County-Level Estimates of the Employment Prospects of Low-Skill Workers

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1. Introduction

There can be no question that the aggregate economic performance of the United States over the last decade has been outstanding. Except for a brief recession in 1990-91, the United States has experienced steady growth, rising productivity, low and falling unemployment, and little inflation. Following sharp run-ups at the start of the decade, there have also been declines in welfare caseloads and poverty. There are questions, however, regarding exactly how the benefits of this performance have been distributed.

By several measures, the benefits have been uneven. While incomes for the wealthiest Americans have increased, inflation-adjusted wages and earnings for the average worker are essentially unchanged from the start of the decade. At the bottom of the income distribution, poverty rates remain higher than levels recorded during the 1970s. The economy has also generated very different outcomes for people in different parts of the country and with different levels of market skills.

To get some feel for the geographic differences in labor market conditions, consider a map (Figure 1) that ranks counties by the percentage of civilian, non-institutionalized working age adults (ages 16-64) who worked at any time during 1989. In the map, counties are ranked into quartiles with progressively lighter shading used to identify higher quartiles and higher employment rates. The map reveals some pronounced differences across regions. Employment was relatively low in Appalachia and the South and relatively high in New England, the mid-Atlantic region, and the central plains. The existence of these types of regional differences is well known and has been documented in earlier analyses by Deming (1996) and Kasarda (1995).

[Figure 1 about here]

What may be more surprising is the variability in employment rates within regions and even within narrower areas such as states and metropolitan statistical areas (MSAs). The map shows that employment rates differed greatly across counties. In fact, there were several places, such as Sonoma and Lake counties in California and Washtenaw and Wayne counties in Michigan, where adjacent counties within the same state or MSA were in the top and bottom quartiles of the employment distribution.

Employment rates and the spatial distribution of employment also vary with workers' demographic characteristics and skill levels. Nationally, employment rates are substantially higher for men than for women and for people with more schooling than for people with less. Figure 2 shows the geographic pattern of employment in 1989 among women who were high school graduates but had not gone on to college. If we compare Figures 1 and 2, the pattern for female high school graduates was mostly similar to that of working adults as a whole. However, there were some differences – employment among female high school graduates was relatively weaker in the western states and stronger in the south Atlantic states than for other adults.

[Figure 2 about here]

The difference in the geographic pattern for more-educated women was even more striking. Figure 3 maps relative employment rates for women who were college graduates. As the figure indicates, there was much less of a general regional pattern and more within-region heterogeneity for high-skilled women than for low-skilled women.[1]

[Figure 3 about here]

Characterizing the labor market outcomes for people with different skill levels in different areas of the country has become increasingly important, especially in the aftermath of welfare reform. The Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996 was enacted with the goals of decreasing families' dependence on government assistance programs, promoting actions that lead to economic self-sufficiency, and increasing the flexibility of states in providing cash assistance, training, and employment support to the poor. The legislation emphasized employment as a route out of poverty by incorporating stringent work and work-readiness requirements for the beneficiaries of different programs and backing these requirements up with strict time limits and other benefits sanctions. With many recipients now reaching the time limits, it is important to identify which local labor markets will offer adequate numbers of low-skill jobs and whether these jobs will pay wages that will lead to self-sufficiency.

This study examines low-skill wage and employment opportunities for men and women at the county level over the period 1989-96. Currently, reliable direct measures of wages and employment rates for different demographic and skill groups are only available for large geographic areas such as regions and populous states or at infrequent intervals (e.g., from the Decennial Census) for some smaller areas.[2] This study constructs indirect annual measures for all counties from 1989-96 by combining skill-specific information on earnings and employment from the Sample Edited Detail File (SEDF) of the 1990 Decennial Census and the 1990-97 Annual Demographic files of the Current Population Survey (CPS) with annual industry-specific information from the Regional Economic Information System (REIS). Special versions of the SEDF and CPS files that identify county of residence are used.

Specifically, the study regresses the low-skill wage and employment data from the SEDF and CPS files on a set of personal variables from the combined files and local employment measures derived from the REIS. The wage regressions are corrected for selectivity from the employment decision and account for county-specific effects as well as general time effects. Estimates from the regressions are then combined with the available employment data from the REIS to impute wage and employment rates for low-skill adults across counties.

The remainder of this paper is organized as follows. Section 2 briefly reviews previous research that has examined the effects of local labor market conditions on earnings and employment for low-skill adults. Section 3 describes the individual- and local-level data that are used in the empirical analysis. Model estimates are reported in Section 4, and wage and employment imputations derived from the models are examined in Section 5. Section 6 discusses the findings and concludes.

2. Previous research

Numerous studies have examined the effects of local labor market conditions on wages, earnings and related outcomes. Additional research has investigated how employment rates vary across different types of workers. For brevity, this review focuses only on the subset of studies that have considered wage and employment outcomes for low-skill workers.

Much of the literature has considered specific groups of low-skill workers. For instance, Freeman (1981) and Freeman and Rodgers (1999) examined earnings among young men with low levels of schooling and found that their earnings were adversely affected by high general rates of metropolitan unemployment. Bartik and Eberts (1999), Card and Lemieux (1997), the Council of Economic Advisors (1997, 1999), Gittleman (2000), Figlio and Ziliak (1999), Fitzgerald (1995), and Harris (1993) examined the effects of labor market conditions on welfare receipt. With the exception of the study by Card and Lemieux, these studies found that tight labor markets reduced recipiency. Related studies by Bartik (1993) and Walters (1990) reported that high levels of labor demand reduced poverty.

The remaining studies have compared the effects of local labor conditions on the earnings of different types of workers. Topel (1986) found that employment growth and positive current employment shocks increased men’s wages and that the effects were stronger for men with low levels of education. Hoynes (1999) similarly reported that low-skill workers’ earnings, and especially low-skill women’s earnings, responded more to labor market shocks than high-skill workers. Bartik (1999) found that the earnings of men who were not college graduates and women who were neither college graduates nor single heads of households were more sensitive to employment shocks than the earnings of more-educated men or women. However, he also found that the earnings of female non-graduates who were also single heads of households were less sensitive to shocks than those of other women.

Katz and Murphy (1992) found that shifts in demand were largely responsible for recent changes in the wage structure for skilled and unskilled workers. Juhn, Murphy and Pierce (1993) provided supporting evidence that increases in the returns to skills contributed to changes in the wage structure. In contrast, Bound and Holzer (1993) found that while industrial shifts (specifically, the decline in manufacturing employment) had a disproportionate negative effect on the employment of low-skill men, these shifts had little effect on their overall earnings.

While the existing research has been successful in identifying factors which determine low-skill employment opportunities, it provides only limited information regarding what the actual distribution of opportunities for men and women across local labor markets might look like. First, only a few of the studies (Bartik 1999; Hoynes 1999; Katz and Murphy 1992) have explicitly considered low-skill women's earnings. Most of the studies have either focused on men's opportunities or obtained information on women's opportunities indirectly (for instance, by examining women's patterns of welfare receipt).

Second, almost all of the studies have considered labor market outcomes for relatively large areas such as major metropolitan areas (Bartik 1993; Bound and Holzer 1993; Freeman 1982; Freeman and Rodgers 1999; Hoynes 1999), states (Bartik 1999; C.E.A. 1997, 1999; Figlio and Ziliak 1999; Topel 1986), regions (Card and Lemieux 1997), or the nation as a whole (Katz and Murphy 1992). As we saw in the earlier figures, labor market opportunities within these broad areas may differ substantially.

Third, many of the studies have examined aggregate outcomes. The use of such data means that studies have been restricted in the types of controls they could include for both observed and unobserved differences across workers. Bils (1985) and Keane, Moffitt and Runkle (1988) have shown that failure to control for selectivity and heterogeneity in the unobserved determinants of wages results in biased estimates of the effects of economic conditions. Additionally, Blundell, Reed and Stoker (1999) have shown that the use of aggregate earnings and employment data to form wage measures introduces other biases.

3. Data

The primary data for this analysis come from the Sample Edited Detail File of the 1990 Decennial Census and confidential versions of the 1990-97 Annual Demographic (March)

Supplements of the Current Population Survey (CPS). The information in the SEDF was coded from the "long forms" which were administered as part of the 1990 Decennial Census. Thus, it represents a very large (one-in-six) cross-section sample of the U.S. population. The March files of the CPS are smaller and sample roughly 60,000 households per year. Detailed geographic information is attached to both the SEDF and confidential versions of the CPS.[3]

Individual-level variables. The SEDF and March files of the CPS record comparable information on whether a person was employed during the previous year, the number of weeks the person worked, the number of hours worked in an average week, and the amount of money earned from different sources.[4] From these measures, I construct three variables: a dummy variable indicating employment during the previous year, weekly earnings during the previous year (total personal earnings divided by weeks worked), and hourly earnings during the previous year (total personal earnings divided by weeks and typical hours worked). Nominal amounts were re-expressed in constant 1998 dollars using the Consumer Price Index for Urban Consumers (CPI-U).

In addition to the economic variables, the SEDF and CPS also contain comparable information on the person's sex, age, ethnic origin, and schooling level. I use the sex and age information as recorded. From the ethnic origin data, I construct dummy indicators for people of African origin and people of other non-European origins (mostly native Americans, Asians, and Pacific Islanders); the omitted category is European origin. I also construct a separate dummy variable for Hispanic origin which may overlap with the other racial/ethnic categories. Using the schooling information, I distinguish between four types of people: those who did not complete high school, those who completed high school (or equivalent) but did not go on to college, those who completed some college, and those who graduated from college. Most of the empirical analysis focuses on people from the two lowest education groups.

From the combined data set, I select non-institutionalized, civilians who were 16 to 64 years of age. I then make a number of data exclusions. First, I exclude people below age 24 who were enrolled in school. Second, I drop observations for individuals whose earnings were in the top one percent of all earnings for each year or whose average weekly hours exceeded 98.[5] Third, I exclude observations if the calculation of real hourly or weekly earnings was unreasonable – below 75¢ or above $250 for hourly wages and below 75¢ or above $10,000 for weekly wages. Fourth, I drop observations with allocated economic or demographic data.[6] Even with these exclusions, the resulting data set still contains several million observations. To make the data more manageable, I randomly sample observations from the SEDF for counties with more than 100,000 residents (the sampling probability is 100,000/population) and re-weight the remaining observations accordingly. All of the statistical analyses incorporate sampling weights scaled to the annual sample sizes.

