populations in the minimum wage-employment literature (Baleman and Wolfson 2014) and they have been the focus of the recent debate in the literature. Based on Current Population Survey Outgoing Rotation Group (CPS ORG) calculations in Allegretto et al. (2017), during the period 1979–2014, 40.2% of working teenagers earned within 10% of the minimum wage and teenagers accounted for 22.7% of all workers earning within 10% of the minimum wage (down from 32.2% in 1979). During the period 2000–2014, 28.3% of restaurant workers earned within 10% of the minimum wage and restaurant workers accounted for 28.6% of all workers earning within 10% of the minimum wage.

Analysis of restaurant employment is based on data from the Quarterly Census of Employment of Wages (QCEW) as in Dube, Lester, and Reich (2010), updated to include more recent years (1990–2010).[10] The QCEW has also been used in the follow-up studies (Allegretto et al. 2013, 2017; Neumark, Salas, and Wascher 2014a, 2014b). 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 the county-quarter total private sector employment and the county population. The employment variables are constructed from the QCEW and the county population comes from the county-level Census Bureau population data which is produced annually. Data is available for the entire time frame of analysis for 1,371 counties.[11] Robustness checks that analyze the effect of minimum wage hikes on restaurant worker earnings are based on average weekly wages, which are constructed by dividing the county-quarter total restaurant payroll by the county-quarter number of restaurant employees. A minimum wage variable is merged to the dataset, which is always the higher of the state and federal minimum wage.[12] Summary

coefficients, ignoring the factor structure, and (2) with the principal components estimates of the factor structure from the raw data, ignoring the independent variables. Then, one keeps whichever set of results has the lowest final sum of squared residuals. Analysis was also performed using the individual slope coefficients from the CCE approach as an initial guess of the regression coefficients. The results were nearly identical between the starting methods, but the results generally converged faster when using the CCE estimates as the starting values. Therefore, analysis below is based on the CCE starting method.

9. Estimation of the factor models using the CCE and IFE estimators was performed in MATLAB. Commands now exist in STATA to perform the mean group version of the CCE estimator (CCEMG) and the IFE estimator: *xtmg* and *regife*. However, researchers should note that *regife* does not currently implement the bias-correction steps outlined in Equations (23) and (24) of Bai (2009). Furthermore, neither command constructs standard errors as outlined in Pesaran (2006) and Bai (2009); special care should be paid to inference if using these commands in STATA.

10. The time period of analysis stops in 2010 because there were classification changes to the four-digit NAICS industry codes, which Dube, Lester, and Reich (2010) use to identify restaurants, beginning in 2011. Results that include more recent years are very similar to the results shown in this paper.

11. For consistency with Dube, Lester, and Reich (2010), results are based on a balanced panel.

12. State and sub-state minimum wage data are available from the Washington Center for Equitable Growth (Vaghul

statistics for the dataset of analysis on restaurant workers are shown in Table 2.

Analysis of teenage employment is based on data from the CPS ORG as in Allegretto, Dube, and Reich (2011), updated to include more recent years (1990–2013). CPS ORG data have been used in each of the follow-up studies on teenage employment (Allegretto et al. 2013, 2017; Neumark, Salas, and Wascher 2014b). 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. Robustness checks that analyze the effect of minimum wage hikes on teenage earnings are based on average hourly earnings, which are based only on those who were working and paid between \$1 and \$100 per hour in 2009 dollars and are constructed by aggregating the CPS ORG individual hourly earnings data to the state-quarter level. A minimum wage variable is merged to the dataset, which is always the higher of the state and federal minimum wage. Summary statistics for the dataset of analysis on teenagers are shown in Table 2.

As robustness checks, two other datasets are used to analyze teenage employment: CPS basic monthly files and Quarterly Workforce Indicators (QWI). These two datasets have been used in some of the more recent minimum wage-employment studies (Allegretto et al. 2013, 2017). The CPS basic monthly files do not have the wage data that the CPS ORG has, which is necessary for the crucial robustness check on the effect of minimum wage hikes on earnings, but it has a much larger monthly sample of employment outcomes. The QWI is a newer dataset which provides county-level teenage employment counts. The data are a public-use aggregation of the matched employer-employee Longitudinal Employer Household Dynamics (LEHD) database, which is provided via a partnership between the Census Bureau and the Labor Market Information (LMI) offices. Both of these datasets are taken directly from the data associated with Allegretto et al. (2017).[13] Summary statistics for these datasets are also shown in Table 2.

B. Cross Section Dependence and Data Size

As discussed in Section I and Section II.A, the presence of unobserved common factors can cause outcomes or residuals to be correlated across areas, known as cross section dependence, which can be problematic for inference and estimation. The factor model approach is commonly used to model the presence of strong, as opposed to weak, cross section dependence. Weak cross section dependence can be thought of as arising from the fact that geographically or economically proximate places will have similar characteristics, due to integrated geography or labor markets, which will cause correlation in outcomes between neighboring areas. Strong cross section dependence, on the other hand, is typically thought of as arising from unobserved forces ("factors") that influence outcomes in heterogeneous ways between areas. Spatial econometric methods are an alternative way to address cross section dependence, which do so by assuming that it arises according to a pre-specified distance metric. However, factor models have two important advantages over spatial econometric methods. The first is that factor models are intended to capture the presence of strong cross section dependence, whereas spatial econometric methods typically require that the cross section dependence is only weak. The second is that the factor model approach assumes no geographic relationship for the correlation between areas before estimation, thus allowing outcomes and residuals to be correlated in ways that depart from geographic proximity.

To validate the use of factor model methods, Table 2 shows the results of a test for strong cross section dependence in the data using the cross section dependence (CD) test from Pesaran (2015). This test is based on the average of pairwise correlations in the data, with greater correlations indicating greater cross section dependence

and Zipperer 2016). Two sub-state areas increased their minimum wage during the time sample of this analysis: San Francisco, CA and Santa Fe, NM. Thus, for the county-level analysis using the QCEW, the minimum wage associated with San Francisco County and Santa Fe County match their own minimum wage law rather than that of their state. For state-level analysis using the CPS discussed below, these sub-state increases will not be accounted for. This should not significantly impact the results, as it only affects two counties. If there were bias, it is not clear in which direction it would occur: it could vary depending on whether there was a state-level hike at the same time and whether the state-level hike was larger or smaller than the sub-state hike.

13. The data can be downloaded here: https://arindube.com/working-papers/

TABLE 2
Data Sources

	(1) Mean	(2) *SD*	(3) CD Test Statistic
Panel A: Restaurant employment (QCEW)			
Restaurant employment	4,786	11,168	4992.8***
Restaurant average weekly wages	$170.77	$43.72	6939.0***
Total private sector employment	68,289	174,797	
Total private sector average wages	$481.37	$136.80	
Population	181,719	423,564	
Minimum wage	$5.26	$1.07	
T *(1990–2010)*	84		
N	1,371		
Panel B: Teenage employment (CPS ORG)			
Fraction of teenagers employed	0.41	0.12	205.2***
Average hourly wage for teens	$8.26	$0.86	88.82***
Unemployment rate	5.68	2.14	
Relative size of teenage population	0.09	0.01	
Minimum wage	$5.58	$1.26	
T *(1990–2013)*	96		
N	51		
Panel C: Teenage employment (CPS basic monthly)			
Fraction of teenagers employed	0.41	0.12	253.9***
Unemployment rate	5.58	1.26	
Relative size of teenage population	0.07	0.01	
Minimum wage	$5.58	$1.26	
T *(1990–2013)*	96		
N	51		
Panel D: Teenage employment (QWI)			
Teenage employment	1,299	4,029	6856.8***
Teenage average weekly wages	$474.61	$868.95	6485.5***
Total private sector employment	41,046	153,885	
Population	357,940	1,237,330	
Teenage population	13,233	44,986	
Minimum wage	$5.98	$0.98	
T *(2000–2011)*	48		
N	2,189		

Notes: Each panel shows a separate group of data used in the analysis. For the restaurant employment analysis, county-quarter employment and wage data come from the Quarterly Census of Employment and Wages (QCEW) and population data come from the annual Census Bureau estimates. For teenage employment analysis using CPS ORG and CPS basic monthly files, all variables are constructed by aggregating the individual-level CPS files to the state-quarter level. For teenage employment analysis using the Quarterly Workforce Indicators (QWI) dataset, county-quarter employment and wage data come from the QWI and population data come from the annual Census Bureau estimates. A minimum wage variable that is always the higher of the state and federal minimum wage is added to each dataset. Tests for cross section dependence are based on the test in Pesaran (2015).

Significance levels are as follows: *10%, **5%, ***1%.

and thus producing a larger test statistic. The null hypothesis of the test, which is distributed standard normal, is that there is only weak cross section dependence, while the alternative is that the cross section dependence is strong. The null hypothesis of weak cross section dependence is rejected at the 1-% level for each of the datasets for restaurant and teenage employment. This suggests the presence of common factors influencing employment across areas and validates the factor model approach. The fact that there is less strong cross section dependence in the state-level CPS datasets is not surprising, given that the unit of analysis occurs at a more aggregated level.

