Minimum wage hikes and their deleterious effect on youth employment

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Abstract

Congress enacted the Fair Minimum Wage Act (FMWA) on May 25, 2007, which raised the federal minimum wage from $5.15 to $7.25 over a three-year period of time ending in July 2009. Proponents of FMWA argued that a higher minimum wage would alleviate poverty and improve the welfare of low-income families. We exploit the disparity in the effective state minimum wage (the maximum of federal and state) that took place between 1998 and 2007 to estimate the impact of its discrete increases in youth employment (16-24) in a spatial econometrics framework. Our results bear evidence of spatial spillover effects of macroeconomic variables in the data. Hence, we estimate the standard panel data model used in the literature with and without spatial correlation correction using maximum likelihood estimation. The results suggest that minimum wage hikes harm young black male workers the most, followed in descending order by Hispanic males, Hispanic females, and black females. The results also suggest that minimum wages hikes have a non-negative effect on the employment of young white females.

1. Introduction

After nearly a decade with the federal minimum hourly wage at $5.15, the then Democrat-led Congress enacted the Fair Minimum Wage Act (FMWA) on May 25, 2007. Proponents of FMWA argued that a higher minimum wage would both alleviate poverty and improve the welfare of low-income families. Starting in July 2007, FMWA increased the federal minimum in three annual discrete 70-cent increments from $5.15 to $7.25 (see Figure 1). During this period, the number of states with minimum wages exceeding the federal limit ballooned from seven in 1998 to twenty nine just nine years later, but fell about 50% thereafter (see Figure 2). Although Figure 1 shows the average state minimum wage rate rising mostly at a constant rate for the two decades, Figure 3 shows a growing disparity in state minimum wage rates between 1998 and 2007. It can be argued that these variations and ratcheting hikes in the federal minimum wage are politically driven since it would appear that when the U.S. Congress is under Republican control the federal minimum wage generally is not hiked. At the state level, the effective minimum wage is generally equal to the federal rate in Republican states, but is not in a typical Democratic state due to its indexation to inflation.

Standard economic theory suggests that well-intentioned minimum wage hikes has several deleterious consequences. A firm can offset a minimum wage hike by reducing general training, fringe benefits, and its workforce. The hike could also potentially increase the number of people actively looking for work if, before the increase, they were either not working or working in an uncovered sector. Consequently, the hike lowers employment and increases unemployment primarily among less skilled individuals, namely teens and minorities, the very same people the policy is intended to help (Partridge and Partridge 1999). These stylized results of minimum wage increases have been explored empirically before. Prior to the convening of the New

Minimum Wage Research Conference (NMWRC) in 1991, a consensus was brewing amongst researchers. Some economists had concluded that a 10 percent increase in the minimum wage reduced teenage employment by one to three percent (Brown 1999). Several of the papers presented at NMWRC used new methodologies to reexamine the issue (e.g., Card 1992a, 1992b; Katz and Krueger 1992), while others used more conventional methods (e.g., Neumark and Wascher 1992). Studies using newer methods challenged the prevailing empirical consensus and economic theory, finding that minimum wage hikes have a non-negative effect on employment. NMWRC's wake sparked a huge debate in the literature and in the halls of Congress. Two comprehensive surveys of the literature (Brown 1999, Neumark and Wascher 2007) reestablished the consensus of minimum wages to having negative employment effects.

More recently, Thompson (2009) concluded that studies using state-level panels show smaller negative employment effects. He attributes this to the considerable heterogeneity that exists in local labor markets. To exacerbate the problem of heterogeneity, most of the recent literature does address the issue of spatial autocorrelation. Statistically, empirical evidence that does not take into account the consequences of spatial effects will produce, in general, biased and potentially inconsistent estimators (Anselin 1988). Intuitively, this makes sense. Consider a state that raises its minimum wage well above the federal limit. If its neighbors do not follow suit, workers from these states may move to the nearby one with the higher effective minimum wage. Holding all else constant, the employment-population rate would fall as the state's labor force swells.

In this study, like in Neumark and Wascher (1992), we exploit the large variation in real value of states' effective minimum wages (the maximum of federal and state) over the last couple of decades using state-level panels; but unlike this and other aforementioned studies, we take into account the possibility of spatial dependence. A scant literature that studies this finds that spatial dependence between neighboring European labor markets is generally very high (Molho 1995, Burda and Profit 1996, Neibuhr 2003, Patacchini and Zenou 2007). Because "U.S. labour markets are characterized by fewer government mandates, less collective bargaining, and significantly higher rates of regional labour market mobility" (Partridge and Rickman 1997, pp. 593), one would expect the spatial autocorrelation to be much more problematic in U.S. state-level panels. Hence, our approach builds upon the vast body of literature studying the minimum wage effects on US teen employment by accounting for autocorrelation across time and space.

2. Data

The variables used in this study were computed or culled primarily from IPUMS-CPS,[1] which are summarized in Table 1. The sample includes all youths (aged 16-24 who are not in the armed forces) residing in the 48 contiguous states and the District of Columbia from 1990 to 2010. Employment-to-population ratios (*epr*) were computed for three cohorts: all youths, all male youths, and all female youths. Figures 4 and 5 show how their means and standard deviations evolve over time. According to Figure 4, the mean state *epr* for all three cohorts of youths were relatively constant until 2001, but then all dropped twice by about 7 to 8 percentage points over roughly two three-year periods: 2001-2003 and 2008-2010. In between these two periods (2001-2003), *epr* was relatively stable. The standard deviations of the three measures of youth *epr*, shown in Figure 5, suggest convergence until 2005. From then on, the disparity in low-skilled labor markets begins to rise back to early 1990s levels. The trends in standard deviations suggest the existence of state-specific effects.