Means and standard deviations for the individual-level variables drawn from the SEDF and CPS files are reported in Appendix A. The appendix lists statistics separately for subsamples of women and men who did not complete high school and women and men who completed high school but did not go on to college.

<u>Policy variables</u>. Two state-level policy variables relevant to the low-skill labor market have been merged into the analysis data set: the maximum AFDC benefits available to a family of three with no other income and the minimum wage in the state. The benefits measure is taken from various editions of the *Green Book* (U.S. House of Representatives, Committee on Ways and

Means, various years) and is used to capture the income available if a family head does not work. The minimum wage measure is taken from papers by Neumark, Schweitzer and Wascher (1998) and Neumark (1999). Over the period of the study there were several increases in the federal minimum wage.[7] Additionally, a small number of states set minimum wages above the federal level and changed their wages at different times. The analysis adjusts the AFDC benefits and minimum wage measures for inflation using the CPI-U. Means and standard deviations for these variables appear in Appendix A.

<u>Measures of local labor market conditions</u>. Using the geographic identifiers in the SEDF and CPS files, I can link the individual-level observations to measures of local labor market conditions. An important issue that must be addressed first, though, is the definition of the market itself – what are the geographic boundaries and what types of labor are involved?

There is little agreement in the existing empirical literature regarding what constitutes a "local" labor market. If we base our definition on the measures that have actually been employed in research, a fair definition of "local" would be any geographic area smaller than a Census region, with states and metropolitan areas being the most popular choices. While research by urban and regional economists and our earlier examination of county employment patterns each suggest that a narrower geographic definition should be adopted, labor market studies have generally not considered smaller areas or incorporated information on commuting.[8]

Some data for smaller areas are available; however, these data have serious limitations. For instance, county-level employment, unemployment and labor force estimates are reported in the Geographic Profile of Employment and Unemployment from the Bureau of Labor Statistics. The problem with these data is that they are very broad. As we saw when we compared Figures 1 - 3, general aggregates may not reflect the opportunities for specific skill groups.

Another source of local economic data is the Regional Economic Information System (REIS) from the Bureau of Economic Analysis, which reports annual total and industry-level earnings and employment. The limitation of the REIS is that its data are specific to industries rather than skill groups and are recorded on a place of work rather than a place of residence basis. Figure 4 illustrates the distortions that arise when place of work data are used. For each county in Figure 4, employment rates are calculated by dividing the number of civilian jobs, as reported in the REIS, by the number of working age adults. Although some of the general regional patterns carry over from Figure 1, others do not. In particular, relative employment rates in Texas look much better in Figure 4 than in Figure 1 while conditions in Maryland and Virginia look much worse. The place-of-work estimates also exhibit more variability within regions than do the place-of-residence estimates. A further shortcoming is that the rates based on place-of-work measures take on values greater than one in locations like the District of Columbia with lots of in-commuting.

[Figure 4 about here]

Measures of skill- and residence-specific opportunities can be estimated using data from the CPS and the SEDF. Both files contain information on worker characteristics including age and education that can be used to infer skill levels as well as data on labor market outcomes. However, once again there are limitations. The CPS can be used to construct annual or even monthly statistics for the nation as a whole and for some large subnational areas; however, there are not enough observations to generate reliable estimates for small areas. The SEDF does include enough observations to produce reliable direct measures of skill- and residence-specific labor market outcomes for small areas but is only available at ten-year intervals.

To consider how the available annual employer-based data for small areas might be adjusted to reflect local, skill-specific job opportunities, I use the SEDF to examine where and in which industries employees with different skill levels work. Table 1 reports summary statistics from the SEDF on the percentages of women and men with different education levels that (a) work and live in the same county and (b) work in various industries. As the figures indicate, commuting and industry patterns vary substantially across gender and skill groups.

[Table 1 about here]

On average, men are more likely than women to travel beyond their county of residence to get to work. Commuting across counties also increases with an employee's level of schooling. Women with the least schooling have the lowest tendency to commute; nevertheless, a substantial number still do commute. Nearly one-sixth of women with less than a high school diploma and one-fifth of women with a diploma (or equivalent) but no college commute across counties.

Table 1 also indicates that the employment of women with low levels of schooling is concentrated in three industries: manufacturing, retail trade, and services. More than four-fifths of women with less than a high school diploma are employed in these three industries with nearly a third working in the low-paid retail sector. Among women with a high school diploma but no college, two-thirds work in these three industries. While manufacturing, retail trade, and services account for more than half the employment among low-skilled men, a fourth industry – construction – is also important. The "big three" also account for just over half of the employment of college-educated men and women; however, the concentrations within specific industries differ substantially from those for less-educated workers, and other sectors such as public service account for a large share of employment.

The observed differences in industry employment and commuting patterns support the study's earlier findings that general population-wide aggregates and simple within-county measures do not accurately describe employment opportunities within gender and skill groups. To form the study's labor market variables, I therefore combine annual county-level place-of-work industry employment information from the REIS with employment weights derived from the SEDF to form county-of-residence measures of skill-specific opportunities. The weighting approach is similar to that developed by Bowen and Finegan (1969) and adopted in numerous subsequent manpower studies to map industry employment data to demographic, skill or occupation groups; to my knowledge, though, the procedure has not been used in research studies to account for commuting patterns or define geographic labor markets.

In particular, I obtain total employment and earnings in one-digit S.I.C. industries for each county from 1989 through 1996. The industry-specific data in the REIS are based primarily on administrative records (ES-202 forms) submitted by employers to state employment agencies.[9] Let $E_{\text{REIS}}(j, c, t)$ denote the total number of employees in industry j (= 1, J) in county c (= 1, C) in year t derived from the REIS.

To re-weight these data, let $e_{\text{SEDF}}(s, r, j, c)$ denote the fraction of employees in industry j and county c with skills s who commute from county r as estimated from the SEDF. I estimate annual skill- and residence-specific employment for year t using the weighting formula

$$\hat{M}(s,r,t) = \sum_{j=1}^{J} \left(\sum_{c=1}^{C} e_{\text{SEDF}}(s,r,j,c) E_{\text{REIS}}(j,c,t) \right). \tag{1}$$

In the empirical analysis, I re-express this figure as a proportion of working adults by dividing through by the total population aged 15-64 in the county of residence.

Table 2 reports the national trends from 1989 to 1996 in different types and measures of employment. The first row of Table 2 lists total civilian employment, as reported in the REIS, divided by the number of working age adults. The next three rows list employment in manufacturing, retail trade, and services, also as reported in the REIS, per working age adult. The figures indicate the effects of the recession in the early 1990s with total employment declining in 1991 and 1992, beginning to rebound in 1993, and moving beyond its pre-recession peak by 1994. The figures also show the general decline in manufacturing employment and the overall growth in retail trade and service employment over the period.

[Table 2 about here]

The remaining rows in Table 2 show the weighted estimates of employment from equation (1) for women and men with different schooling levels. The figures suggest the recession during the early 1990s had a more severe effect on jobs that were consistent with men's skills than with those consistent with women's skills. The weighted employment figures for men at all skill levels fell from 1990 to 1992, while the corresponding figures for women were essentially unchanged. Over the entire period 1989-96, the total growth in "women's jobs" was also stronger than the growth in "men's jobs." The weighted employment figures for women for women with a high school education or less grew roughly six to seven percent from 1989 to 1996, while the figures for men grew by only two percent. Jobs consistent with high levels of skills grew faster; the rates were seven to eight percent for women with more than a high school education and about four percent for men with more than a high school education.

Table 3 reports the correlations between the alternative county-level employment measures.

The top half of the table lists correlations between the estimated employment rates for each gender and skill group and the unadjusted total civilian employment measure from the REIS. The bottom half of the table lists similar correlations for changes over time (first differences) in the measures. The correlations among the estimated rates in the top half of the table confirm our earlier analysis that the geographic distribution of employment opportunities varies greatly over skill groups. Indeed, the estimated employment rates for workers without any college are negatively related to the rates for workers with college. The figures also indicate that the unadjusted total employment measure from the REIS is weakly and, worse yet, negatively related to the low-skill employment measures. These results point to the need to adjust the employment measures to account for skill-specific commuting and industrial employment patterns.

[Table 3 about here]

The results from the bottom half of Table 3 point to a much different conclusion. All of the correlations among the measures of employment change are positive, and most of the correlations are relatively large. One explanation for the switch in results is that differencing the employment measures eliminates permanent or slowly changing compositional effects that lead to negative correlations in the levels. Given that employment rises with schooling levels, counties with a high proportion of residents workers would naturally tend to have high overall employment rates while counties with a low proportion of such residents would have low overall rates. Thus, the negative correlation in levels between the low-skill and overall employment measures might be an artifact of counties with large proportions of low-skill jobs also having large proportions of low-skill residents. Another explanation is that there might be a high degree of spatial correlation in employment shocks. For instance, the employment effects of product demand or productivity shocks might be spread over relatively large areas.

In the subsequent regression analysis, I consider both the skill-specific and unadjusted total employment measures. The skill-specific measures are preferred on methodological grounds. However, the results in Table 3 suggest that there might not be much practical importance in using the skill-specific measures in certain types of analyses.