Because CPS data do not allow for reliable estimates at the county level, the teenage dataset has a relatively small cross section dimension of 51, containing all 50 states and Washington, DC. Westerlund and Urbain (2015) show that both the IFE and CCE estimators perform better when $N > T$, which is not the case for the CPS datasets. It is therefore possible that the factor model estimators may not be able to capture the common factors as reliably for the CPS datasets as they can for the QCEW and QWI and therefore may not be able to fully remove any cross section dependence and bias that is caused by common factors. Nonetheless, the IFE and CCE estimators still provide significant improvements over traditional OLS methods when common factors exist in the data and still perform well without the presence of common factors in the data even when $N < T$, as shown in Pesaran (2006) and Bai (2009) and in the simulations in Section V.

IV. RESULTS

A. Minimum Wage-Employment Elasticity

All OLS results are based on the traditional two-way fixed effects specification in Equation (1). Factor model results are based on the two-way fixed effects specification in Equation (1) and the multi-factor error structure in Equation (2). Results are reported separately for each of the datasets. The results tables first show the OLS estimate of the two-way fixed effects specification, and then show results using each of the factor model estimators described in Section II. Confidence intervals and significance reported in the tables are based on bootstrapped t-statistics using the *wild cluster bootstrap-t* procedure from Cameron, Gelbach, and Miller (2008), clustered at the state level.[14]

The effect of minimum wage hikes on restaurant employment is shown in Table 3. Column (1) shows that the OLS estimate of the traditional two-way fixed effects specification is in line with other estimates from the literature, with an elasticity of −0.138 that is statistically significant. However, the factor model estimators in columns (2)−(4) produce very different elasticity estimates. The CCEMG, CCEP, and IFE estimators produce elasticity estimates of −0.013, −0.013, and −0.023, respectively. None of the factor model estimates are statistically different from zero. In addition to producing smaller elasticity estimates, the factor model estimates are more precise: the confidence intervals are much tighter for the factor model estimators than OLS, and they rule out elasticities larger than approximately −0.050 with 95% confidence. Tighter confidence intervals for the factor model estimates is consistent with there being common factors that the OLS estimator is not controlling for, as this would cause inefficiency, in addition to bias, in the OLS estimator. Interestingly, the factor model estimates for the other covariates are much more similar to OLS in terms of both the point estimate and the confidence interval length; it appears that the unobserved common factors are correlated with the minimum wage more so than total private sector employment or population.

Table 3 also shows residual diagnostics that test for the presence of strong cross section dependence in the residuals. There is still strong cross section dependence in the OLS residuals, which have a test statistic of 26.98, suggesting the presence of unobserved common factors remaining in the OLS residuals. The factor model estimators do a better job of controlling for common factors and removing cross section dependence from the data, with test statistics of 8.46, 17.19, and −0.22 for the CCEMG, CCEP, and IFE estimators, respectively.

The effect of minimum wage hikes on teenage employment is shown in Table 4. Column (1) shows that the OLS estimate of the minimum wage-employment elasticity is once again in line with other estimates from the literature, with an elasticity of −0.178 that is statistically significant. Just as with the restaurant employment dataset, the factor model estimators in columns (2)−(4) produce very different elasticity estimates than OLS: the CCEMG, CCEP, and IFE estimators produce elasticity estimates of −0.040, −0.065, and −0.036, respectively, none of which are statistically different from zero. Regarding the other covariates, the factor model estimators produce slightly smaller estimates than OLS for the effect of the unemployment rate and produce estimates of the opposite sign for the effect of the teenage population share. The CCEP and IFE estimators also produce tighter confidence intervals than OLS. The IFE confidence interval rules out minimum wage elasticity estimates larger than −0.116 with 95% confidence, while the CCE estimators rule out elasticity estimates larger than around −0.200.

Although the factor model estimators produce significantly smaller elasticity estimates than OLS for teenage employment, the improvement in confidence interval length is not as dramatic as it was for restaurant employment, and the factor model estimators do not further remove cross section dependence from the residuals. This may be due to the relatively small size of the cross section dimension of the teenage

14. The decision to use bootstrapped *t*-statistics is based on evidence that tests following the limiting theory in Bai (2009) can be over-sized (Chudik, Pesaran, and Tosetti 2011; Kapetanios, Pesaran, and Yamagata 2011). Indeed, similar results are found in this application: the IFE confidence intervals are especially narrow when based only on the limiting theory in Bai (2009), resulting in statistically significant results even in cases where the point estimate is very close to zero, while confidence intervals based on bootstrapped *t*-statistics are less narrow and reject the null hypothesis of no effect less often. Tests and confidence intervals for the CCE estimates are nearly identical with or without bootstrapped *t*-statistics, but tests shown remain based on bootstrapped *t*-statistics because they should perform at least as well as non-bootstrapped *t*-statistics.

TABLE 3
Minimum Wage-Employment Elasticity—Restaurant Employment

	(1) OLS	(2) CCEMG	(3) CCEP	(4) IFE
	Dependent variable: log(employment)			
log(Minimum wage)	**−0.138***	**−0.013**	**−0.013**	**−0.023**
	[−0.297, 0.019]	[−0.042, 0.026]	[−0.046, 0.028]	[−0.052, 0.009]
log(Total private sector emp.)	0.512***	0.704***	0.585***	0.542***
	[0.430, 0.595]	[0.667, 0.742]	[0.515, 0.653]	[0.428, 0.641]
log(Population)	0.587***	0.373***	0.412***	0.214***
	[0.432, 0.742]	[0.184, 0.566]	[0.285, 0.547]	[0.123, 0.284]
Period fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
CD test statistic	26.98***	8.46***	17.19***	−0.22
TxN	115,164	115,164	115,164	115,164

Notes: Each column uses a different estimator applied to the traditional two-way fixed effects specification shown in Equation (1). IFE results are based on five common factors. OLS standard errors are clustered at the state level. Standard errors for CCEMG, CCEP, and IFE are calculated according to Bai (2009) and Pesaran (2006). The confidence intervals and significance reported for CCEMG, CCEP, and IFE are based on bootstrapped t-statistics following the *wild cluster bootstrap-t* procedure in Cameron, Gelbach, and Miller (2008), clustered at the state level. Residual diagnostics for strong cross section dependence are based on the test in Pesaran (2015).

Significance levels are as follows: *10%, **5%, ***1%.

TABLE 4
Minimum Wage-Employment Elasticity—Teenage Employment

	(1) OLS	(2) CCEMG	(3) CCEP	(4) IFE
	Dependent variable: log(employment/population)			
log(Minimum wage)	**−0.178****	**−0.040**	**−0.065**	**−0.036**
	[−0.323, −0.033]	[−0.214, 0.135]	[−0.191, 0.061]	[−0.116, 0.061]
Unemployment rate	−3.608***	−2.660***	−2.805***	−1.787***
	[−4.243, −2.973]	[−3.162, −2.158]	[−3.415, −2.195]	[−2.889, −1.864]
Teen population share	−0.154	0.482	0.274	0.249
	[−0.709, 0.401]	[−0.104, 1.068]	[−0.223, 0.771]	[−0.232, 0.819]
Period fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
CD test statistic	−5.96***	−6.01***	−6.03***	−6.69***
TxN	4,896	4,896	4,896	4,896

Note: IFE results are based on eight common factors. See Table 3 for additional details about standard errors, inference, and CD test statistics.

employment dataset, an issue discussed in Section III.B: because the CCE estimator is only $\sqrt{N}$-consistent and the IFE estimator, while $\sqrt{NT}$-consistent for the estimation of regression coefficients, is based on common factor estimates than are only $\sqrt{N}$-consistent, it is possible that the relatively small cross section dimension of the CPS data may lead to imprecise estimates of the common factors, which could then leave the residuals contaminated with cross section dependence despite removing bias from the coefficient estimates; the purpose of the CCE and IFE estimators in the literature and in this paper is to produce unbiased estimates of regression parameters, rather than to reduce cross section dependence per se, and thus the ability of the two estimators to do both in a variety of settings has not been studied.