[1] Miriam King, Steven Ruggles, J. Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, and Rebecca Vick. *Integrated Public Use Microdata Series, Current Population Survey: Version 3.0*. [Machine-readable database]. Minneapolis: University of Minnesota, 2010.

Since labor market variables (like labor force participation rates, employment-to-population ratios, and unemployment rates) usually exhibit strong co-movements, it is important to understand their dynamics. This is necessary to avoid problems associated with spurious regression among non-stationary variables that are not cointegrated. Table 2 reports several panel unit root test results with H_0: All panels contain unit roots. We used several unit root panel data tests. The Fisher type test operates under more general assumptions than the LLC (Levin, Lin and Chu, 2002) and IPS (Im, Pesaran, and Shin, 2003) because it allows for heteroskedasticity and serial correlation to be present in errors of ADF regressions, and permits heterogeneity in autoregressive coefficients. The first three sets of test results were conducted assuming no structural breaks, while the lower three sets of tests use *epr* measures that have been de-trended for recessions. All six LLC panel unit root tests reject panel unit roots, while the Fisher and IPS tests only do so for the disaggregated models.

The independent variable of interest in this study is the effective real minimum wage rate (*Wmin*), which is the maximum of the state and federal minimum wage rates (Partridge and Partridge 1998). The growing disparity in state minimum wages and its subsequent convergence between 1999 and 2006 (see Figure 3) coincides with convergence then divergence in the employment-to-population ratios of our cohorts. Hence, state minimum wages appear to wield significant influence in low-skilled labor markets. At the lowest level of disparity in minimum wages across states, which occurred in 1999 (see Figure 3), the average effective minimum wage was \$6.97. Seven years later the average minimum wage is \$6.28 when its disparity was at its peak. This paper exploits the variation in minimum wages across states to study how minimum wages affect the low-skilled labor markets.

The analysis uses standard controls for aggregate labor market conditions and demographics (Neumark and Wascher 2007) from IPUMS-CPS, Bureau of Labor Statistics at the U.S. Department of Labor, and Bureau of Economic Analysis at the U.S. Department of Commerce. State level and cohort controls include unemployment rates, real per-capita personal income, unemployment insurance coverage rate, race, urbanization, and measures of family composition. The controls are also summarized in Table 1 for select years.[2] Variables in upper case letters represent state-wide controls. All variables in lower case letters were computed using our cohort of youths aged 16-24. Data sources for the variables are listed in the footnotes of Table 1. The shares of states' residents who are Hispanic (*HSP*) grew more rapidly than the share that is black (*BLK*). It appears that more and more people moved to urban centers because the share living in rural areas (*RURAL*) shrank from 30 to 27% between 1999 and 2006, and then to 26% by 2010. As for the variables that measure family characteristics of youths, the share of youths that have kids (*kid*) or are married (*mar*) fell by about the same amount for the three years summarized in the table. The percentage of youths whose mother or father is not present (*nomom* or *nodad*) rose than fell a bit. From 1999 to 2006, the gap between these two variables fell from 15.25 to 14.29 percentage points, but then climbed to 14.66 percentage points by 2010.

The remaining variables summarized in Table 1 control for the overall health of the economy, the dynamic effects caused by the business cycle, or differences in states' minimum wage policies. Real personal income (*PCPI*) grew for the all three years shown despite the effects of the Great Recession. State unemployment rate (*U*), as expected, is under 5% for years 1999 and 2006, but then jumps up to 9.76% in 2010. The unemployment insurance coverage rate (*COV*) helps account for differences in states' minimum wage policies. States with higher

[2] The years 1999, 2006, and 2010 were chosen because they represent turning points in the standard deviation of state minimum wages (see Figure 3). Disparity in state minimum wages grew from 1999 to 2006, which disappeared by 2010.

coverage rates likely have more liberal employment regulations. Although the coverage rate is relatively constant over time, its standard deviation increased by nearly 2 percentage points between 1999 and 2006, suggesting widening disparity in states' low-skilled labor markets.

3. Methodology

Typical state-level panel data minimum wage studies estimate a regression equation of the form

$$y_{it} = \alpha_1 \ln(Wmin_{it}) + \mathbf{x}_{it}'\boldsymbol{\beta} + \upsilon_i + \tau_t + \varepsilon_{it} \quad (1)$$

where i indexes states, t indexes years, y_{it} is a low-skilled labor market outcome (e.g., employment-population ratio or unemployment rate) and $\mathbf{x}_{it}$ is vector of aggregate labor market and demographic controls, τ_t is the fixed effect for year t, υ_i is the fixed effect for state i, and ε_{it} is the disturbance (Neumark and Wascher 2007).