4. Regression analysis

To examine employment opportunities more carefully, I use the combined individual-level data from the SEDF and CPS linked with the local labor market and policy variables to estimate a series of skill-specific employment probits of the form

$$\begin{aligned} Y^*(i,s,r,t) = \gamma_{1s}\hat{M}(s,r,t) + \gamma_{2s}\hat{M}(s,r,t-1) \\ + \mathbf{\Gamma}'_{\mathbf{Xs}}\mathbf{X}(i,s,r,t) + \theta_{st} + \pi_{sk} + \eta(i,s,r,t). \end{aligned} \tag{2a}$$

$$Y(i,s,r,t) = \begin{cases} 1 \text{ (employed)} & \text{if } Y^*(i,s,r,t) > 0 \\ 0 \text{ (not employed)} & \text{otherwise} \end{cases} \tag{2b}$$

and log wage regressions of the form

$$\begin{aligned} \ln W(i,s,r,t) = \beta_{1s}\hat{M}(s,r,t) + \beta_{2s}\hat{M}(s,r,t-1) \\ + \mathbf{B}'_{\mathbf{Xs}}\mathbf{X}(i,s,r,t) + \delta_{st} + \mu_{sk} + \lambda(i,s,r,t) + \varepsilon(i,s,r,t). \end{aligned} \tag{3}$$

In the equations, $Y^*(i, s, r, t)$ is a continuous latent variable for employment; $Y(i, s, r, t)$ is the actual binary employment outcome, and $W(i, s, r, t)$ denotes hourly or weekly wages. The right hand sides of the equations include the current and lagged value of the estimated skill-specific county employment rate and a vector of other observed variables, $\mathbf{X}(i, s, r, t)$. Each equation also includes controls for year-specific fixed effects, θ_{st} and δ_{st}, and area-specific fixed effects, π_{sk} and μ_{sk}. The terms $\eta(i, s, r, t)$ and $\varepsilon(i, s, r, t)$ are individual-specific errors, and $\lambda(i, s, r, t)$ is the inverse mills ratio, which is used to correct the log wage equation for selectivity from the employment decision. Following Heckman (1979), a two-stage approach is used in which coefficient estimates from the employment probit are used to form estimates of $\lambda(i, s, r, t)$.

The employment and wage specifications were selected after some experimentation and consideration of trade-offs. One trade-off involves the definition of the area-specific effects. The preferred approach would be to account for as much geographic heterogeneity as possible by including controls for all 3,105 counties and county-equivalents in the data set. This approach, however, led to a number of problems. First, most of the counties in the United States have relatively few residents – the population size for the median county is roughly 25,000 people. When the sample selection criteria were applied and the analysis data set was stratified, cell sizes for many of the counties became too small to provide reliable estimates of county-specific effects. Second, small cell sizes also increased the possibility of inadvertent disclosure of personal information. USC Title 13 prohibits the Census Bureau from releasing data where the responses of particular individuals or establishments can be identified. Third, including controls for all counties was computationally unwieldy. Although the county fixed effects could be conditioned out of certain analyses, estimates of these effects (along with standard errors) were required for the imputations.

In light of these considerations, the analysis includes separate controls for each of the counties that had 1990 populations in excess of 35,000 people (1,132 counties). While this identifies only about a third of all counties, the included counties account for nearly 90 percent of the total U.S. population. For the remaining counties, the analysis includes controls for labor market areas (LMAs) within states. Specifically, I use the LMAs defined by Tolbert and Sizer (1996), who grouped counties on the basis of commuting ties reported in the 1990 Decennial Census.[10] Their groupings extend across state boundaries; my controls distinguish between portions of LMAs that are in different states.[11] Altogether, the analysis accounts for 1,578 different areas: 1,132 individual counties and 446 balance-of-LMA-within-state areas. The sizes of the resulting cells are relatively large; the median stratified area cell (area × gender × schooling level) contains 661 employment observations and 435 wage observations. More than 99 percent of the stratified area cells contain at least 100 employment observations, and 96.5 percent have at least 100 wage observations. The smallest cell contains 16 employment observations and 10 wage observations.

Initial tests revealed that the inclusion of area fixed effects significantly improved the fit of the models relative to models with state effects or no effects. The inclusion of fixed effects in the probit models leads to potentially inconsistent estimates because of the incidental parameters problem; however, because of the large numbers of observations for most areas, this should not be a serious issue. Tests also supported the inclusion of general time effects, the choice of lag structure for the local employment variables, and the use of selectivity adjustments.

Employment probit results. Table 4 lists coefficient estimates and standard errors from the employment probit models. The first two rows contain the coefficients for the current and lagged skill-specific employment rates. Note that because the specifications include area- and year-specific effects, the employment coefficients must be interpreted as the effects of deviations from both the local average and national trend in employment. The estimates indicate that local employment deviations have modest positive effects on low-skill women's employment and negligible effects on low-skill men's employment. For women who did not complete high school, the elasticity of labor supply with respect to a change in the current employment rate (evaluated at the means of the data) is .07. For the same group, the elasticity with respect to a change in the previous year's employment rate is .20, and the long-term (combined) elasticity is .27. For women who are high school graduates, the estimated long-term elasticity is .21. The corresponding long-term elasticities for men are much weaker – .07 for men who did not complete high school and .05 for those who did.

[Table 4 about here]

In the next row in Table 4, the estimated coefficient on the log of AFDC benefits is significantly negative for women who did not complete high school (elasticity -.24), zero for women who completed high school, insignificantly negative for men who did not complete high school (elasticity -.06), and significantly negative but small for men who completed high school (elasticity -.05). For women, the finding of some negative effects is consistent with theory. For men, the negative results might reflect the effects of the AFDC-UP program or the effects of AFDC acting as a substitute for own child support payments.

The next row lists coefficients from the log minimum wage variable. The coefficients are positive for three out of the four groups (positive for everyone but men who did not complete high school). The positive coefficients are unexpected but not unprecedented (see, e.g., Card and Krueger 1995). The results are, of course, consistent with the predicted effect of the minimum wage on labor supply. The lack of a strong labor demand response may reflect the study's use of an annual employment measure rather than a weekly measure; the demand effects might be more prominent if employment were examined along another margin.[12]

The next five rows contain the coefficients for the age, race and ethnicity variables. The results for these variables are consistent with expectations and previous research. Employment increases initially with age then decreases. Employment is lower for men and women of African and other non-European, non-Hispanic origins than for those of European origin. The coefficients for African men are particularly strong; their employment is estimated to be 12 to 18 percent lower than for white men. The coefficients are also negative for Hispanic women as well as for Hispanic men who completed high school; however, the coefficient is positive for Hispanic men who did not complete high school.

The remaining rows list coefficients from a dummy variable indicating whether the observation came from the CPS rather than the SEDF and dummy variables for specific years of data. The CPS/SEDF sample dummy is included to capture systematic differences in reporting between the different surveys. The coefficient is identified because there are overlapping observations from the 1990 CPS and the SEDF. The estimates indicate that the CPS recorded slightly higher (2 to 4 percent) employment rates than did the SEDF.

The coefficients on the time dummies indicate that, conditional on other economic and demographic changes, employment fell for low-skill women and men through about 1993. Although employment recovered, the conditional rates in 1996 were still lower than in 1989. The drop in conditional employment was smallest for women who completed high school; their employment in 1993 was only 3 percent below the 1989 rate. For each of the other groups, the conditional rates in 1993 were 6 to 8 percent lower than the 1989 rates.

<u>Wage regression results</u>. Table 5 reports coefficient estimates and heteroskedasticity-

consistent standard errors for the regressions of log hourly earnings. The earnings regressions include all of the independent variables from the employment probits except for the maximum AFDC benefits variable.

[Table 5 about here]

In the regressions, the estimated coefficients for the current and lagged skill-specific employment variables are significant only for women who completed high school. The elasticity of hourly wages with respect to a long-term change in employment for this group is .28. The coefficients on current and lagged employment for women who did not complete high school are also positive but weaker (elasticity .12). For men, the net estimated effects are negative and close to zero. The finding that low-skill women's wages are more sensitive than men's wages to changes in employment is consistent with the results reported by Hoynes (1999). Beyond this, however, the estimated effects are much weaker than those reported in earlier studies. The principal source of the difference appears to be the inclusion of the detailed area effects; specifications (not shown) of the models which only include state fixed effects generate stronger estimated effects that are more in line with previous findings.

Hourly wages among low-skill workers are estimated be more sensitive to changes in the minimum wage. The minimum wage coefficients are all significantly positive with elasticities that range from .26 to .42. Consistent with expectations, the effects of the minimum wage are estimated to decrease with skill level. When these coefficients are combined with the mostly positive estimates from the employment probits, the results indicate that increases in the minimum wage benefit low-skill adults by both encouraging and rewarding work.

Among the other variables in the hourly earnings regressions, age has a significantly positive coefficient, and age squared has a significantly negative coefficient for all four groups. The coefficients for the racial and ethnic minority indicators are all significantly negative and large. The estimated effects of African origin on men's wages are especially strong; the coefficients imply wage reductions of 26 to 29 percent.

The coefficients on the sample dummy indicate that the calculated wages for women and men who did not complete high school are 10 to 12 percent lower in the CPS than in the SEDF. There are also statistically significant, though substantively smaller, differences between the samples for women and men who completed high school. The results suggest that there are systematic differences in the ways that data are reported in the CPS and SEDF and that combining data from the two data sets may not be entirely appropriate. While I cannot be sure of the exact cause of the differences, a likely candidate is misreporting in the SEDF.

As with the employment probits, the time dummies in the wage regressions generate a downward trend. Conditional wages for all four groups fell through about 1993 then recovered somewhat. For men, conditional wages began to fall again in 1996. The results are consistent with previous findings of declining wages for low-skill men and women over this period.

One additional result that deserves some discussion is the relatively weak fit of the regressions, especially the two regressions for women. Although low R^2 statistics are common in regressions such as these with limited controls for skills and abilities, one might expect the inclusion of detailed area effects to lead to a better fit. Given that the combination of area effects, time effects, and local employment variables captures much of the possible market-level variation, the weak fit statistics suggest that general market conditions play only a modest role in determining individual wage outcomes and that personal characteristics play a more prominent role.

Table 6 presents results from regressions of computed weekly, rather than hourly, earnings. Weekly earnings capture more of an element of labor supply than do hourly earnings. However, they also provide a better indication of the availability of full-time work. Despite these differences, the estimation results for the weekly earnings regressions are very similar to the results from the previous table. The coefficients have nearly identical sign and significance patterns across tables, and the magnitudes of the estimated effects are broadly similar. For instance, the implied elasticity of weekly earnings with respect to a long-term change in local skill-specific employment is .11 for women who did not complete high school, .26 for women who completed high school, -.02 for men who did not complete high school, and .02 for men who completed high school.

[Table 6 about here]

<u>Other specifications</u>. Table 7 presents results from specifications of the employment and wage regression models that use the unadjusted total civilian employment variable in place of the skill-specific employment variable as a measure of local employment conditions. Because the coefficients for the other variables in the models were all essentially unchanged from the results reported in Tables 4-6, Table 7 only lists the coefficients from the local employment measures.