Nonetheless, the factor model estimators do still appear to be capturing the presence of common factors in the teenage employment dataset. As shown in the literature, the factor model estimators still perform well when there are no common factors in the error term (Bai 2009; Kim and Oka 2014; Pesaran and Tosetti 2011). Thus, the OLS estimator and factor model estimators will produce results that are essentially identical if the specification to which they are applied is correct (i.e., the specification shown in Equation (1), without the multi-factor error structure). Thus, the difference between the OLS estimate and factor model estimates

TABLE 5
Minimum Wage-Employment Elasticity—Teenage Employment, Other Data Sources

	(1) OLS	(2) CCEMG	(3) CCEP	(4) IFE
Panel A: CPS basic monthly				
log(Minimum wage)	−0.116*	0.001	−0.066	0.053
	[−0.245, 0.014]	[−0.182, 0.184]	[−0.179, 0.047]	[−0.032, 0.172]
CD test statistic	−6.06***	−5.19***	−6.02***	−6.78***
TxN	4,896	4,896	4,896	4,896
Panel B: Quarterly workforce indicators				
log(Minimum wage)	−0.019	−0.089**	−0.039**	−0.036**
	[−0.277, 0.239]	[−0.164, −0.014]	[−0.077, −0.001]	[−0.068, −0.002]
CD test statistic	95.85***	51.81***	76.63***	20.93***
TxN	105,072	105,072	105,072	105,072
Period fixed effects	Yes	Yes	Yes	Yes
County/State fixed effects	Yes	Yes	Yes	Yes

Notes: IFE results are based on eight common factors for the CPS basic monthly data and six common factors for the QWI data. Panel A also controls for state-quarter unemployment rate, state-quarter relative size of the teenage population, and state-quarter mean demographics for sex, age, race, Hispanic heritage, and marital status. Panel B controls for county-quarter total population, teenage population, and total private sector employment. See Table 3 for additional details about standard errors, inference, and CD test statistics.

suggests the presence of common factors in the error term of Equation (1). Section V will confirm that the factor model estimators produce elasticity estimates very similar to OLS when applied to the two-way fixed effects specification if the specification is correct, even for the teenage employment dataset.[15]

B. Alternative Teenage Employment Data Sources

As discussed in Section III.A, CPS basic monthly files and the QWI have been used to analyze teenage employment in more recent studies. The advantage of the CPS basic monthly files is that they provide a much larger sample of monthly employment outcomes than the CPS ORG. The advantage of the QWI data is that they provide county-level teenage employment counts, which could address the cross section dimension issue associated with the CPS data for teenage employment.

Table 5 shows the results for these two datasets. Panel A is based on CPS basic monthly files. Column (1) shows that the OLS estimate is once again consistent with the literature, with a negative and statistically significant elasticity. Similar to the CPS ORG results, the factor model estimators in columns (2)–(4) produce much smaller elasticity estimates that are not statistically different from zero. Also similar to the CPS ORG results, the CCEP and IFE estimates provide only modest improvement to the confidence interval length and each of the factor model estimators fail to remove more of the cross section dependence from the residuals.

Panel B is based on the QWI data. In this case, even the OLS estimator produces a small elasticity that is not statistically different from zero. Allegretto et al. (2017) find significant negative effects when using this dataset and only two-way fixed effects, but they analyze only contiguous counties for the border discontinuity approach, rather than the entire sample. Although the OLS point estimate is small and not statistically significant, the confidence interval is very large and cannot rule out elasticity estimates of nearly −0.300. The factor model estimators also produce elasticity estimates that are small and close to zero, although they are statistically significant. However, this statistical significance is due entirely to very precise confidence intervals relative to the OLS results; the factor model estimates are still much smaller in magnitude than the traditional OLS estimates, which are in the range of −0.1 to −0.2, and the factor model estimates

15. As described in the Appendix, the multi-factor error structure can incorporate traditional additive two-way fixed effects. Thus, these fixed effects could be left out of the model for the factor model estimators to handle. The results shown in the paper model them explicitly for two reasons: (1) it is more efficient to model additive fixed effects explicitly if they represent the "correct" specification and the existence of additive fixed effects is much less debatable than the state-specific time trends or time-varying regional fixed effects and (2) it more accurately addresses the debate in the minimum wage-employment literature, which is about what controls to include in addition to two-way fixed effects. Nonetheless, the factor model results are essentially unchanged if the two-way fixed effects are removed from the specification. These results are available upon request.

TABLE 6
Summary Statistics for Common Factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Factor #p									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A: Restaurant employment										
AR1($\widehat{f}_{pt}$)	0.990	0.975	0.527	0.447	0.988	0.969	0.954	0.884	0.882	0.867
R_p^2	0.538	0.707	0.785	0.857	0.899	0.928	0.951	0.971	0.987	1.000
Panel B: Teen employment (CPS ORG)										
AR1($\widehat{f}_{pt}$)	0.496	0.295	−0.014	−0.009	0.021	0.031	−0.015	0.008	0.122	0.028
R_p^2	0.195	0.374	0.470	0.561	0.648	0.730	0.806	0.879	0.944	1.000
Panel C: Teen employment (CPS basic monthly)										
AR1($\widehat{f}_{pt}$)	0.825	0.086	0.440	0.281	0.430	0.363	0.382	0.263	0.337	0.140
R_p^2	0.274	0.477	0.563	0.640	0.713	0.775	0.836	0.899	0.950	1.000
Panel D: Teen employment (QWI)										
AR1($\widehat{f}_{pt}$)	0.827	0.032	0.917	0.941	0.901	0.876	−0.059	0.844	0.622	0.523
R_p^2	0.377	0.586	0.734	0.809	0.861	0.899	0.932	0.960	0.982	1.000

Notes: The first 10 common factors for each data source come from the IFE results with 10 pre-specified common factors. R_p^2 shows the relative importance of each factor, calculated as the fraction of the total variance of the residuals explained by factors 1 to p. This is given as the sum of the first p largest eigenvalues of the sample second moment matrix of the OLS residuals divided by the sum of all eigenvalues. AR1($\widehat{f}_{pt}$) is the first-order autocorrelation coefficient for the given factor.

rule out elasticity estimates larger than −0.070 for CCEP and IFE and −0.164 for CCEMG. This is a considerable reduction from the −0.300 lower bound of the OLS confidence interval. Finally, the factor model estimators also remove more of the cross section dependence from the residuals than OLS. This confidence interval length and cross section dependence improvement is more evidence that the lack of improvement in confidence interval length and cross section dependence associated with the factor model results for the CPS data may be due to the relatively small cross section dimension of the CPS data.

C. Number of Common Factors for IFE Estimation

One important feature of the IFE procedure is the selection of the number of common factors. As discussed in Section II.B, one way to determine the number of common factors is to use the information criteria from Bai and Ng (2002), which estimates the number of strong common factors in the data. This approach was developed for pure factor models, but the supplementary material for Bai (2009) shows that it can be extended to settings with IFE and independent regressors. However, this approach proved to be uninformative, as it picked the minimum number of factors allowed in some cases and the maximum allowed in other cases. This has occurred in other empirical papers using this method (Bailey, Holly, and Pesaran 2016; Kim and Oka 2014; Moon and Weidner 2015). Therefore, in the analysis above, the IFE results were based on the minimum number of factors needed to explain approximately 90% of the variation in the residuals. This meant five common factors for restaurant employment, eight common factors for CPS ORG and CPS basic monthly teenage employment, and six common factors for QWI teenage employment. This can be seen in Table 6, which shows the relative importance of each common factor, R_p^2. The relative importance of each common factor is calculated as the fraction of the total variance in the residuals explained by factors 1 to p, given as the sum of the first p largest eigenvalues of the second moment matrix of the OLS residuals divided by the sum of all eigenvalues. Because unit roots in the common factors can be problematic for the performance of the factor model estimators, Table 6 also shows the AR(1) coefficient for each of the common factors. Some of the factors show large AR(1) coefficients, but in most cases this is due to the presence of time trends.[16]

16. For example, the AR(1) coefficient for the first factor of restaurant employment decreases from 0.990 to 0.406 when the factor is detrended using a quadratic trend.

TABLE 7

IFE Estimates for Different Numbers of Common Factors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Number of Common Factors						
	2	**3**	**4**	**5**	**6**	**7**	**8**
Panel A: Restaurant employment							
log(Minimum wage)	−0.016	−0.035	−0.042**	−0.023	−0.035*	−0.008	−0.007
	[−0.046,0.015]	[−0.066,-0.006]	[−0.085,0.015]	[−0.052,0.009]	[−0.061,0.001]	[−0.041,0.021]	[−0.042,0.021]
CD test statistic	29.02***	29.39***	−0.30	−0.22	0.40	0.61	0.74
Panel B: Teen employment (CPS ORG)							
log(Minimum wage)	−0.104**	−0.093*	−0.069	−0.064	−0.061	−0.018	−0.036
	[−0.183,-0.005]	[−0.175,0.002]	[−0.145,0.025]	[−0.143,0.026]	[−0.141,0.029]	[−0.100,0.077]	[−0.116,0.061]
CD test statistic	−6.45***	−6.45***	−6.48***	−6.52***	−6.64***	−6.66***	−6.72***
Panel C: Teen employment (CPS basic monthly)							
log(Minimum wage)	−0.072	−0.069	−0.078	0.013	0.031	0.045	0.053
	[−0.158,0.051]	[−0.152,0.052]	[−0.164,0.043]	[−0.065,0.133]	[−0.068,0.149]	[−0.041,0.161]	[−0.032,0.172]
CD test statistic	−6.29***	−6.53***	−6.71***	−6.74***	−6.77***	−6.77***	−6.78***
Panel C: Teen employment (QWI)							
log(Minimum wage)	−0.098***	−0.071**	−0.009	−0.031	−0.035**	0.042*	0.008
	[−0.138,-0.053]	[−0.113,-0.032]	[−0.036,0.033]	[−0.071,0.010]	[−0.068,-0.002]	[−0.002,0.069]	[−0.034,0.035]
CD test statistic	20.17***	17.00***	21.42***	18.75***	20.93***	13.25***	12.49***

Notes: Each column is a separate IFE estimate of the minimum wage-employment elasticity based on the traditional two-way fixed effects specification shown in Equations (1) and (2). Each column assumes a different number of pre-specified common factors for the IFE procedure. See Table 3 for additional details about standard errors, inference, and CD test statistics.