There is a debate on whether year effects should be included. Burkhauser et al. (2000a, 2000b) argue that year effects need not be included if $\mathbf{x}$ includes variables that account for the business cycle, inflation, and productivity growth because fixed year effects eliminate the identification associated with changes in minimum wages. Neumark and Wascher (2007) argue that omitting year effects biases estimates because economic controls used in studies using state-level panels cannot include all relevant macroeconomic or other aggregate effects. We account for the business cycle and other dynamics using lags of overall state unemployment and per-capita personal income:

$$y_{it} = \alpha_1 \ln(Wmin_{it}) + \theta_1 y_{it-1} + \theta_2 U_{it-1} + \theta_3 \ln(PCPI_{it-1}) + \mathbf{x}_{it}'\boldsymbol{\beta} + \mu_i + \varepsilon_{it} \quad (2)$$

The lagged dependent variable is included in the specification because test results summarized in Table 2 suggest it may play a role in the evolution of the employment rate of youths.

Because the unit of analysis is a measure of aggregated employment across not only time but also states, spatial dependence must be accounted for. Whereas OLS yields inconsistent standard errors when errors are non-spherically distributed, it generally yields inconsistent parameter estimates when spatial dependence is present (Anselin 1988). After all, a low-unemployment state will attract workers from high-unemployment neighboring states. Hence, it is important that the relationship that captures the dynamics of youth employment accounts for the spillover effects of low-skilled workers migrating from high unemployment states. To capture the spatial heterogeneity, we use row-standardized queen contiguity matrix **W**. So, when state *i* shares a border or corner with *j*, which is one of n_i states neighboring *i*, the element in the i^{th} row and j^{th} column of **W** equals $1/n_i$. If state *i* doesn't share a border or corner with *j*, then w_{ij} equals zero. Since state *i* isn't a neighbor of itself, w_{ii} equals zero. Hence, each row of **W** sums to one because only the 48 contiguous states and the District of Columbia (henceforth, we it considered the 49th state) are included in the panel. The inner product of $\mathbf{U}_t$, a vector of 49 state unemployment rates in time *t*, and the i^{th} row of **W** yields state *i*'s spatial lag of unemployment at time *t*. In this context, the spatial lag represents the average unemployment rate of state *i*'s neighbors. For this reason, we denote it as $\bar{U}$. Including a one year lag of the spatial lag in model (2) yields:

$$y_{it} = \alpha_1 \ln(Wmin_{it}) + \theta_1 y_{it-1} + \theta_2 U_{it-1} + \theta_3 \bar{U}_{it-1} + \theta_3 \ln(PCPI_{it-1}) + \mathbf{x}'_{it}\boldsymbol{\beta} + \mu_i + \varepsilon_{it} \qquad (3)$$

One year lags of unemployment rate and its spatial lag are used because causation flows from *U* and $\bar{U}$ to *y*, and vice versa. Falling youth employment can cause a state's and its neighbors' unemployment rates to rise. While the reasoning behind the former is obvious, the latter arises if unemployed youths search for work in other states. On the other hand, rising unemployment can cause youth employment to fall. This can be compounded by unemployed low-skilled workers migrate in, making it more difficult for young natives to find work. Although similar feedback exists among the lags of these variables, the causality between y and the lags of $\bar{U}$ and U is one way. Hence, feedback between the lags included in (3) is more of an issue of multicollinearity.

4. Results

Table 3 displays results of regression (2), while the results of two sets of regressions using specification (3) are shown in Tables 4 and 5. Autocorrelation does not appear to be present in any of the results shown because, in all cases, the Durbin-Watson statistic is essentially equal to two. Heteroskedasticity …

In all specifications, more cohort controls are significant in the young male specifications than in others. Although all estimated coefficients of *nodad* are positive, as expected, absence of fathers in youths' homes does not appear to have any effect on youth employment. Adding the spatial lag has a negligible effect on the size and significance of the coefficients of these controls. A seven percentage point (roughly one standard deviation) increase in the share of youths whose mother is not present in the household is associated with a one percentage point rise in youth employment. The affect is slightly higher for males than females. Having kids or being married has dissimilar effects on young male and female workers. For young male workers, a 4.5-percentage point (roughly one standard deviation) increase in the marriage rate of youths raises their employment rate by about one percentage point. Changes in youth marriage rates have no effect on the employment rate of young females. An increase of 3.5 percentage points (approximately one standard deviation) in the share of youths with kids raises young male employment by 0.8 percentage points, but has no effect on that of females.

With regard to state level demographic controls, including the spatial lag of state unemployment affects the size and significance of these coefficients. Young male employment rates are approximately five percentage points lower in states that are 24% black versus states with an average share of black residents.This one standard deviation difference in the share of black residents is associated with a much smaller 2.5-percentage point decline in employment of young women. Both of these affects become more pronounced when the spatial lag is included; with both declines in employment falling by an additional 0.5 percentage points. When spatial dependence is ignored, young male or female employment rates are roughly two and 1.9 percentage points lower, respectively, in states that are 18% Hispanic versus states that have an average share of Hispanics. Both of these effects become more pronounced when the spatial lag is included, rising from 2 percentage points to 2.3 and from 1.9 to 2.1, respectively. When spatial dependence is accounted for, minimum wage coverage has a negligible effect on employment. However, when the spatial lag is omitted, states that cover 10.5% more workers (a one standard deviation increase in minimum wage coverage from its average) should expect an increase 1.9 percentage point increase in female youths' employment (using average shares of rural residents in 1999 and 2010). States can expect a much smaller increase in that of young males (a 0.3 percentage point rise in 1999 but only a 0.2 rise by 2010). Young male and female employment, when spatial dependence is ignored, are roughly 1.7 percentage points higher in states that have about 70% more rural residents. This one standard deviation increase in the mean share of rural residents affects only young female workers with about the same magnitude if spatial dependence is accounted for.