[Table 7 about here]

Changing from the skill- and residence-specific employment measures to the unadjusted, place-of-work measures has little substantive impact on the results. In the employment probits, the long-term elasticities going across Table 7 are .31, .17, .13 and .07.; these are comparable to the elasticities calculated for Table 4. In the wage regressions, there are more coefficients that are individually significant when the unadjusted employment measures are used; however, the implied long-term elasticities remain similar to those from Tables 5 and 6. The long-term elasticities for hourly wages going across Table 7 are .17, .24, .05 and .04., and the elasticities for weekly wages are .13, .22, .06 and .06. The results confirm the analysis from Table 3 that the skill-specific and unadjusted employment measures are closely related once area-specific effects are taken into account.[13]

Versions of the wage regressions have also been run without controls for selectivity. When selectivity controls are omitted, the predicted levels of wages are higher, especially for women. However, the coefficients and implied marginal effects of the observed variables change only slightly. Similar to the findings of Bils (1985), wages appear to be slightly less sensitive to changes in economic conditions when models do not account for selectivity.

5. Employment and wage imputations

The study uses the estimates from Tables 4 and 5 along with the county-level data from the REIS and the state-level policy variables to impute annual employment rates and hourly earnings over all counties from 1989-96. To abstract from demographic differences across areas, it fixes the age and racial/ethnic background and imputes labor market outcomes for a representative person with given set of characteristics.

Figures 5 and 6 graph trends from 1989-96 in the average imputed employment and wage rates for 30-year-old, non-Hispanic, whites. In each graph, separate trends are shown for women and men who did and did not complete high school. To approximate national population estimates, the annual averages are weighted by the number of working-age adults in each county.

[Figure 5 about here]

From Figure 5, the imputed employment rates in each year were higher for men than for women and higher for people who completed high school than for those who did not. Employment probabilities among men declined over the period, with men from the lowest skill group experiencing the sharpest decline. Among women who did not complete high school, employment probabilities dipped during the early 1990s and then rebounded to about their initial 1989 level. For women who competed high school, the trend in employment probabilities was essentially flat. The results across all four groups indicate that low-skill employment fell during the recession at the start of the decade and staged a weak, incomplete recovery through the middle of the decade. The results differ from the estimates based only on weighted industrial employment from Table 2 which suggested a slight improvement in the availability of jobs for low-skill workers over this period.

The top graph in Figure 6 shows the trends in imputed hourly wages based on the models from Table 5 that adjust for employment selectivity. The bottom graph displays the corresponding trends derived from models that do not include a selectivity adjustment. As mentioned in the previous section, models that incorporate the Heckman correction produce wage estimates that are somewhat lower for men and much lower for women than models without the adjustment. While the year-to-year trends in the adjusted and unadjusted wage measures are very similar, the large difference between the levels of the series for women is a cause for concern. For women who did not complete high school, the selectivity-corrected estimates are so low that the averages actually fall below the Federal minimum wage in several years. Also, the premium associated with school completion for women is very small (about 15 percent versus about 35 percent for men).

[Figure 6 about here]

Are the selectivity-corrected estimates reasonable? The selectivity adjustments are included to make the wage measures representative for the general population rather than just the subset of people who work. If people choose their employment status by comparing their available market wage with their reservation wage, we would expect the average market wage for all people to be lower than the average wage for workers. The observed controls in the regressions account for some of the differences in the wages available to workers and non-workers; the selectivity procedure adjusts for bias from the remaining, unobserved differences.

The magnitude of the underlying bias, and hence the impact of the correction, depends on the amount of selection and the strength of the relationship between the unobserved determinants of employment and wages. Several of the requirements for a large correction seem to be present in the sample of low-skill women. First, there is a great deal of selection – wages are observed for 67 percent of women who finished high school and 43 percent women who did not. Second, some research suggests that women's employment is more sensitive than men's employment to wage changes (Killingsworth and Heckman 1986) and thus more sensitive to a given difference in unobserved wage characteristics.[14] Third, the unobserved determinants of wages among non-working women with a high school education or less are likely to be especially weak. The unmeasured job market skills in this group are likely to be low due to a lack of work experience or interrupted job histories. Compensating differentials associated with jobs that accommodate household responsibilities such as child care might be another unmeasured factor.

The graphs in Figure 6 show that imputed hourly wages for men and women declined over the period 1989-96. The decline for men was steeper than that for women. The difference between the 1989 and 1996 selectivity-adjusted wages was about $1.00 (11 percent) for men who did not complete high school and about $1.45 (12 percent) for men who completed high school. For women, selectivity-adjusted wages fell by 15 cents (2-3 percent). Although the levels were lower, the unadjusted wage imputations for men and women exhibited similar declines.

Tables 8 and 9 show how the imputed employment and wage outcomes were distributed across counties. Table 8 lists predicted employment in 1996 for the average county and for different percentiles in the distribution of counties.[15] As in the previous figures, estimates are reported assuming a representative 30-year-old, non-Hispanic white. However, to give some indication of how differences in race and age affect the estimates, Table 8 also reports statistics assuming a representative 30-year-old, non-Hispanic black and an 18-year-old, non-Hispanic white. Table 9 reports a similar set of statistics for imputed, selectivity-adjusted hourly wages.

[Table 8 about here]

The results from Table 8 reveal that the geographic distribution of employment outcomes was wider for people who did not complete high school than for those who did. The distribution also varied more for women than for men. The employment rate for 30-year-old, non-Hispanic, white women who did not complete high school was 40 percent in the county at the 5th percentile and 72 percent in the county at the 95th percentile; in the median county, the employment rate for this group was 59 percent. These figures compare to employment rates of 89 percent at the 5th percentile, 95 percent at the median, and 98 percent at the 95th percentile for 30-year-old, non-Hispanic, white men who completed high school.

The estimates from Table 8 also indicate that outcomes for younger workers and workers of

African origin were substantially worse that outcomes for prime-aged workers of European origin. For women who did not complete high school, the change in race shifts the employment probabilities down by about 7 percentage points, and the change in age shifts the probabilities down by 11 percentage points. For men who did not complete high school, the differences are even larger. The change to African origin shifts the employment probabilities down by 12-20 percentage points, and the change in age shifts the probabilities down by 9-15 percentage points. The results imply that rates of joblessness among certain groups in certain areas of the country were extremely high. For instance, in the counties at or below the 5th percentile (about 155 counties), fewer than half of the 30-year-old, African men without a high school diploma would have worked at all during the year.

Table 9 shows how wages varied across different groups and across counties. As with the employment results, there was a substantial amount of heterogeneity in the imputed wage outcomes. The estimates paint a bleak picture for low-skill workers and indicate that the average wage opportunities were very low. In 1996, the poverty threshold for a family of three (in constant 1998 dollars) was roughly $13,000. Ignoring taxes and transfers, a full-time, full-year job would have to pay about $6.50/hour to generate this much income. For women who did not complete high school, none of the computed wage cells rose to this level. Most of the cells computed for women who completed high school also fell below the poverty wage level. Among men who did not complete high school, average wages were computed to be below the poverty level in over 25 percent of counties for 30-year-old, non-Hispanic whites, in over 90 percent of counties for 30-year-old, non-Hispanic blacks, and in virtually all counties for 18-year-old, non-Hispanic whites. Even among men who completed high school, average wages were below the poverty level for some groups in some areas.

[Table 9 about here]

The low wage levels in Table 9 help to explain why employment and wages were found to be so sensitive to minimum wage changes in the econometric analyses. The estimates from Table 9 imply that state and Federal minimum wages are higher than the wages that would otherwise be available to many low-skill people. The findings contrast with previous results which suggest that few people are directly or meaningfully affected by the minimum wage (see, e.g., Neumark et al. 1998). The difference in findings stems from the fact that most previous research has only compared the minimum wage to the wages of workers, not the wider population of workers and non-workers.[16]

Figure 7 shows how imputed employment rates for low-skill men and women changed across six selected counties over the period 1989-96. To prepare the figure, I selected two large urban counties/areas, the District of Columbia (1990 population 604,000) and Los Angeles County (population 8,876,000), two counties with medium size cities, Linn County in Iowa (population 169,000, contains Cedar Rapids) and Ohio County in West Virginia (population 51,000, contains Wheeling), and two counties with medium population sizes but no major cities, Monroe County in Pennsylvania (population 97,000, largest city East Stroudsburg) and Mississippi County in Arkansas (population 58,000, largest city Osceola). The counties were selected from different regions and indicate the types of counties that are uniquely identified in the analysis data set. As with the previous figures and tables, outcomes are imputed for 30-year-olds of non-Hispanic, European origin.

[Figure 7 about here]

The graphs in Figure 7 show that both the levels and trends in different types of low-skill employment varied greatly across counties. The graphs also show that employment for different groups of workers varied within counties – strong employment conditions for one group in an area did not necessarily imply strong conditions for all groups. For instance, the levels and trends in low-skill men's employment in the District of Columbia were near the national averages; however, the levels of women's employment were higher than average, and women's employment in the District trended upward over time, rather than downward. In contrast, Los Angeles is an example of a county where employment for all groups was uniformly lower and dropped more sharply than the national average.

In Linn County, low-skill employment was higher than the national average and remained relatively constant over the period. In Ohio County, employment among people who finished high school was slightly below average; however, employment among those who did not finish school was much lower than average. In Monroe County, low-skill employment rates were initially higher than the national rates in 1989 but converged toward the national rates over the next seven years by falling more sharply than the national average. Low-skill employment rates also converged toward the national average in Mississippi County but from different starting points – rates were lower in 1989 and grew more (or fell less) than the national average.

Figure 8 shows the trends in imputed, selectivity-adjusted hourly wages for the same groups and counties. Once again, the outcomes varied greatly across areas. In the District of Columbia, low-skill wages were higher than average in 1989. Wages for low-skill men fell, but not as much as the national average, and wages for low-skill women actually rose. In Los Angeles, low-skill wages were also initially higher than average but fell more sharply than the national trend.

[Figure 8 about here]

In the other four counties, there were some differences from the national levels. Wages were slightly higher than average in Monroe County, slightly lower than average in Linn County, and much lower than average in Ohio County and Mississippi County. Nevertheless, the trends in low-skill wages in these four counties over time were very similar to the national trends.