Because the IFE estimator assumes that the number of common factors is known and reliable estimation of the number of common factors is an unresolved issue, robustness checks are important. Moon and Weidner (2015) show that regression parameter estimates tend to stabilize once the true number of factors has been reached; the IFE approach still performs well when the number of common factors is over-estimated, while the approach will produce biased estimates of regression parameters if the number of common factors is under-estimated. Therefore, Table 7 shows IFE results based on two to eight common factors. For restaurant employment, the IFE estimate of the minimum wage-employment elasticity is generally invariant to the number of factors, with elasticity estimates that remain small and not statistically significant for different numbers of factors. The teenage minimum wage-employment elasticity based on the CPS ORG data is not entirely invariant to the number of common factors: the IFE estimates are somewhat large and statistically significant when only two or three common factors are included, although they are still not as large as the OLS estimate from Table 4. However, once four common factors are included, the IFE estimates become fairly small and similar to the CCE estimates reported in Table 4 and they remain relatively small for up to eight common factors.

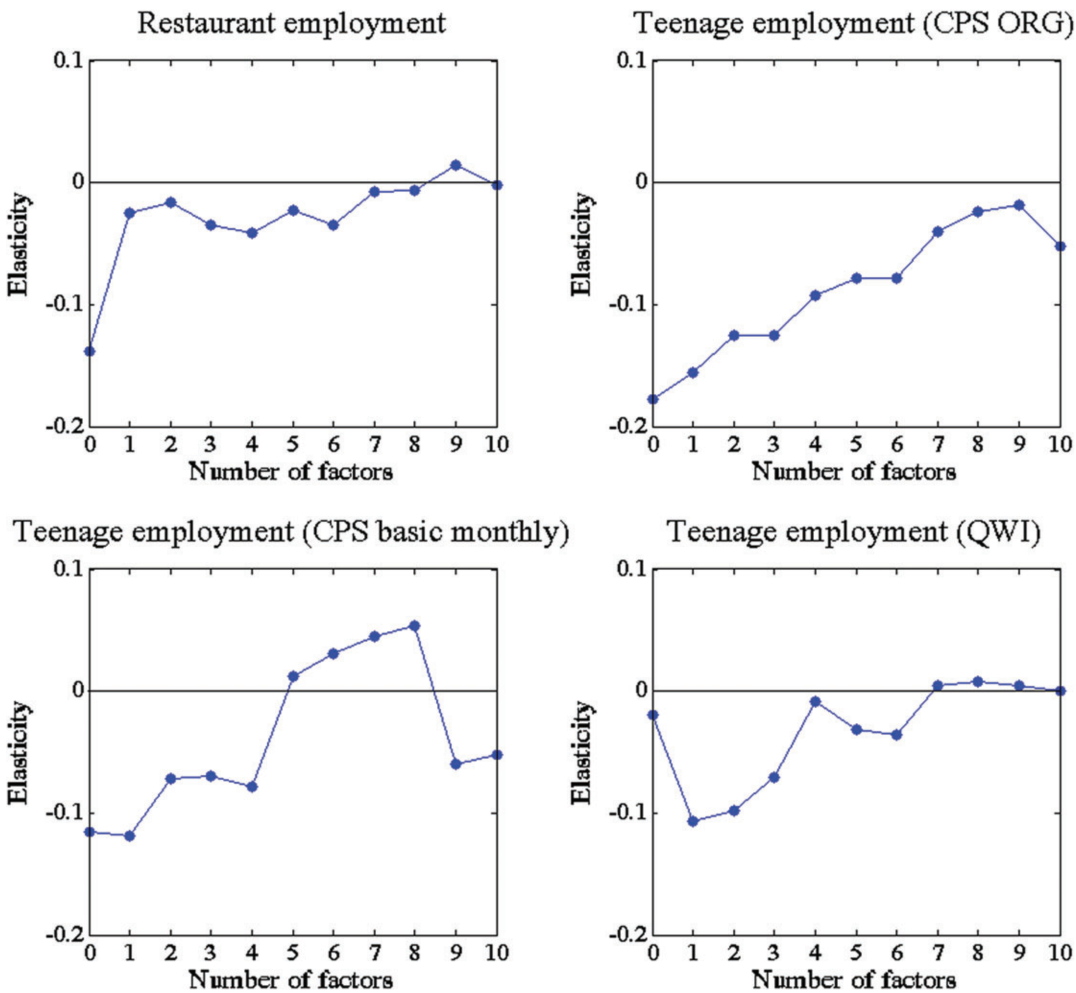
The fact that it takes a larger number of common factors for the IFE elasticity estimate based on CPS ORG data to become small is consistent with the result in Table 6 that it takes a larger number of common factors to explain the variation in the CPS ORG residuals; it takes four factors to explain roughly the same fraction of the variation in the CPS ORG residuals that is explained by the first common factor for restaurant employment. Results for the other teenage employment data sources are similar: estimates are somewhat large and in some cases statistically significant for one to two factors, but become much smaller once additional factors are added and a larger fraction of the variance in the residuals is explained.[17]

Figure 2 plots the IFE elasticity estimate for 1–10 common factors for each dataset. These figures and the results just discussed in Table 7 suggest that the IFE elasticity estimates are generally more stable for higher numbers of common factors. This result is consistent with the result in Moon and Weidner (2015) that the IFE estimator still performs well when the number of common factors is over-estimated, while the IFE estimator can be biased when the number of common factors is under-estimated.

17. Robustness of the IFE results up to only eight factors and not further is an arbitrary decision based on three items: (1) the IFE results do not change significantly beyond eight factors, (2) in general, the purpose of factor models is to account for residual cross section dependence with as few factors as possible, and (3) space considerations in the paper. Results based on a higher number of factors are available upon request.

FIGURE 2

IFE Minimum Wage-Employment Elasticity Estimates, Different Numbers of Factors



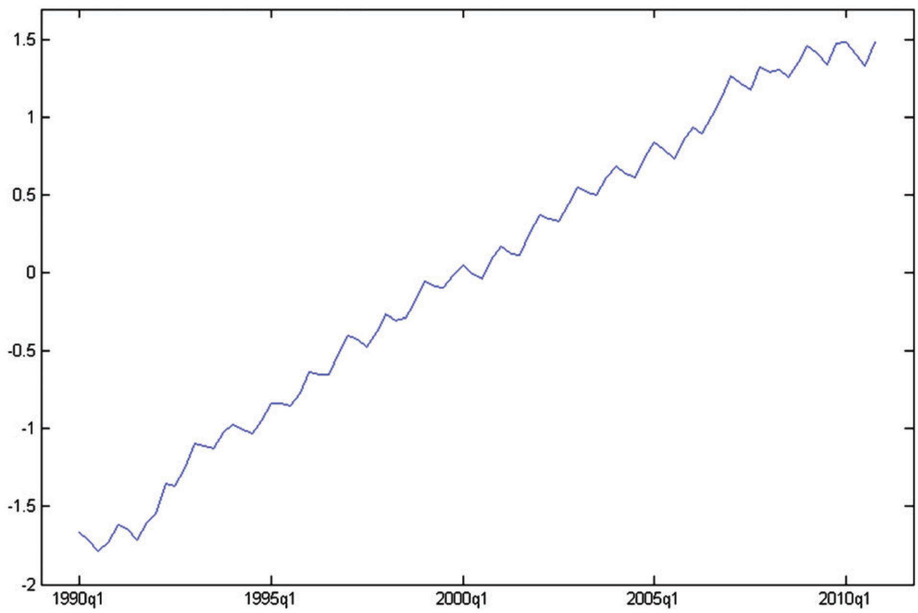
Notes: Each figure shows the IFE estimate of the minimum wage-employment elasticity for different numbers of common factors. Zero common factors is equivalent to OLS. Corresponding confidence intervals are shown in Table 7.