As expected, the inclusion of the spatial lag of state unemployment rates has a large effect on economic controls. For example, including spatial lags reduce the effect of the real effective minimum wage. The same is true with regard to the coefficients of the lags of youth employment, overall state unemployment, log of per-capita personal income. The opposite is true regarding the coefficient of the recession dummy, which is more influential when spatial dependence is accounted for. When spatial dependence is ignored, the 21% increase in the effective real minimum wage that occurred between 2006 and 2010 lowers employment rates of young males by 2.3 percentage points but does not significantly affect employment rates young females. When spatial dependence is accounted for, the decline in male employment resulting from the 21% drop in the minimum wage is two percentage points instead. Furthermore, according to the coefficients of the interactions of race and the log of the effective minimum wage (see Table 5), minimum wage hikes appear to disproportionately affect black male youths. Young Hispanic males appear to be harmed by the hikes, too. The same interactions in the female equation suggest, when compared to the insignificant coefficient of (non-interacted) log of the minimum wage (see Table 4), suggest that young Hispanic and black females are also harmed by minimum wage hikes. The insignificant coefficient of log minimum wage (reported in Table 4) suggests that minimum wages hikes have a non-negative effect on employment of young white females given the significance and signs of the coefficients of the interactions between log minimum wage and race/ethnicity variables.

Youth employment rates are approximately 1.2 and 1.4 percentage higher for males and females, respectively, in states where youth employment rates in the previous year are one standard deviation higher (about 7 percentage points for males and 8 for females) than the average when the spatial lag is omitted. When the spatial lag is included, the one standard deviation difference in last year’s employment rate changes the female effect negligibly. The decline in male employment is closer to a 1-percentage point decline when spatial dependence is accounted for rather than 1.2 when it’s not. The absolute values of the coefficients of lagged overall state unemployment decline by about the same amounts when spatial dependence is accounted. Accounting for spatial dependence has a similar affect on the coefficients of the lag of log per-capita personal income. States with an unemployment rate that was two percentage points above the average a year ago (this difference is about two standard deviations in 2006 but only one in 2010) should expect 2 and 1.6 percentage point declines in male and female contemporaneous employment rates, respectively, when spatial dependence is ignored; when the spatial lag is included the declines are 1 and 0.8, respectively. The female employment rate is about 1.3 percentage points lower than that of young males, when spatial dependence is ignored, in states with per-capita personal income 18 percentage points above the mean, which is roughly one standard deviation. When the spatial lag is included, the 1.3 percentage point difference between female and male employment rates rises to 1.4. As expected, recession substantially lowers youth employment opportunities with slightly large effect on male employment. The effects of recession are more pronounced when spatial dependency is accounted for. In this scenario, recession lowers male and female employment rates by 2.3 and 1.9 percentage points, respectively.

5. Conclusions

Using the aggregated measure of youth employment clouds our understanding of how changes in the minimum wage, marriage and childrearing attitudes among youths, racial composition, and per-capita personal income affect employment of youths. The signs, size, or significance of their coefficients differ greatly by gender. As we mentioned above, while employment rates of female youths is not affected by either the marriage rates of young people or the share that have children, both raise the employment rate of young males. While the share of the population that is Hispanic affects young male and female employment rates equally, the share of blacks does not. The employment rate of male youths falls about two times more than females for the same increase in the share of residents who are black. Per-capita personal income appears to have about twice the impact on young female workers than it does on male youths. Accounting for spatial dependence is less problematic in assessing the impact of increases in the effective minimum wage on youth employment.

When the effective minimum wage was increased by 21% from 2006 to 2010 male employment fell two percentage points when spatial dependence is not ignored. Female employment did not appear to be affected by minimum wage hikes until log minimum wage was interacted with race/ethnicity variables. The interactions uncover the deleterious effects of this well-intentioned policy. The hikes, which are intended to alleviate poverty, appear to hurt the very same people they are intended to help. The interactions suggest minimum wage hikes harm young black male workers the most, followed in descending order by Hispanic males, Hispanic females, and black females. We conclude that the negative and significant coefficients of the interactions involving and log minimum wage reported in Table 4 and its non-interacted coefficient reported in Table 5 suggest that minimum wages hikes have a non-negative effect on the employment of young white females.