6. Conclusion

This study employed a variety of data and methods to examine wage and employment opportunities at the county-level for low-skill men and women over the period 1989-96. First, it constructed simple county-level aggregates of employment levels for different types of individuals using micro-data (the SEDF) from the 1990 Decennial Census and analyzed the geographic distribution of skill-specific employment rates at a single point in time. Next, it applied weights derived from the SEDF on the industry of employment and commuting patterns of workers with different skill levels to annual, county-level data from the REIS on the industrial composition of jobs to form time-varying indices of the local availability of skill-specific jobs. It used these measures to examine how skill-specific employment changed over the period 1989-96 within and across counties. Finally, the study combined individual-level data from the SEDF and different years of the CPS with the skill-specific, county-level employment indices and estimated econometric models of low-skill employment and wage outcomes. Estimates from the models were used to impute wage and employment rates for low-skill adults across counties and over time. There are several important substantive and methodological conclusions that can be derived from these various analyses.

First, to modify the Hon. Thomas P. O'Neill's popular adage, *all labor markets is local*. Previous research has greatly strained the definition of "local" and relied on employment and wage data that are aggregated across large areas such as states and major metropolitan areas. This study shows that the proper geographic definition of a local labor market is closer to the county level. Employment and wage outcomes vary greatly from county to county, even within the same state or MSA. Most workers also live and work in the same county; this is especially true of women and workers with low-levels of schooling.

Second, *employment and wage trends within local markets differ according to skill level – accounting for gender and skill differences matters.* Local markets that offer good opportunities to some types of workers do not necessarily offer good opportunities to other types. The analysis showed that there were counties where employment conditions for men were relatively strong while opportunities for women were relatively weak and vice versa. It also showed that there were areas where conditions were relatively strong for people who completed high school but weak for people who did not and vice versa. There were many areas where conditions for one skill group improved while conditions for other groups deteriorated. General employment statistics aggregated over different types of people do not capture this heterogeneity.

Third, *despite the aggregate growth in the economy, employment conditions remained very weak for low-skill workers in certain parts of the country.* Imputations based on the employment and wage models indicated that outcomes across different areas were very heterogenous. In the bottom tail of the distribution, employment and wage rates were extremely, and in some cases wretchedly, low. For instance, the imputations indicated that in 5 percent of counties in 1996 less than half of the 30-year-old African-American men who had not completed high school and less than a third of the 30-year-old African-American women who had not completed high school worked at all during the year. In many counties, the wages that low-skill men and women could expect were well below the level needed to escape poverty.

Fourth, *the wages available to men and women with low levels of schooling continued to decline over the 1990s*. Estimates from the study's models indicate that wages available to men with a high school education or less fell noticeably over the period 1989-96 in most parts of the country. Wages for women with the same level of education also declined slightly in most areas.

Fifth, *low-skill men and women's employment and wages are not sensitive to local employment shocks*. Results from the econometric models indicate that low-skill women's wage and employment elasticities to local employment shocks were generally below .3 and that men's elasticities were generally below .1. Permanent differences across areas, as captured by the area fixed effects, were significant determinants of employment and wages. Previous findings by researchers such as Hoynes (1999) and Topel (1986) that low-skill workers were sensitive to employment changes may have reflected these permanent local differences.

Sixth, *changes in the minimum wage appear to boost both low-skill employment and wages*. Because the wages that low-skill individuals could command are so paltry in so many areas, there is a sizeable population that might not only see their available wages increase if the minimum were raised, but see wages increase by a great deal. Estimates from the study's models indicate that such an increase would encourage more low-skill people to work.

The primary goals of this study were to capture the detailed local labor market information available from the 1990 Decennial Census, to extrapolate from that baseline and approximate conditions in later years, and to analyze the resulting estimates. In the next few years, new micro-data will be directly available from the 2000 Decennial Census and thereafter from the American Community Survey. Once the ACS is on-line, it will be possible to examine annual local labor market conditions without extrapolating the data. There will still, however, be a need for inter-censal estimates for earlier years. Future work will consider how the 2000 Census and ACS can be combined with the existing data to improve the inter-censal estimates.

Endnotes

1. Maps of relative employment among working-age men with different schooling levels (not shown) are very similar to those for women.

2. Starting in 2003, direct measures of these variables for small geographic areas will be available from the American Community Survey.

3. I obtained access to these files through a NSF/ASA/Census Bureau research fellowship.

4. Although several of the data concepts and questions in the surveys are similar, the collection methods are very different. The long forms of the Decennial Census are mostly self-administered, while the CPS is administered by trained interviewers. Several of the CPS questions involve both initial probes and follow ups. Because of these differences, responses to the two surveys are likely to differ (indeed, item non-response is much higher in the SEDF than the CPS). See Patterson (1985) for a discussion of differences in responses to the 1980 Census and CPS.

5. Both the SEDF and the CPS mask (top-code) information for people with earnings above certain levels; however, the levels differ across data sets. The percentile cut-off trims the data more uniformly than dropping the top-coded observations would.

6. If a survey question in the SEDF or CPS was unanswered, the Census Bureau "allocated" a response using a hot deck procedure. Instead of using the allocated information, my study treats these data as missing and drops the corresponding observations. See Lillard et al. (1986) for a thorough discussion of allocation procedures and their potential effects on empirical labor analyses. Dropping observations with allocated data reduced the sample sizes in the SEDF by about a quarter and in the CPS files by about a tenth.

7. The federal minimum wage was $3.35 in 1989. It increased to $3.80 in 1990, $4.25 in 1991, and $4.75 in 1996.

8. Two exceptions are the public use Census data assembled by Tolbert and Killian (1987) and Tolbert and Sizer (1996) which use commuting data to group counties into labor market areas and the personal income measures assembled by the U. S. Bureau of Economic Analysis (1998) which account for inter-county commuting patterns in allocating earnings to counties. Hanushek (1981) also carefully considered the proper geographic dimensions of local labor markets but was forced to examine large and somewhat arbitrary groupings of counties because data for smaller areas were unavailable.

9. For confidentiality purposes, the REIS suppresses some information for counties with small numbers of employers. In some instances, the REIS indicates that $50,000 or less was earned in a particular industry for a given year; in these cases, the analysis imputes an earnings figure of $25,000. In all other instances of suppression, the analysis applies the state-level percentage of employment or earnings for the industry in that year to the reported total level of county

employment or earnings. The imputed entries are then rescaled so that all of the industry-specific data for the county sums to the county's aggregate employment or earnings.

10. Alternative groupings of counties could be adopted. For instance, the Bureau of Labor Statistics defines its own set of labor market areas, and the Bureau of Economic Analysis groups counties into "economic areas." The analysis adopts the definitions from Tolbert and Sizer (1996) because the researchers (1) impose fewer extraneous conditions on their county groupings and (2) have made available a companion data set containing these definitions and individual data from the 1990 Decennial Census.

11. For instance, LMA 32 from Tolbert and Sizer (1996) contains Catahoula, Concordia, La Salle, Madison and Tensas parishes from Louisiana and Adams, Claiborne, Franklin, Jefferson and Warren counties from Mississippi. Of these parishes and counties, only two – Adams and Warren counties – have populations greater than 35,000. In my analysis, Adams and Warren counties are uniquely identified; Catahoula, Concordia, La Salle, Madison and Tensas parishes are grouped together, and Claiborne, Franklin and Jefferson counties are grouped together.

12. There are a host of other specification issues such as including lags in the minimum wage measure, scaling the minimum wage measure by some local wage or coverage index, etc. that could also be considered (see Card and Krueger 1995 and Neumark 1999 for discussions of the implications of alternative research designs). A complete investigation of these issues is beyond the scope of the present study.

13. Estimates based on the skill-specific and unadjusted measures differ noticeably when state fixed effects are used in place of the more detailed area effects. The skill-specific measures provide a much better fit than the unadjusted measures in those models.

14. Mroz (1987) found that econometric specification issues could account for much of married women's wage sensitivity.

15. The statistics in Tables 8 and 9 do not use population weights.

16. For instance, in making the case that the benefits of a minimum wage increase would be small, Neumark et al. (1998, Table 1) presented statistics on 16-24 year-old workers in 1995. They reported that 4.3 percent of young workers earned less than the then existing minimum wage of \$4.25 and that an additional 21.3 percent earned less than the prospective minimum wage of \$5.15.

Table 1. Percentages of employees working in county of residence and in different industries by gender and education, 1989

	Women				Men			
Working in	less than high school	high school or GED	some college	college graduate	less than high school	high school or GED	some college	college graduate
County of residence	85.4	81.1	79.6	75.8	78.0	72.3	72.2	70.3
Agriculture	1.8	1.2	0.9	0.6	6.6	3.8	2.3	1.5
Mining	0.1	0.2	0.3	0.2	1.2	1.3	0.8	0.8
Construction	1.0	1.5	1.5	0.8	14.0	12.5	8.4	3.6
Manufacturing	21.3	16.5	10.0	7.1	24.3	27.1	21.5	17.1
Trans. and utilities	1.9	4.1	4.6	3.0	6.4	9.2	8.7	4.9
Wholesale trade	2.7	3.5	3.2	2.2	5.0	6.2	6.3	5.0
Retail trade	32.9	23.0	17.0	7.2	21.8	15.9	16.8	7.9
Fin., ins., real est.	3.3	9.9	11.4	7.8	1.6	2.4	5.3	10.0
Services	27.2	27.2	35.8	38.9	12.8	11.6	16.0	28.4
Federal government	1.2	2.9	3.8	3.2	1.0	2.9	4.5	4.9
St./loc. government	6.7	10.0	11.5	29.1	5.3	7.1	9.3	16.0

Note: Data for non-institutionalized, civilian workers aged 16-64 from SEDF. Calculations use sample weights from SEDF.