D. Accounting for the Difference between OLS and Factor Model Estimators

The previous results showed that the factor model estimators consistently produce elasticity estimates that are smaller than the traditional two-way fixed effects OLS estimates. The goal of this section is to attempt to shed some light on what the factor model estimators are capturing in the error term of Equation (1) that OLS cannot account for by analyzing the estimated factor structure from the IFE estimator. No direct economic interpretation can be given to the common factors, as they are defined purely in a statistical sense: the factors are the eigenvectors that correspond to the largest eigenvalues of the second moment matrix of the regression residuals. Additionally, while the product $\lambda_i' f_t$ is identifiable, the factors and factor loadings themselves are identifiable only up to a sign change. Nonetheless, the factor structure does have some interpretable patterns that are relevant to the recent debate about the appropriateness of state-specific time trends and Census division-by-period fixed effects.

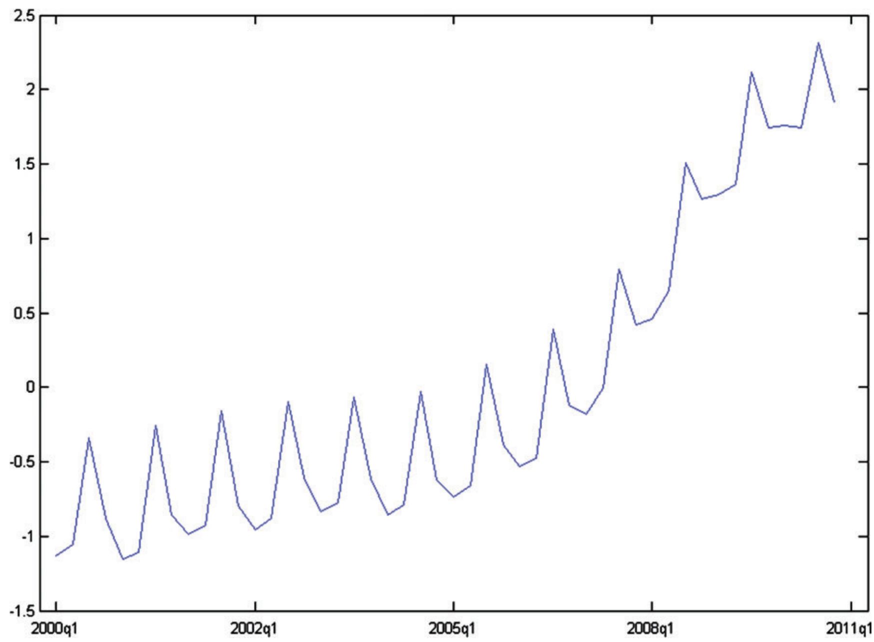
Figures 3 and 4 show the first common factor from the IFE estimator for restaurant employment and teenage employment from the QWI,

FIGURE 3
First Common Factor—Restaurant Employment



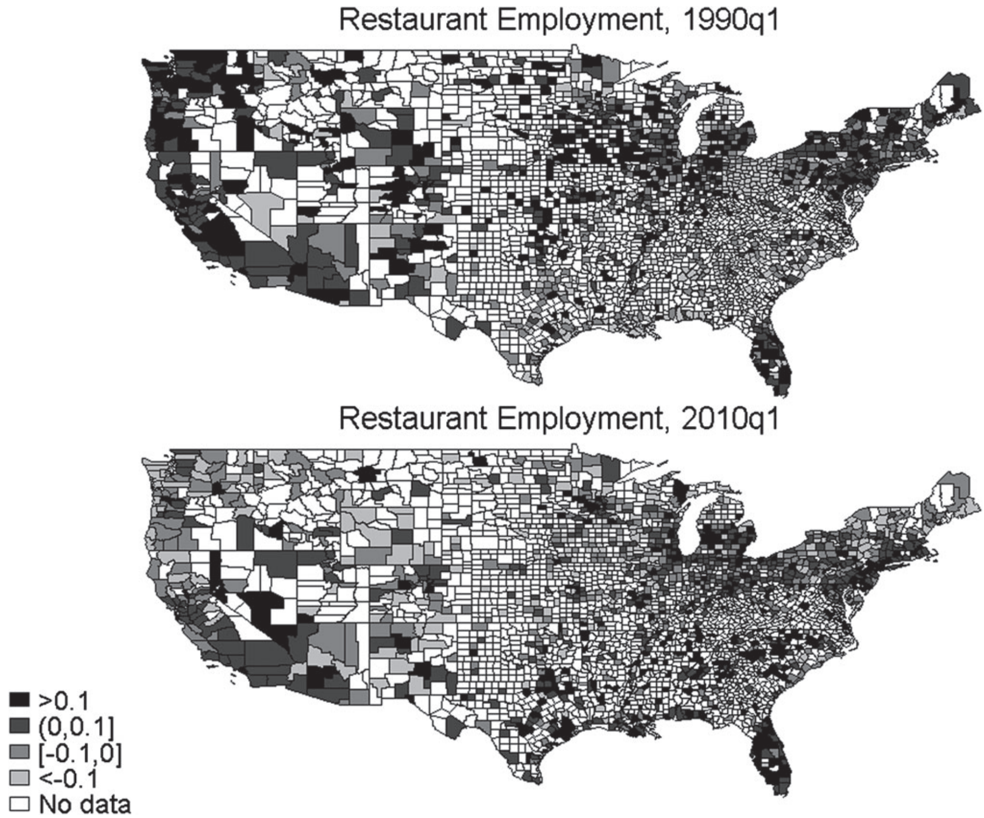
Note: The figure shows the first common factor for restaurant employment, corresponding to the IFE estimate in Table 3. Common factors are estimated jointly with the regression coefficients in the IFE procedure.

FIGURE 4
First Common Factor— Teenage Employment (QWI)



Notes: The figure shows the first common factor for teenage employment (QWI), corresponding to the IFE estimate in Panel B of Table 5. Common factors are estimated jointly with the regression coefficients in the IFE procedure.

FIGURE 5
Effect of Common Factors on Restaurant Employment ($\widehat{\lambda}_i'\widehat{f}_t$, Five Factors)



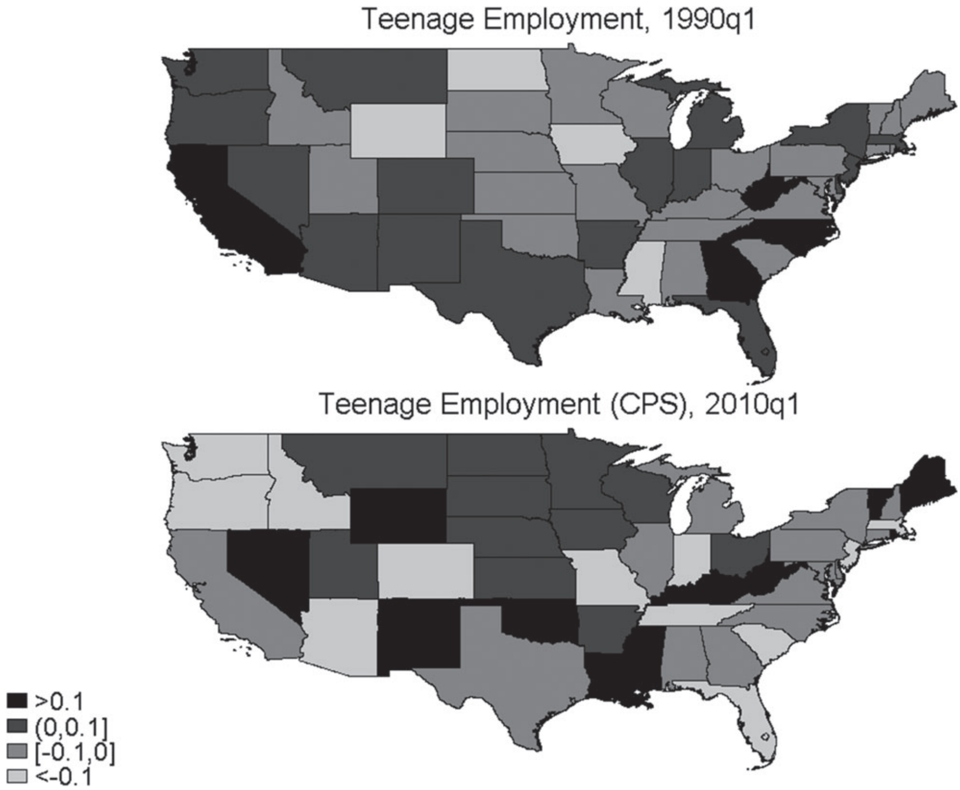
Notes: Each figure plots the combined effect of the common factors for the specified time period on each county's log employment, based on the IFE results in Table 3. Common factors and factor loadings are estimated jointly with the regression coefficients in the IFE procedure. Counties without data in the figure had missing observations in the raw data and were therefore not included in the balanced sample used for analysis.

respectively. The common factor for restaurant employment looks similar to a linear time trend with seasonality. The common factor for teenage employment from the QWI looks similar to a quadratic time trend with seasonality. This produces a structure very similar to county-specific time trends when each factor is multiplied by its factor loading for each county. This lends some support to the inclusion of time trends in the two-way fixed effects specification, but only for restaurant employment and teenage employment from the QWI. Additionally, these common factors that resemble unit-specific time trends represent only a portion of what remains in the error term of the two-way fixed effects specification; it takes several more factors to explain a large fraction of the variance in the OLS residuals for these datasets and the QWI IFE estimates do not become significantly different from OLS until additional factors are included, as seen in Tables 6 and 7. The other factors are not shown because they do not have such interpretable or relevant patterns. State-specific time trends do appear to be a part of what is being accounted for by the factors, but not all of it.