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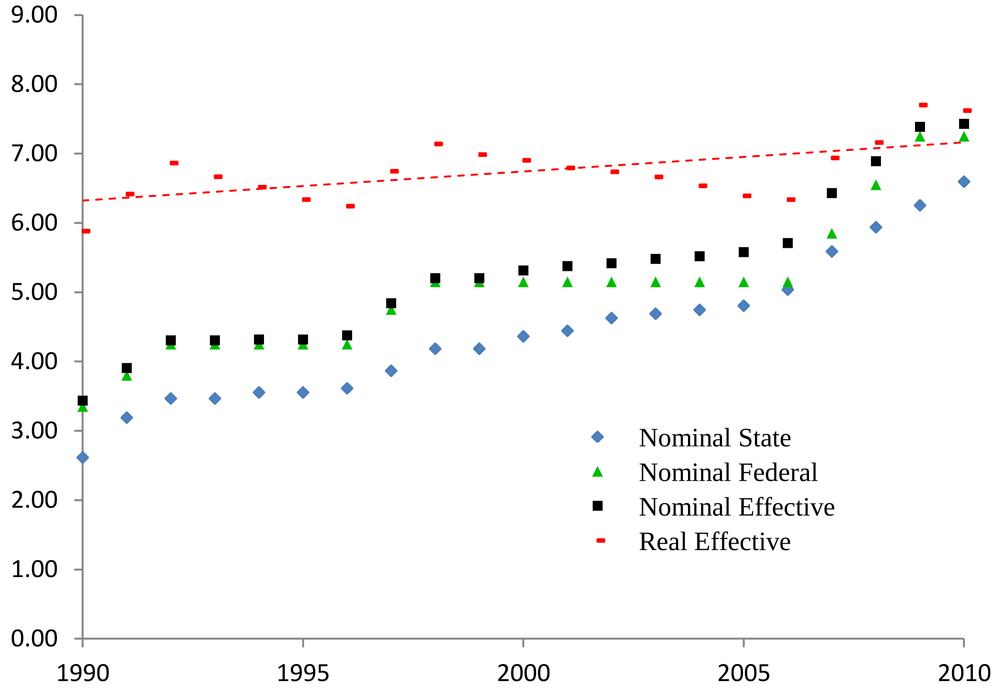
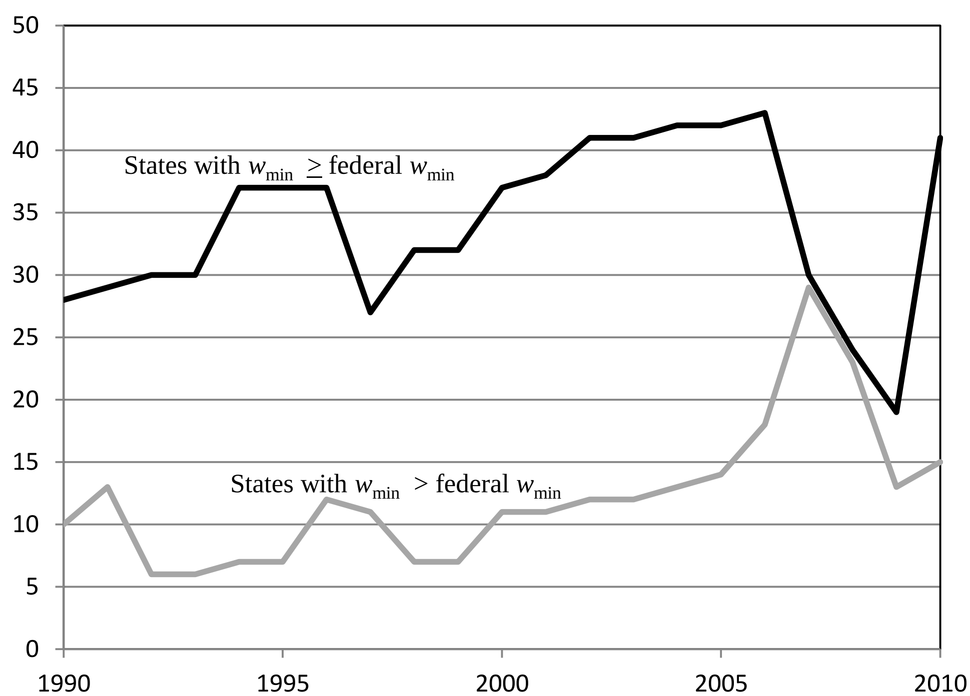
Figure 1—Average minimum wage rates across states