Table 2. Trends in earnings and employment: 1989-96

	1989	1990	1991	1992	1993	1994	1995	1996
Employment per working-age adult								
Total	0.826	0.831	0.824	0.820	0.829	0.843	0.857	0.865
Manufacturing	0.123	0.120	0.115	0.112	0.111	0.112	0.112	0.111
Retail trade	0.139	0.139	0.138	0.138	0.139	0.144	0.147	0.148
Service	0.229	0.236	0.240	0.243	0.249	0.254	0.262	0.267
Estimated skill-specific employment ($\hat{M}(s,r,t)$) for women								
without HS	0.050	0.050	0.050	0.050	0.050	0.051	0.052	0.053
with HS	0.117	0.118	0.118	0.118	0.119	0.122	0.124	0.125
some college	0.129	0.131	0.131	0.131	0.132	0.135	0.138	0.139
BA or more	0.090	0.091	0.091	0.091	0.092	0.093	0.095	0.096
Estimated skill-specific employment ($\hat{M}(s,r,t)$) for men								
without HS	0.076	0.076	0.075	0.074	0.075	0.076	0.077	0.078
with HS	0.122	0.122	0.120	0.119	0.120	0.122	0.124	0.125
some college	0.125	0.125	0.123	0.122	0.123	0.126	0.127	0.129
BA or more	0.117	0.118	0.117	0.116	0.117	0.118	0.120	0.121

Note: Estimates are population-weighted averages across counties using employment weights from the SEDF and total and industry-specific employment data from the REIS.

Table 3. Correlations between alternative county-level employment measures: 1989-96

	Estimated skill-specific employment for women				Estimated skill-specific employment for men			
	without HS	with HS	some college	BA or more	without HS	with HS	some college	BA or more
				Correlations in levels				
Women without HS	-							
Women with HS	0.26	-						
Women with some college	-0.28	-0.12	-					
Women with BA or more	-0.44	-0.37	0.41	-				
Men without HS	0.84	0.18	-0.40	-0.54	-			
Men with HS	0.26	0.89	-0.23	-0.52	0.30	-		
Men with some college	-0.24	-0.09	0.89	0.24	-0.29	-0.13	-	
Men with BA or more	-0.45	-0.35	0.50	0.95	-0.53	-0.51	0.38	-
Total employment	-0.07	-0.12	0.30	0.61	-0.20	-0.20	0.19	0.55
				Correlations in changes				
Women without HS	-							
Women with HS	0.84	-						
Women with some college	0.73	0.86	-					
Women with BA or more	0.54	0.66	0.82	-				
Men without HS	0.72	0.69	0.64	0.47	-			
Men with HS	0.61	0.76	0.68	0.51	0.81	-		
Men with some college	0.60	0.75	0.81	0.68	0.76	0.85	-	
Men with BA or more	0.57	0.71	0.84	0.90	0.60	0.66	0.83	-
Total employment	0.75	0.83	0.83	0.73	0.77	0.79	0.83	0.79

Note: Figures are population-weighted correlations between estimated county-level skill-specific employment rates. Estimated employment rates use employment weights from the SEDF and total and industry-specific employment data from the REIS.

Table 4. Probit results for employment in previous year

	Women		Men	
	w/o HS	with HS	w/o HS	with HS
Current estimated skill-specific employment in county	1.380	3.516***	1.401	1.856**
	(1.787)	(0.822)	(1.093)	(0.886)
Lagged estimated skill-specific employment in county	4.259**	-0.432	0.362	-0.074
	(1.835)	(0.835)	(1.108)	(0.893)
Log maximum AFDC benefits	-0.265**	0.006	-0.134	-0.232**
	(0.103)	(0.073)	(0.115)	(0.098)
Log minimum wage	0.371***	0.295***	-0.066	0.471***
	(0.073)	(0.056)	(0.084)	(0.075)
Age	0.078***	0.058***	0.112***	0.123***
	(0.001)	(0.001)	(0.001)	(0.001)
Age squared (/100)	-0.113***	-0.098***	-0.159***	-0.184***
	(0.001)	(0.001)	(0.001)	(0.001)
African origin	-0.184***	-0.139***	-0.527***	-0.604***
	(0.004)	(0.004)	(0.005)	(0.005)
Hispanic origin	-0.140***	-0.084***	0.129***	-0.059***
	(0.005)	(0.005)	(0.006)	(0.007)
Other non-white origin	-0.081***	-0.177***	-0.142***	-0.226***
	(0.005)	(0.005)	(0.006)	(0.007)
Observation from CPS	0.075*	0.103***	0.060	0.090**
	(0.040)	(0.026)	(0.044)	(0.038)
Year = 1990	-0.052	-0.030	-0.007	-0.074*
	(0.042)	(0.028)	(0.047)	(0.042)
Year = 1991	-0.107**	-0.059**	-0.072	-0.181***
	(0.044)	(0.029)	(0.048)	(0.043)
Year = 1992	-0.161***	-0.066**	-0.116**	-0.244***
	(0.044)	(0.029)	(0.049)	(0.043)
Year = 1993	-0.189***	-0.072**	-0.248***	-0.324***
	(0.045)	(0.030)	(0.050)	(0.044)
Year = 1994	-0.124***	-0.066**	-0.259***	-0.301***
	(0.046)	(0.030)	(0.051)	(0.044)
Year = 1995	-0.135***	-0.054*	-0.246***	-0.299***
	(0.047)	(0.031)	(0.052)	(0.045)
Year = 1996	-0.146***	-0.035	-0.213***	-0.323***
	(0.049)	(0.033)	(0.054)	(0.047)
Log likelihood	-598,174	-1,076,190	-468,970	-460,002
Observations	930,276	1,805,308	884,160	1,497,090

Note: Data from combined SEDF and CPS files. All models also include county/LMA dummy variables. Standard errors appear in parentheses.

*** Significant at .01 level. ** Significant at .05 level. * Significant at .10 level.

Table 5. Log hourly earnings regression results

	Women		Men	
	w/o HS	with HS	w/o HS	with HS
Current estimated skill-specific employment in county	0.502	1.363***	-0.106	-0.297
	(1.023)	(0.371)	(0.487)	(0.258)
Lagged estimated skill-specific employment in county	1.798	0.890**	-0.245	0.219
	(1.107)	(0.357)	(0.491)	(0.260)
Log minimum wage	0.418***	0.315***	0.363***	0.261***
	(0.069)	(0.038)	(0.049)	(0.036)
Age	0.062***	0.089***	0.082***	0.097***
	(0.007)	(0.002)	(0.003)	(0.001)
Age squared (/100)	-0.073***	-0.119***	-0.089***	-0.108***
	(0.011)	(0.004)	(0.004)	(0.002)
African origin	-0.098***	-0.159***	-0.291***	-0.258***
	(0.018)	(0.007)	(0.015)	(0.008)
Hispanic origin	-0.157***	-0.118***	-0.134***	-0.076***
	(0.016)	(0.008)	(0.008)	(0.008)
Other non-white origin	-0.075***	-0.206***	-0.135***	-0.161***
	(0.012)	(0.010)	(0.008)	(0.008)
Observation from CPS	-0.099***	0.015**	-0.119***	-0.039***
	(0.013)	(0.006)	(0.009)	(0.006)
Year = 1990	-0.042***	-0.037***	-0.047***	-0.054***
	(0.016)	(0.008)	(0.013)	(0.008)
Year = 1991	-0.067***	-0.084***	-0.106***	-0.113***
	(0.018)	(0.009)	(0.014)	(0.009)
Year = 1992	-0.065***	-0.081***	-0.113***	-0.135***
	(0.020)	(0.009)	(0.014)	(0.009)
Year = 1993	-0.103***	-0.081***	-0.126***	-0.135***
	(0.022)	(0.009)	(0.015)	(0.009)
Year = 1994	-0.052***	-0.065***	-0.095***	-0.130***
	(0.018)	(0.009)	(0.015)	(0.009)
Year = 1995	-0.058***	-0.067***	-0.099***	-0.130***
	(0.019)	(0.009)	(0.015)	(0.009)
Year = 1996	-0.065***	-0.058***	-0.137***	-0.140***
	(0.020)	(0.009)	(0.015)	(0.009)
λ	0.510***	1.307***	0.347***	0.371***
	(0.143)	(0.067)	(0.053)	(0.034)
R^2	0.100	0.134	0.186	0.213
Observations	401,107	1,204,250	631,580	1,340,226

Note: Data from combined SEDF and CPS files. All models also include county/LMA dummy variables. Heteroskedasticity-adjusted standard errors appear in parentheses.

*** Significant at .01 level. ** Significant at .05 level. * Significant at .10 level.

Table 6. Log weekly earnings regression results

	Women		Men	
	w/o HS	with HS	w/o HS	with HS
Current estimated skill-specific employment in county	0.862	1.532***	0.047	0.068
	(1.235)	(0.455)	(0.527)	(0.270)
Lagged estimated skill-specific employment in county	1.296	0.541	-0.267	0.089
	(1.340)	(0.439)	(0.531)	(0.271)
Log minimum wage	0.460***	0.289***	0.456***	0.314***
	(0.082)	(0.047)	(0.055)	(0.040)
Age	0.072***	0.090***	0.103***	0.120***
	(0.009)	(0.003)	(0.003)	(0.002)
Age squared (/100)	-0.084***	-0.119***	-0.113***	-0.136***
	(0.012)	(0.005)	(0.004)	(0.002)
African origin	-0.102***	-0.111***	-0.347***	-0.319***
	(0.022)	(0.008)	(0.016)	(0.008)
Hispanic origin	-0.121***	-0.098***	-0.144***	-0.095***
	(0.018)	(0.009)	(0.009)	(0.008)
Other non-white origin	-0.031***	-0.145***	-0.138***	-0.168***
	(0.013)	(0.011)	(0.009)	(0.009)
Observation from CPS	-0.112***	0.010	-0.134***	-0.047***
	(0.016)	(0.008)	(0.011)	(0.006)
Year = 1990	-0.020	-0.029***	-0.042***	-0.056***
	(0.019)	(0.010)	(0.015)	(0.009)
Year = 1991	-0.078***	-0.080***	-0.118***	-0.123***
	(0.023)	(0.011)	(0.016)	(0.010)
Year = 1992	-0.067***	-0.074***	-0.132***	-0.140***
	(0.025)	(0.011)	(0.017)	(0.010)
Year = 1993	-0.098***	-0.083***	-0.120***	-0.136***
	(0.027)	(0.011)	(0.017)	(0.010)
Year = 1994	-0.056**	-0.065***	-0.099***	-0.130***
	(0.022)	(0.011)	(0.017)	(0.010)
Year = 1995	-0.039*	-0.054***	-0.088***	-0.125***
	(0.023)	(0.011)	(0.018)	(0.010)
Year = 1996	-0.046**	-0.049***	-0.143***	-0.144***
	(0.024)	(0.011)	(0.018)	(0.011)
λ	0.269	1.026***	0.275***	0.318***
	(0.170)	(0.083)	(0.059)	(0.037)
R^2	0.098	0.100	0.200	0.229
Observations	401,107	1,204,250	631,580	1,340,226

Note: Data from combined SEDF and CPS files. All models also include county/LMA dummy variables. Heteroskedasticity-adjusted standard errors appear in parentheses.