Figures 5 and 6 plot the combined effect of the unobserved common factors for a given time period for restaurant employment and teenage employment based on the CPS ORG, respectively. This is constructed as the inner product of the (1 x r) vector of factor loadings for each cross section unit, λ_i', and the (r x 1) vector of common factors for the given time period, f_t. Each of these figures shows time-varying regional clustering in the effect of the unobserved common factors. In Figure 5, for example, much of the

FIGURE 6

Effect of Common Factors on Teenage (CPS ORG) Employment ($\widehat{\lambda}_i'\widehat{f}_t$, 8 factors)



Notes: Each figure plots the combined effect of the common factors for the specified time period on each county's log employment, based on the IFE results in Table 4. See Figure 5 for details.

West Coast, Midwest, and Northeast experience positive effects on employment from the unobserved common factors in 1990q1. However, in 2010q1, the Southwest, parts of the South and Southeast, and parts of the Northeast experience positive employment effects from the unobserved common factors. Similar patterns of time-varying regional clustering appear in Figure 6.[18]

Interestingly, this time-varying regional clustering could roughly be approximated by a Census division-by-period fixed effect. For example, in Figure 5 for 1990q1, the darker regions align fairly well with the Pacific, East North Central, Middle Atlantic, and New England Census divisions. This lends some support for the use of Census division-by-period fixed effects, as proxies for this time-varying regional clustering. However, the figures also illustrate the flexibility of the factor approach over a Census division-by-period fixed effect or the border discontinuity approach: while regional clustering does occur, there are also many cases in which same-division states or counties on opposite sides of a state border experience very different effects from the common factors. For example, in Figure 5 for 1990q1, Ohio clearly stands out on the map from the states around it; it appears to be experiencing a very different shock than other same-division states, and counties on the opposite side of the border from Ohio appear to be poor control groups for counties in Ohio for a border discontinuity approach. Therefore, like how Figures 3 and 4 showed that time trends appear to be a part, but not all, of what is being accounted for in the factors, these maps suggest that Census division-by-period fixed effects are a useful, but not perfect, approximation of the

18. Plots based on the CPS basic monthly files and QWI data also show time-varying regional clustering. These maps are available upon request.

TABLE 8

Proportion of Variance (R^2) Explained by Controls for Unobserved Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
	Controls (without two-way fixed effects)			**Controls (with two-way fixed effects)**		
Dependent Variable	**CDxP Fixed Effects and State-Specific Time Trends**	**Common Factors Estimated from IFE Procedure**	**Cross Section Averages from CCE Procedure**	**CDxP Fixed Effects and State-Specific Time Trends**	**Common Factors Estimated from IFE Procedure**	**Cross Section Averages from CCE Procedure**
Panel A: Restaurant employment						
log(Employment)	0.174	0.013	0.014	0.587	0.505	0.505
log(Minimum wage)	0.944	0.837	0.874	0.973	0.931	0.931
Panel B: Teenage employment (CPS ORG)						
log(Employment/population)	0.629	0.186	0.336	0.656	0.566	0.566
log(Minimum wage)	0.935	0.643	0.882	0.968	0.941	0.941
Panel C: Teenage employment (CPS basic monthly)						
log(Employment/population)	0.693	0.258	0.372	0.784	0.704	0.704
log(Minimum wage)	0.935	0.715	0.880	0.970	0.943	0.943
Panel D: Teenage employment (QWI)						
log(Employment)	0.189	0.015	0.015	0.594	0.551	0.551
log(Minimum wage)	0.885	0.753	0.766	0.943	0.912	0.912

Notes: Each column shows the proportion of the variance in the data for the given dependent variable that is explained by the controls for unobserved heterogeneity. This is computed by regressing the dependent variable on Census division-by-period ("CDxP") fixed effects and state-specific time trends for columns (1) and (4), regressing the dependent variable on the common factors estimated from the IFE procedure for columns (2) and (5), and regressing the dependent variable on the cross section averages used in the CCE procedure for columns (3) and (6). Columns (4)–(6) also include period fixed effects and unit fixed effects (county for Panel A and Panel D, state for Panel B and Panel C).

time-varying heterogeneity in the error term of the two-way fixed effects specification.[19]

E. Throwing Out the Baby with the Bathwater?

The factor model results presented above are more similar to results from the literature that include Census division-by-period fixed effects and state-specific time trends than results based on only two-way fixed effects. Additionally, analysis of the factor structure estimated from the IFE estimator revealed some similarities to unit-specific time trends and Census division-by-period fixed effects. One of the main critiques of Census division-by-period fixed effects and state-specific time trends has been that they "throw out the baby with the bathwater" (Neumark, Salas, and Wascher 2014b). That is, they potentially discard too much valid identifying variation in pursuit of ideal counterfactuals. This critique is mostly driven by the fact that synthetic controls sometimes place very little weight on same-division states, suggesting same-division states may not provide a better counterfactual than a randomly selected state.

The same critique could potentially be applied to the factor model approach: the factors from the IFE estimator and the cross section averages which proxy for factors in the CCE estimator may explain a lot of the identifying variation themselves, leaving a small amount of variation in the data with which to estimate the minimum wage-employment elasticity. In order to address this critique, Table 8 shows the fraction of the variation in both the dependent employment variables and the minimum wage variable that is explained by each of Census division-by-period fixed effects and state-specific time trends, the common factors from the IFE estimator, and the cross section averages from the CCE estimator. This is computed by regressing each variable on one of the three sets of controls for unobserved heterogeneity and reporting the r-squared. The table shows the results with and without additionally controlling for unit and period fixed effects. The results without two-way fixed effects more

19. Another interesting feature of the figures is that in Figure 5 for 2010q1, the areas experiencing positive effects from the common factors are primarily clustered around the major cities in the United States. This is a remarkable result given that the factor structure does not know where counties are relative to each other on a map when it estimates their factor loadings.

TABLE 9
Minimum Wage-Earnings Elasticity Estimates

	(1) OLS	(2) CCEMG	(3) CCEP	(4) IFE
Panel A: Restaurant average weekly wages				
log(Minimum wage)	0.209***	0.231***	0.222***	0.148***
	[0.160,0.257]	[0.175,0.264]	[0.199,0.251]	[0.096,0.201]
	5.12***	6.00***	2.88***	0.21
Panel B: Teenage hourly earnings (CPS ORG)				
log(Minimum wage)	0.104***	0.097**	0.110***	0.165***
	[0.041,0.167]	[0.010,0.188]	[0.034,0.184]	[0.108,0.231]
	−6.18***	−6.10***	−6.20***	−6.77***
Panel C: Teenage average weekly wages (QWI)				
log(Minimum wage)	0.193***	0.307***	0.294***	0.308***
	[0.143,0.243]	[0.235,0.383]	[0.244,0.331]	[0.274,0.344]
	108.05***	101.32***	74.31***	18.18***
Period fixed effects	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes

Notes: Each column uses a different estimator applied to the traditional two-way fixed effects specification to estimate the minimum wage-earnings elasticity. The dependent variable is county-quarter average weekly wages for restaurant workers in Panel A, individual hourly earnings for teenage workers in the CPS aggregated to the state-quarter level in Panel B, and county-quarter average weekly wages for teenagers in the QWI in Panel C. Independent variables are the same as those for employment regressions, except log(Total private sector employment) is replaced with log(Total private sector average weekly wages) for restaurant earnings regressions. Results are based on five common factors for restaurant earnings, eight for CPS earnings, and six for QWI earnings.

clearly illustrate the raw correlation between each of the three controls for unobserved heterogeneity and the minimum wage-employment data; the two-way fixed effects absorb a great deal of variation to begin with, which makes it less clear to what extent the additional controls absorb variation on their own. The results with two-way fixed effects are perhaps more relevant to the debate in the literature of what should be controlled for beyond two-way fixed effects.

In either case, the factor model approach appears to be less subject to this particular critique from Neumark, Salas, and Wascher (2014b): the common factors from the IFE estimator and the cross section averages from the CCE estimator consistently explain a smaller fraction of the variance in the data across datasets and for both the employment and minimum wage variables. The difference between the fraction explained by Census division-by-period fixed effects and state-specific time trends compared to the fraction explained by factor model controls is largest for the employment variables, but there is also a significant reduction for the minimum wage variable. It is not obvious how much variation being removed by controls for unobserved heterogeneity would be too much, but the factor model approach does at least do a better job of not removing as much variation as Census division-by-period fixed effects and state-specific time trends.