Source: www.dol.gov/whd/state/stateMinWageHis.htm

Figure 2—State's minimum wage laws



Source: www.dol.gov/whd/state/stateMinWageHis.htm

Figure 3—Standard deviation of effective minimum wages across states

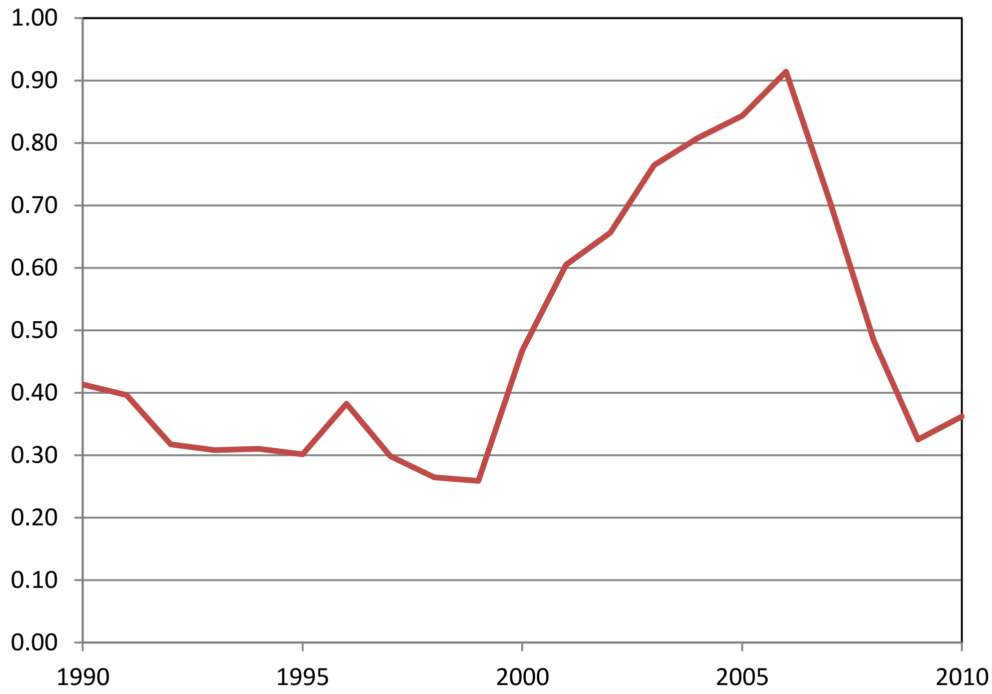


Figure 4—Mean state employment-population ratios (16-24)

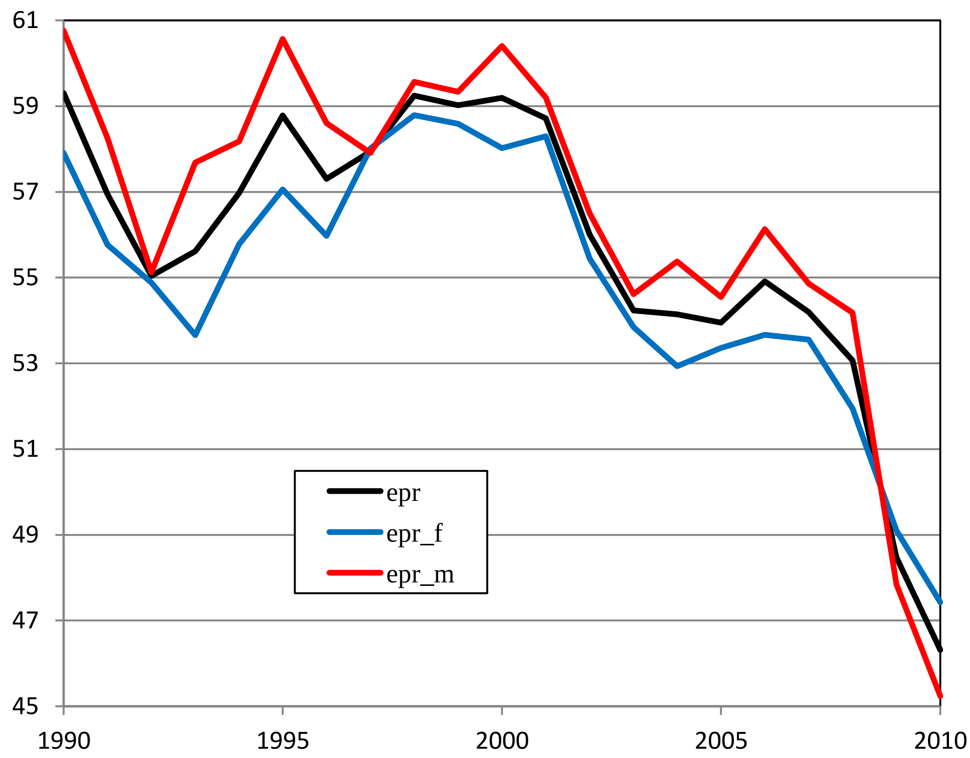


Figure 5—Standard deviation of state employment-population ratios (16-24)