*** Significant at .01 level. ** Significant at .05 level. * Significant at .10 level.

Table 7. Estimation results using total employment as a local labor market measure

	Women		Men	
	w/o HS	with HS	w/o HS	with HS
	Probit estimates for employment last year			
Current employment per working age adult in county	0.203	0.332***	0.380**	0.380**
	(0.161)	(0.124)	(0.177)	(0.175)
Lagged employment per working age adult in county	0.222	0.053	-0.021	0.006
	(0.166)	(0.128)	(0.182)	(0.181)
Log likelihood	-598,221	-1,076,267	-468,958	-460,001
	Regression estimates for log hourly earnings			
Current employment per working age adult in county	0.250***	0.297***	0.254***	0.040
	(0.097)	(0.056)	(0.081)	(0.054)
Lagged employment per working age adult in county	-0.035	0.003	-0.197**	0.016
	(0.100)	(0.057)	(0.083)	(0.055)
R^2	0.100	0.134	0.186	0.213
	Regression estimates for log weekly earnings			
Current employment per working age adult in county	0.305***	0.367***	0.316***	0.085
	(0.118)	(0.069)	(0.090)	(0.057)
Lagged employment per working age adult in county	-0.138	-0.094	-0.235**	-0.006
	(0.122)	(0.070)	(0.093)	(0.059)
R^2	0.098	0.100	0.200	0.229

Note: Data from combined SEDF and CPS files. All models also include county/LMA dummy variables. Standard errors appear in parentheses.

*** Significant at .01 level. ** Significant at .05 level. * Significant at .10 level.

Table 8. Distribution of imputed employment outcomes across counties: 1996

	Women who did not complete high school			Women who completed high school			Men who did not complete high school			Men who completed high school		
	white age 30	black age 30	white age 18	white age 30	black age 30	white age 18	white age 30	black age 30	white age 18	white age 30	black age 30	white age 18
Mean	0.58	0.51	0.47	0.79	0.75	0.76	0.82	0.66	0.69	0.94	0.84	0.88
95th percentile	0.72	0.66	0.62	0.88	0.85	0.85	0.92	0.80	0.83	0.98	0.92	0.94
90th percentile	0.70	0.63	0.59	0.86	0.83	0.83	0.90	0.77	0.80	0.97	0.91	0.93
75th percentile	0.65	0.58	0.54	0.84	0.80	0.80	0.87	0.73	0.76	0.96	0.88	0.91
50th percentile	0.59	0.52	0.48	0.81	0.77	0.77	0.83	0.66	0.70	0.95	0.84	0.88
25th percentile	0.53	0.45	0.41	0.76	0.72	0.72	0.78	0.60	0.64	0.93	0.81	0.85
10th percentile	0.46	0.39	0.35	0.71	0.66	0.67	0.73	0.54	0.58	0.91	0.76	0.82
5th percentile	0.40	0.33	0.29	0.68	0.63	0.63	0.69	0.49	0.53	0.89	0.73	0.79

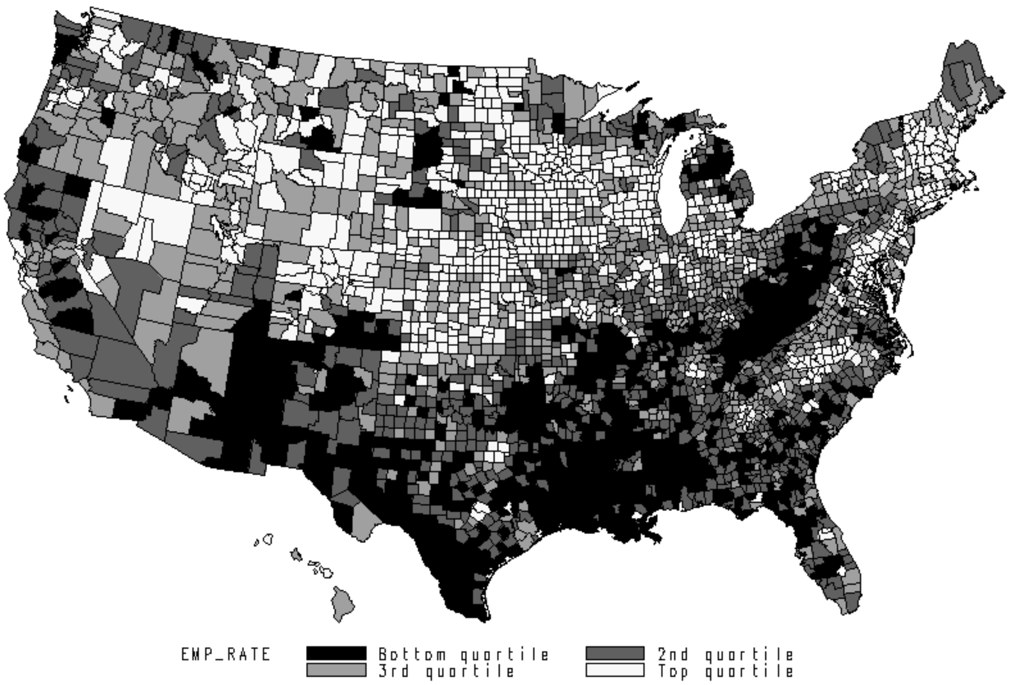
Note: Figures calculated using probit coefficients from Table 4.

Table 9. Distribution of imputed hourly wage outcomes across counties: 1996

	Women who did not complete high school			Women who completed high school			Men who did not complete high school			Men who completed high school		
	white age 30	black age 30	white age 18	white age 30	black age 30	white age 18	white age 30	black age 30	white age 18	white age 30	black age 30	white age 18
Mean	4.12	3.74	3.00	4.62	3.94	3.17	7.12	5.32	4.43	9.64	7.44	5.57
95th percentile	5.47	4.96	3.97	6.44	5.50	4.43	9.40	7.03	5.85	12.22	9.44	7.06
90th percentile	5.07	4.60	3.69	5.98	5.10	4.10	8.57	6.41	5.34	11.37	8.78	6.57
75th percentile	4.48	4.06	3.25	5.15	4.39	3.54	7.65	5.72	4.77	10.33	7.98	5.97
50th percentile	4.01	3.63	2.91	4.49	3.83	3.09	6.88	5.14	4.29	9.47	7.31	5.47
25th percentile	3.65	3.31	2.65	3.97	3.39	2.73	6.37	4.76	3.97	8.69	6.71	5.03
10th percentile	3.34	3.03	2.43	3.47	2.96	2.38	5.93	4.43	3.69	8.17	6.31	4.73
5th percentile	3.11	2.82	2.26	3.14	2.68	2.16	5.69	4.26	3.55	7.82	6.04	4.52

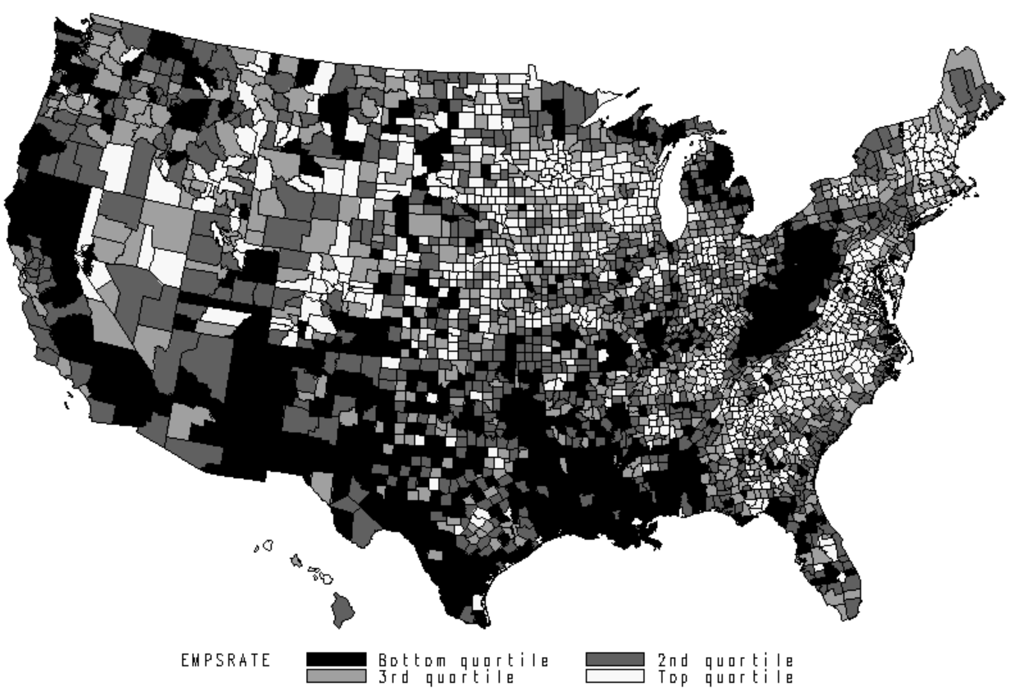
Note: Figures calculated using regression coefficients from Table 5.