F. Robustness Checks

A number of robustness checks were performed. These included the effect of minimum wage hikes on earnings, which serves as a first-stage test; results based on specifications with state-specific time trends, in order to compare the sensitivity of each estimator to different specifications; results based on sub-samples of the time-dimension of the data, in order to address the limitation associated with the factor model approach of assuming time-invariant factor loadings; a falsification test based on the manufacturing industry, in order to confirm that the factor model estimators find neither an employment nor earnings effect for an industry which should not be impacted by a minimum wage hike[20]; a test for pre-existing trends, which compares the ability of each estimator to account for pre-existing employment trends in areas of minimum wage hikes; and results based on the sample of contiguous counties from Dube, Lester, and Reich (2010). For the sake of space, only the earnings results are

20. Only 2.8% of manufacturing workers earn within 10% of the minimum wage (Dube, Lester, and Reich 2010). The manufacturing industry therefore should not experience significant employment or earnings effects from minimum wages hikes; finding an effect would be evidence of spurious spatial correlation between minimum wage hikes and regional employment patterns that the factor model approach has not accounted for.

shown here. The other results are available upon request.

One potential explanation for finding no significant effect of minimum wage hikes on employment is that minimum wage hikes may not be binding wage floors for restaurant and teenage workers. Table 9 investigates this further and shows that the factor model estimators find positive and statistically significant effects of minimum wage hikes on earnings, which are very similar in magnitude to the OLS results.[21,22] This is important because it shows that minimum wage hikes are binding for restaurant and teenage workers and because it confirms that the factor model estimators do not remove too much of the variation in the data to be able to detect significant effects.

TABLE 10
Minimum Wage-Employment Elasticity Simulation Results—No Factors in DGP

	(1)	(2)	(3)	(4)	(5)	(6)
	Restaurant Employment			*Teenage Employment*		
	Median	**2.5%**	**97.5%**	**Median**	**2.5%**	**97.5%**
True value	***−0.138***			***−0.178***		
OLS	**−0.139**	−0.152	−0.128	**−0.177**	−0.223	−0.134
CCEMG	**−0.139**	−0.167	−0.111	**−0.179**	−0.248	−0.107
CCEP	**−0.138**	−0.159	−0.120	**−0.177**	−0.234	−0.124
IFE	**−0.138**	−0.153	−0.124	**−0.177**	−0.225	−0.131

Notes: This table reports simulation results for the case without common factors in the data generating process. The DGP is $y_{it} = \widehat{\beta} ln\left(MW_{it}\right) + X_{it}\widehat{\Gamma} + \widehat{\alpha}_i + \widehat{\delta}_t + v_{it}$, where the independent variables are the same variables used in Section IV, the parameters are from the OLS results for the traditional two-way period and location fixed effects specification reported in Tables 3 and 4, and v_{it} is an idiosyncratic error term whose variance is equal to the variance of the OLS residuals. The number of repetitions is 1,000.

V. SIMULATION

This section assesses the relative ability of OLS and the factor model estimators to estimate the minimum wage-employment elasticity under different assumptions about the unobserved heterogeneity in the data. Specifically, the performance of OLS, CCEMG, CCEP, and IFE are compared with and without the presence of common factors in the data-generating process. The goals of these simulations are (1) to confirm the precision of the factor model estimates of the minimum wage-employment elasticity from the two-way fixed effects specification when no common factors exist in the data and (2) to confirm the direction of the bias in the OLS estimate of the minimum wage-employment elasticity from the two-way fixed effects specification caused by the common factors. The simulations use the same data from the results section in the data generating process (DGP), but impose different assumptions on the unobserved heterogeneity to simulate new employment observations.

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 the OLS results as the true value of the coefficients in the DGP, with independent and identically distributed (IID) normal errors. For the restaurant employment DGP, these coefficients come from the OLS estimates in 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 in Table 4. The simulation is performed for 1,000 repetitions for each dataset.[23]

The results from this simulation are shown in Table 10. Columns (1) and (4) report the median of the estimates for each of the estimators for restaurant and teenage employment, respectively, and columns (2)–(3) and (5)–(6) report the 95% range of the estimates. All four estimators perform well without the presence of factors in the DGP; the median estimate of the minimum wage-employment elasticity is near the true value for each estimator. The factor model estimators also perform well in terms of the 95% range of the estimates, with only slightly wider ranges than OLS. Thus, there are two key takeaways from this simulation. The first key takeaway is that the factor model estimate of the minimum wage-employment elasticity from the

21. Earnings results from the CPS are only based on CPS ORG files, because the basic monthly files do not contain the wage data that exists in the ORG files. These regressions are based on the same specifications as the employment results, except with earnings as the dependent variable and with log(total private sector average weekly wages) instead of log(total private sector employment) as a control variable for restaurant earnings regressions.

22. Sensitivity of the earnings results to different numbers of common factors is also available upon request.

23. The DGP is $y^*_{it} = \widehat{\beta} ln\left(MW_{it}\right) + X_{it}\widehat{\Gamma} + \widehat{\alpha}_i + \widehat{\delta}_t + v_{it}$. The independent variables are the same variables from the main results section, 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 recovered from the data and included in the DGP.

two-way fixed effect specification still performs well without the presence of factors in the DGP, even with the small cross section dimension of the teenage dataset. The second key takeaway is that the pattern of results in this simulation does not match the pattern of results in Section IV.A: the factor model results were very different from OLS in Section IV.A, but they are very similar here. Overall, these results show that the factor model estimators would produce minimum wage-employment elasticity estimates similar to OLS if the two-way fixed effects specification was correct.[24]

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 IID normal errors. For the restaurant employment DGP, the true value of the coefficients and factor structure comes from the IFE estimates in 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, factor structure, and the error variance come from the IFE estimates in Table 4. The simulation is performed for 1,000 repetitions for each dataset.[25]

The results from this simulation are shown in Table 11. For restaurant employment, the CCEP, CCEMG, and IFE estimators all perform well. The OLS estimator, however, shows consistent and severe negative bias across repetitions; the true value of the coefficient for the minimum wage-employment elasticity is not even in the 95% range of the OLS estimates. For teenage employment, the OLS estimator once again shows significant negative bias, with the 95% confidence range not containing the true value of the minimum wage-employment elasticity coefficient. The CCEP and CCEMG estimators also show some negative bias for the teenage dataset, although not as much as OLS. This is consistent with the discussion in Section III.B that the factor model estimators may not be able to remove all of the bias caused by common factors in the teenage employment data due to the relatively small cross section dimension of the data. This simulation produces two key takeaways. The first key takeaway is that the OLS estimate of the minimum wage-employment elasticity from the two-way fixed effects specification is negatively biased when the common factors for restaurant and teenage employment are included in the DGP. The second key takeaway is that the pattern of results from this simulation matches the pattern of results seen in Tables 3 and 4: the OLS estimates of the minimum wage-employment elasticity are much larger in magnitude than the factor model estimates both in Tables 3 and 4 and in simulations with common factors included in the DGP.

In summary, the simulations show that the CCEP, CCEMG, and IFE estimators would produce minimum wage-employment elasticity estimates similar to OLS when applied to the two-way fixed effects specification if state/county and period fixed effects fully represented the unobserved heterogeneity in the underlying data generating process. When common factors are included in the DGP, the OLS estimate of the minimum wage-employment elasticity is negatively biased, while the factor model estimators perform much better. These results suggest that the presence of common factors in the true underlying DGP can cause the different estimates of the minimum wage-employment elasticity seen across approaches in Tables 3 and 4.

TABLE 11
Minimum Wage-Employment Elasticity Simulation Results—Factors in DGP

	(1)	(2)	(3)	(4)	(5)	(6)
	Restaurant Employment			*Teenage Employment*		
	Median	**2.5%**	**97.5%**	**Median**	**2.5%**	**97.5%**
True value	***−0.042***			***−0.036***		
OLS	**−0.175**	−0.203	−0.135	**−0.175**	−0.222	−0.129
CCEMG	**−0.045**	−0.092	0.007	**−0.134**	−0.198	−0.058
CCEP	**−0.041**	−0.087	−0.002	**−0.101**	−0.158	−0.047
IFE	**−0.043**	−0.072	−0.011	**−0.038**	−0.088	0.026

Notes: This table reports simulation results for the case with common factors in the data generating process. The DGP is $y_{it} = \widehat{\beta} ln\left(MW_{it}\right) + X_{it}\widehat{\Gamma} + \widehat{\alpha}_i + \widehat{\delta}_t + \widehat{\lambda}_i' \widehat{f}_t + v_{it}$, where the independent variables are the same variables used in Section IV, the parameters are from the IFE results for the traditional two-way period and location fixed effects specification reported in Tables 3 and 4, and v_{it} is an idiosyncratic error term whose variance is equal to the variance of the IFE residuals. The number of repetitions is 1,000.