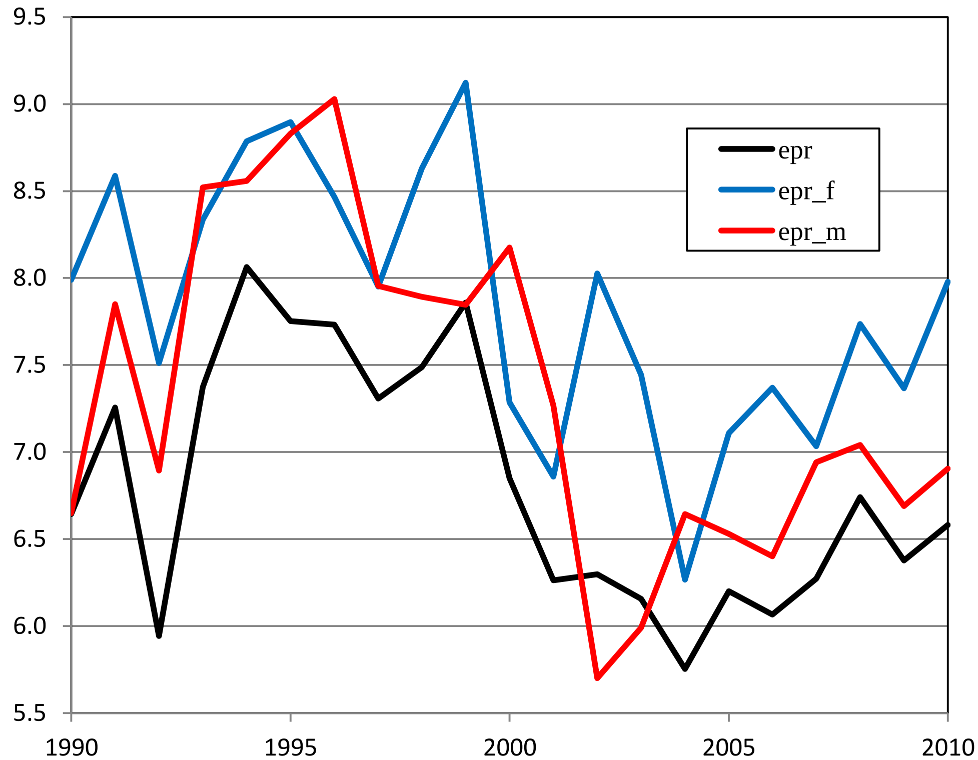


Table 1—Descriptive statistics for select years

Variable	1999 Mean	1999 Std. Dev.	2006 Mean	2006 Std. Dev.	2010 Mean	2010 Std. Dev.
Dependent [1]						
epr	59.02	7.86	54.91	6.07	46.32	6.58
epr_m	59.33	7.85	56.13	6.40	45.24	6.90
epr_f	58.59	9.12	53.67	7.37	47.43	7.98
Cohort controls						
kid	11.95	3.95	10.49	3.44	9.33	3.20
nomom	26.22	7.38	29.42	6.11	28.67	7.48
nodad	41.47	7.22	43.71	7.05	43.33	7.08
mar	11.94	5.04	10.66	4.42	9.34	3.99
State controls						
U	4.53	1.39	4.91	1.15	9.76	2.12
COV	86.22	8.02	86.47	9.47	84.62	9.71
PCPI	36504.59	5615.47	40826.39	7037.99	41041.59	7355.84
BLK	11.53	12.16	11.56	11.34	11.92	11.16
HSP	7.58	8.92	8.96	9.58	9.46	9.58
RURAL	30.01	21.59	26.06	18.91	25.74	18.35
Policy [3]						
Wmin	6.97	0.25	6.28	0.89	7.62	0.37

[1] Computed using IPUMS-CPS sample that includes all youths (aged 16-24 who are not in the armed forces) for all 48 contiguous states and the District of Columbia.

[2] All but *U*, *COV* and *PCPI* were computed or culled using data from IPUMS-CPS using all persons aged 16-65 who are not in the armed forces for all 48 contiguous states and the District of Columbia. *UR* is annualized state unemployment rates from the Bureau of Labor Statistics. *COVER* is the ratio of the number of employees covered by state unemployment insurance (from U.S. Department of Labor's Employment and Training Administration) and the size of the civilian labor force (from the Bureau of Labor Statistics). *PCPI* is from the Bureau of Economic Analysis.

[3] U.S. Department of Labor (www.dol.gov/whd/state/stateMinWageHis.htm)

Table 2—Panel unit root tests (Ho: All panels contain unit roots)

	All youths		Male youths		Female youths	
	stat	lags	stat	lags	stat	lags
epr						
LLC[1]	-1.4*	0.59	-6.08***	0.41	-7.4***	0.39
Fisher[2]	89.92	1	141.36***	1	162.46***	1
IPS[3]	-0.58	0.59	-5.13***	0.41	-6.28***	0.39
epr†						
LLC[1]	-1.49*	0.63	-6.11***	0.41	-7.97***	0.37
Fisher[2]	92.1	1	142.29***	1	165.25***	1
IPS[3]	-0.72	0.63	-5.17***	0.41	-6.92***	0.37

***,**,* Coefficient significant at the 1, 5 and 10% level.

† Recession effects subtracted out state unemployment rate trend.

[1]Levin, Lin, and Chu (2002) test (Ha: Panels are stationary) with number of lags determined by AIC criterion, statistic = adjusted t*, and lags = average lags used in ADF regressions.

[2]Fisher Test (Ha: At least one panel is stationary) with statistic = P-statistic (inverse chi-squared with df = 98) and number of lags set = 1.

[3]Im, Pesaran, and Shin (2003) test (Ha: Some panels are stationary) with number of lags determined by AIC criterion, statistic = W-t-bar, and lags = average lags used in ADF regressions.

Table 3—Youth employment-to-population ratio regression results

	All	Males	Females
$y_{t\text{-}1}$	0.2966 ***	0.1666 ***	0.1798 ***
	0.0325	0.0346	0.0344
ln$PCPI_{t\text{-}1}$	-10.5141 ***	-9.0351 ***	-16.7677 ***
	2.5441	3.4420	3.5540
$U_{t\text{-}1}$	-0.7662 ***	-1.0793 ***	-0.7950 ***
	0.1039	0.1190	0.1241
ln*Wmin*	-6.9981 ***	-11.9268 ***	-2.8175
	1.4439	1.9962	1.9449
BLK	-0.2819 ***	-0.4115 ***	-0.2146 **
	0.0868	0.1568	0.1094
HSP	-0.2048 ***	-0.2249 **	-0.2067 **
	0.0677	0.0949	0.0829
COV	0.0970	0.0862	0.1842 **
	0.0624	0.0808	0.0834
COV×*RURAL*	0.0010 **	0.0011 *	0.0010 **
	0.0004	0.0006	0.0005
nomom	0.1511 ***	0.1766 ***	0.1586 ***
	0.0479	0.0672	0.0599
nodad	0.0417	0.0415	0.0377
	0.0426	0.0652	0.0494
mar	0.0615	0.2057 **	-0.0649
	0.0753	0.0976	0.0826
kid	0.1481	0.2464 **	0.0924
	0.0928	0.1029	0.1190
RECESSION	-1.1895 **	-1.3099 *	-1.2239 *
	0.5367	0.6753	0.6397
n	49	49	49
T	21	21	21
state dummies	yes	yes	yes
constant	yes	yes	yes
R-squared	0.7723	0.6734	0.7053
Adjusted R-squared	0.7579	0.6528	0.6868
S.E. of regression	3.8226	5.0199	4.7578
F-statistic	53.7553	32.6902	37.9469
Durbin-Watson stat	1.9761	1.9603	2.0003