24. The factor model estimators also perform well when the two-way fixed effects are left out of the model for the factor structure to handle.

25. The DGP is $y_{it}^* = \widehat{\beta} ln\left(MW_{it}\right) + X_{it}\widehat{\Gamma} + \widehat{\alpha}_i + \widehat{\delta}_t + \widehat{\lambda}_i' \widehat{f}_t + v_{it}$. The independent variables are the same variables from the main results section, 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 recovered from the data and included in the DGP.

VI. DISCUSSION AND CONCLUSION

The recent minimum wage-employment debate in the literature has focused on how to generate credible estimates of employment effects when using aggregated panel data. Doing so is very difficult, as both outcomes and minimum wage policy are likely to be correlated across areas due to unobservable confounders. Many approaches have been proposed in order to control for or remove these confounders, including saturating the two-way fixed effects specification with additional controls, using a border discontinuity approach to identify the effect based on policy discontinuity at state borders, and using synthetic controls. Each approach has its drawbacks. More importantly, the various approaches have produced inconsistent results, and it is not obvious which approach is best or which set of results to believe.

The factor model estimators from Pesaran (2006) and Bai (2009) are very well-suited to address the issues in the minimum wage-employment literature; they are intended to control for unobservable factors in panel data in order to generate unbiased estimates of regression parameters for observed covariates. These estimators have specific advantages over the other approaches that have recently been used in the literature. They also satisfy the main concerns from each side of the recent debate, which is that they facilitate the control of unobserved confounders without discarding a significant amount of identifying variation, changing the identifying variation, or discarding data altogether.

The factor model estimators produce minimum wage-employment elasticity estimates in the range of −0.01 to −0.03 for restaurant employment and −0.03 to −0.07 for teenage employment. These results are generally robust to a number of robustness checks, including alternative sources for teenage employment data and different assumptions about the number of common factors in the data. Furthermore, the pattern of relatively large negative OLS elasticity estimates and small factor model estimates cannot be replicated in simulations which include only two-way fixed effects as the true unobserved heterogeneity, suggesting that the traditional two-way fixed effects specification is not correct. The simulations also confirm that common factors from the minimum wage-employment data cause negative bias in the OLS estimate of the minimum wage-employment elasticity from the two-way fixed effects specification.

Overall, the factor model results suggest that there has been little to no effect of minimum wage hikes on restaurant or teenage employment over the last three decades. However, the size of the minimum wage hike is important. Most minimum wage hikes in the U.S. during this time have been in the range of 5%–15%. There is some evidence that different hike sizes even within this relatively compact range can have different consequences for workers (Lopresti and Mumford 2016). The results in this study, or any other study based on data from past U.S. minimum wage hikes, therefore may not be informative about the effects of larger hikes. Furthermore, while there is an abundance of research on the employment effects of minimum wages, minimum wages could affect workers and firms in many other ways, including through effects on fringe benefits (Simon and Kaestner 2004), employee turnover (Dube, Lester, and Reich 2016), prices (Aaronson, French, and MacDonald 2008; Harasztosi and Lindner 2015; Lemos 2008), and firm profitability (Hirsch, Kaufman, and Zelenska 2015), to name a few. Evidence on these other channels is somewhat sparse and mixed. Given that these channels have important implications for the impact of minimum wages on society as a whole, they should receive more attention in future work.

APPENDIX: PRIMER ON FACTOR MODELS

ADVANTAGES AND LIMITATIONS OF THE FACTOR MODEL APPROACH

The primary benefit of the CCE and IFE estimators is the ability to allow for unobservable time effects that vary by cross section unit and are correlated with independent variables in large panel settings. This allows researchers to make more flexible assumptions about the error term in traditional panel regressions, including allowing for the possibility of omitted variables that are correlated with independent variables of interest. These estimators have been shown to perform well in a wide variety of settings, including in the presence of weak cross section dependence (Chudik, Pesaran, and Tosetti 2011), non-stationary factors (Bai 2009; Pesaran 2006), co-integrated factors (Bai, Kao, and Ng 2009; Kapetanios, Pesaran, and Yamagata 2011), dynamic factors (Chudik and Pesaran 2015; Moon and Weidner 2017), and zero factors (Bai 2009; Kim and Oka 2014; Pesaran and Tosetti 2011).

The primary drawback of the CCE and IFE estimators is that they can only control for unobserved heterogeneity that fits into the form from Equation (2). Most relevantly, this means that there cannot be variation in the factor loadings over time. However, there is some evidence to suggest that the factor model estimators may still perform well in this setting: Bates et al. (2013) show that the principal components estimation of common factors still performs well even when there is time variation in the factor loadings. While this is a test of the estimation of common factors rather than the estimation of regression coefficients in specifications that include estimated common factors, it does suggest that the IFE estimator may still perform well. Nonetheless, one way to test this is to estimate the model separately for different periods of time. As discussed in Section IV.F, this was one of the robustness checks. The results were consistent with the results shown in the paper and are available upon request.

FACTOR MODEL APPROACH VERSUS OTHER APPROACHES IN LITERATURE

As described in Section I, three methods have been used in the recent literature to control for unobserved heterogeneity: (1) adding Census division-by-period fixed effects and/or state-specific time trends to the two-way fixed effects specification, (2) using a border discontinuity approach to identify the effect based on policy changes between two neighboring counties, and (3) using synthetic controls. The factor model approach has specific advantages over each of these approaches.

The advantage of the factor model approach over the inclusion of Census division-by-period fixed effects and/or state-specific time trends is that the factor model approach embeds these controls as special cases of the factor structure: they can be rewritten as the inner product of a vector of time-specific common shocks, $f_t = (t, \delta_t)'$, and a vector of unit-specific factor loadings, $\lambda_i = (\alpha_i, \zeta_{CD})'$, where t is a time trend, δ_t is a time period dummy variable, α_i is a state dummy variable, and ζ_{CD} is a Census division dummy variable. The important difference is that the factor approach lets the data determine the form of the common shock, f_t, and the nature of the spatial correlation in λ_i, rather than imposing a fixed form for the unobserved heterogeneity ex ante. Because the factor model estimators have also been shown to perform well when there are zero common factors in the error term, they should produce elasticity estimates very similar to OLS if the traditional two-way fixed effects specification is correct, but will be able to account for unobserved factors, including time trends or time-varying regional fixed effects, if the specification is not correct.

The border discontinuity approach moves away from the panel specification debate and instead tries to embed the case study approach into the panel data setting by comparing employment in cross-state neighboring counties before and after one state implements a minimum wage hike. As discussed in Section I, two separate, but related, critiques have been raised with respect to this approach: that it throws out too much valid identifying information and that it may actually worsen policy endogeneity (Neumark, Salas, and Wascher 2014a, 2014b). Both critiques are related to the primary drawback of the border discontinuity approach, which is that it relies on the non-testable assumption that unobservable confounding factors are removed by comparing contiguous areas. The factor model approach avoids these critiques by obtaining estimates of the unobserved confounders and controlling for their presence directly, rather than only comparing local areas.

The factor model approach also has advantages over the synthetic control approach. Synthetic controls and the factor model estimators used in this paper could be seen as complimentary; synthetic controls can also allow for a multifactor error structure. However, recent work by Gobillon and Magnac (2016) shows that if the true model is a linear factor model as in Equations (1) and (2), then the synthetic control estimator from Abadie, Diamond, and Hainmueller (2010) can match the factor structure only when the observable covariates and unobservable factor loadings for the treated areas belong to the support of observable covariates and unobservable factor loadings for the untreated areas. Dube and Zipperer (2015) find evidence that this support requirement may not be satisfied for the minimum wage application. Monte Carlo simulations and an empirical application also support IFE over synthetic controls.

Furthermore, there are drawbacks associated with the synthetic control approach that are specific to the minimum wage application. The synthetic control approach was designed for the setting in which there is a single area receiving a one-time policy treatment; it requires the existence of long pre- and post-treatment windows during which no additional treatment occurs and the existence of many untreated areas to serve as donor units. These two requirements are difficult to satisfy in the minimum wage application: federal minimum wage hikes are difficult to analyze because nearly every state is treated, leaving very few untreated areas with which to construct a synthetic control, and state minimum wage hikes occur so frequently across states and within states over time that it is difficult to construct long pre- and post-treatment windows during which many other states are untreated and no additional treatment occurs within the treated state. Thus, it is apparent that synthetic controls are not well-suited for the minimum wage application to begin with, while the linear factor model estimators are entirely amenable to this setting.

In summary, the factor model approach addresses the issues of both camps simultaneously and provides a middle ground: it facilitates the control of unobserved confounders for the purpose of generating unbiased estimates of regression coefficients, but does so without discarding data or changing the identifying variation to within Census divisions or across state borders.

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