***,**,* Coefficient significant at the 1, 5 and 10% level.
Standard errors are listed below coefficients.
Variables in capitals represent statewide aggregates, while those in lower case measure outcomes for youths.

Table 4—Youth employment-to-population ratio regression results

	All	Males	Females
$y_{t\text{-}1}$	0.2813***	0.1509***	0.1759***
	0.0322	0.0361	0.0337
$\ln PCPI_{t\text{-}1}$	-8.2468***	-6.2730*	-14.5476***
	2.8530	3.6905	3.8208
$U_{t\text{-}1}$	-0.3270**	-0.5575***	-0.3863**
	0.1292	0.1800	0.1588
$\bar{U}_{t-1}$	-0.8446***	-1.0055***	-0.7570***
	0.1385	0.2328	0.1786
ln*Wmin*	-5.6240***	-10.3335***	-1.5457
	1.4478	1.9666	2.0033
BLK	-0.3244***	-0.4610***	-0.2500**
	0.0790	0.1437	0.1097
HSP	-0.2290***	-0.2530**	-0.2277***
	0.0723	0.1004	0.0869
COV	-0.0132	-0.0471	0.0827
	0.0682	0.0879	0.0841
COV×*RURAL*	0.0008**	0.0009	0.0009*
	0.0004	0.0006	0.0005
nomom	0.1505***	0.1753***	0.1570***
	0.0466	0.0658	0.0578
nodad	0.0495	0.0510	0.0448
	0.0415	0.0622	0.0502
mar	0.0685	0.2153**	-0.0592
	0.0746	0.0962	0.0819
kid	0.1300	0.2251**	0.0745
	0.0899	0.1010	0.1162
RECESSION	-1.9908***	-2.2553***	-1.9345***
	0.5149	0.7029	0.6196
n	49	49	49
T	21	21	21
state dummies	yes	yes	yes
constant	yes	yes	yes
R-squared	0.7797	0.6822	0.7103
Adjusted R-squared	0.7655	0.6618	0.6918
S.E. of regression	3.7618	4.9550	4.7196
F-statistic	55.1376	33.4398	38.2104
Durbin-Watson stat	1.9654	1.9467	2.0001

***,**,* Coefficient significant at the 1, 5 and 10% level.
Standard errors are listed below coefficients.
Variables in capitals represent statewide aggregates, while those in lower case measure outcomes for youths.

Table 5—Youth employment-to-population ratio regression results

	All		Males		Females	
$y_{t\text{-}1}$	0.2865	***	0.1576	***	0.1787	***
	0.0319		0.0362		0.0340	
$\ln PCPI_{t\text{-}1}$	-8.6222	***	-7.0200	*	-14.5570	***
	2.8439		3.7405		3.8443	
$U_{t\text{-}1}$	-0.3293	**	-0.5522	***	-0.3992	**
	0.1291		0.1815		0.1598	
$\bar{U}_{t-1}$	-0.8629	***	-1.0626	***	-0.7364	***
	0.1411		0.2271		0.1865	
$\ln Wmin \times BLK$	-0.1664	***	-0.2597	***	-0.0975	**
	0.0377		0.0671		0.0496	
$\ln Wmin \times HSP$	-0.1270	***	-0.1574	***	-0.1116	**
	0.0387		0.0506		0.0475	
COV	-0.0182		-0.0502		0.0754	
	0.0669		0.0866		0.0845	
$COV \times RURAL$	0.0009	**	0.0010	*	0.0009	*
	0.0004		0.0006		0.0005	
nomom	0.1558	***	0.1849	***	0.1596	***
	0.0467		0.0660		0.0577	
nodad	0.0503		0.0557		0.0407	
	0.0420		0.0628		0.0496	
mar	0.0733		0.2196	**	-0.0519	
	0.0741		0.0951		0.0844	
kid	0.1247		0.2247	**	0.0620	
	0.0889		0.0990		0.1194	
RECESSION	-2.1480	***	-2.6317	***	-1.8889	***
	0.5076		0.6810		0.6099	
n	49		49		49	
T	21		21		21	
state dummies	yes		yes		yes	
constant	yes		yes		yes	
R-squared	0.7783		0.6784		0.7099	
Adjusted R-squared	0.7643		0.6581		0.6916	
S.E. of regression	3.7715		4.9816		4.7211	
F-statistic	55.6564		33.4391		38.7856	
Durbin-Watson stat	1.9779		1.9651		1.9995	

***,**,* Coefficient significant at the 1, 5 and 10% level.
Standard errors are listed below coefficients.
Variables in capitals represent statewide aggregates, while those in lower case measure outcomes for youths.