Figure 1. Civilian employment in U.S. Counties: 1989



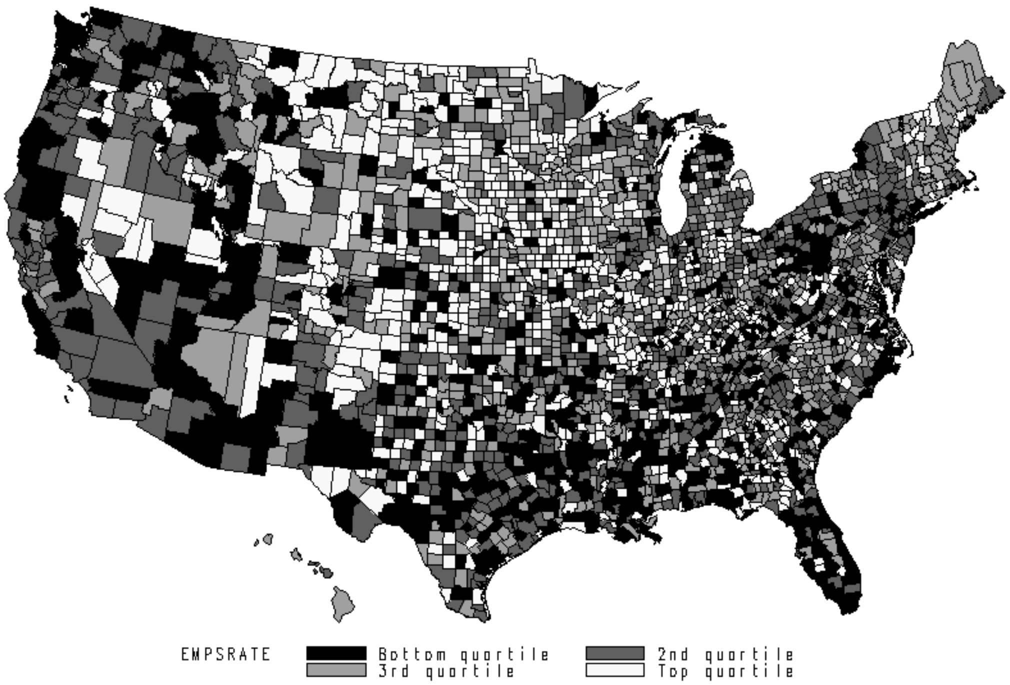
County estimates computed from non-allocated SEDF data.

Figure 2. Employment among female high school graduates: 1989



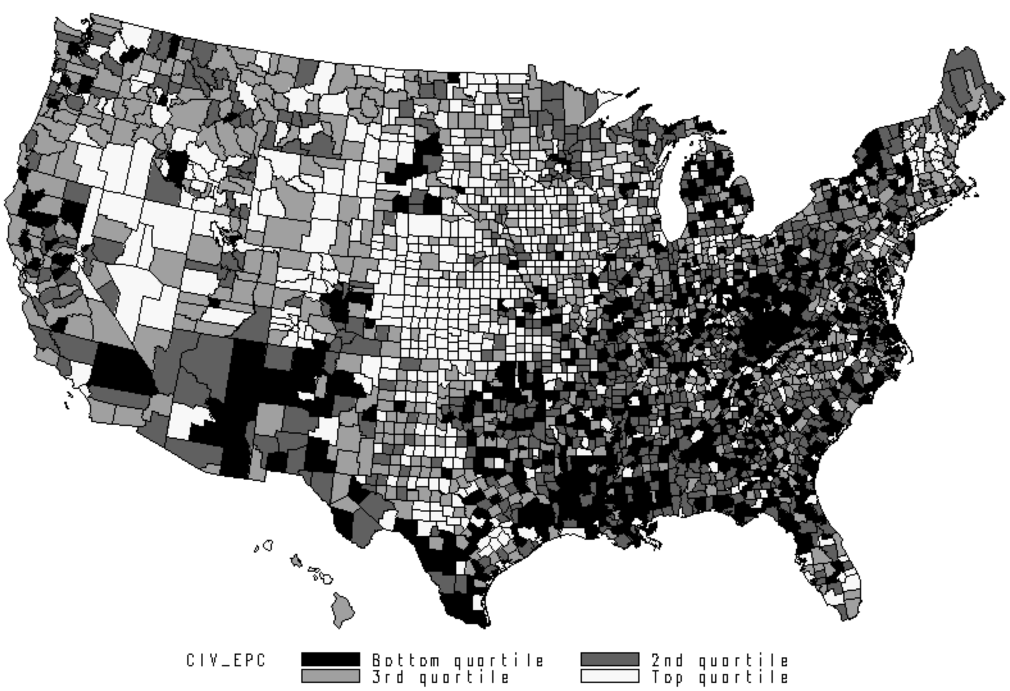
County estimates computed from non-allocated SEDF data.

Figure 3. Employment among female college graduates: 1989



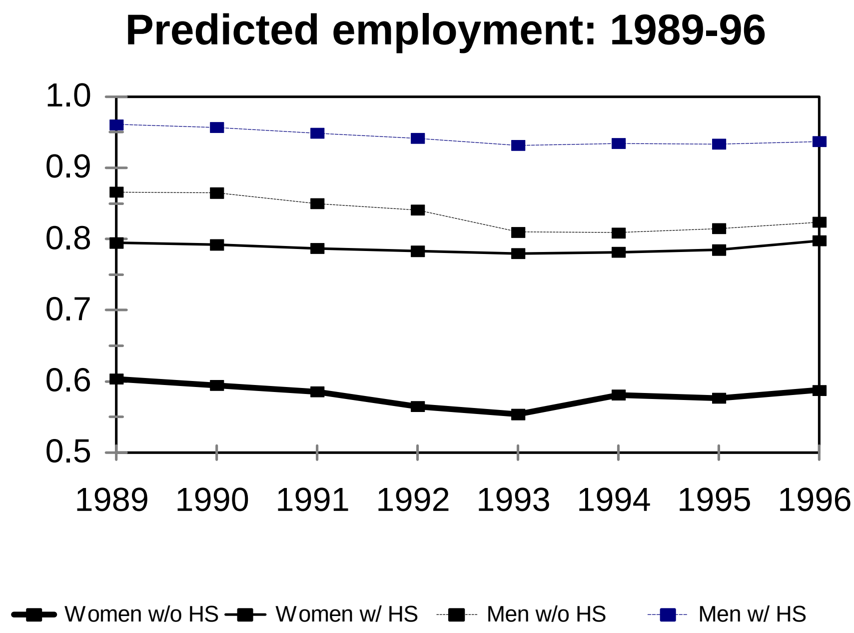
County estimates computed from non-allocated SEDF data.

Figure 4. Civilian employment on a place-of-work basis: 1989



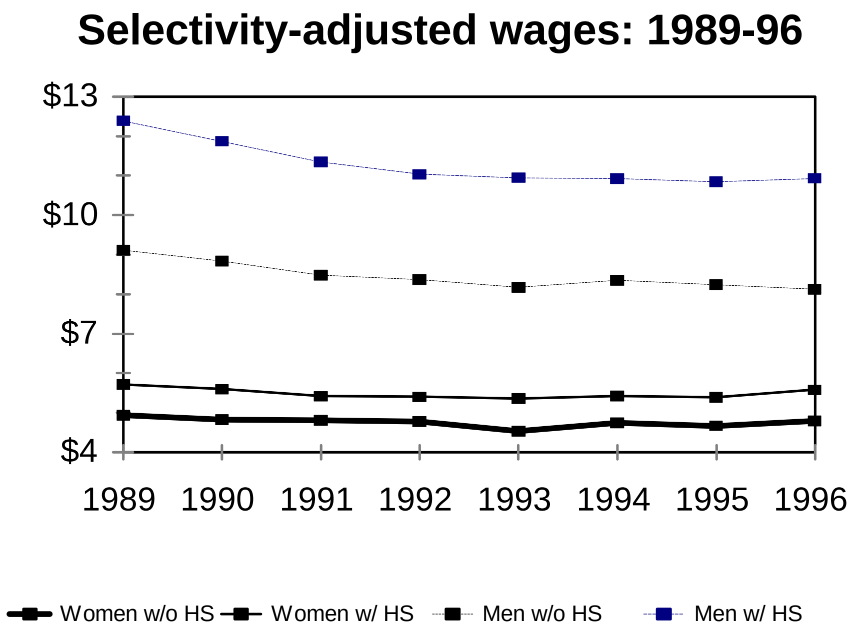
County employment data from REIS.

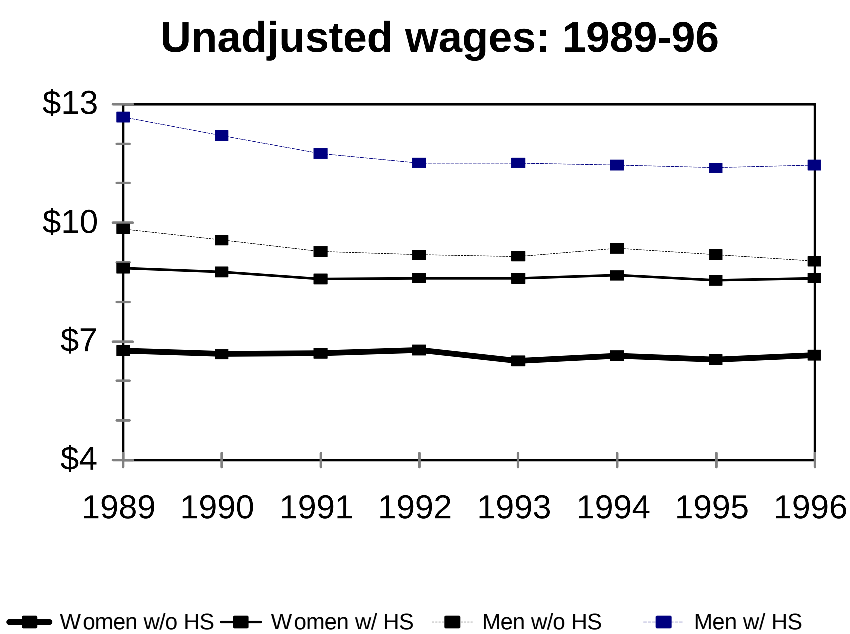
Figure 5. Trends in imputed employment: 1989-96



Note: Figures based on population-weighted averages across counties using probit coefficients from Table 4 calculated for 30 year-old, non-Hispanic, whites.

Figure 6. Trends in imputed wage measures: 1989-96





Note: Figures based on population-weighted averages across counties using regression coefficients from Table 5 and similar models without selectivity corrections calculated for 30 year-old, non-Hispanic, whites.

Figure 7. Trends in imputed employment for selected counties

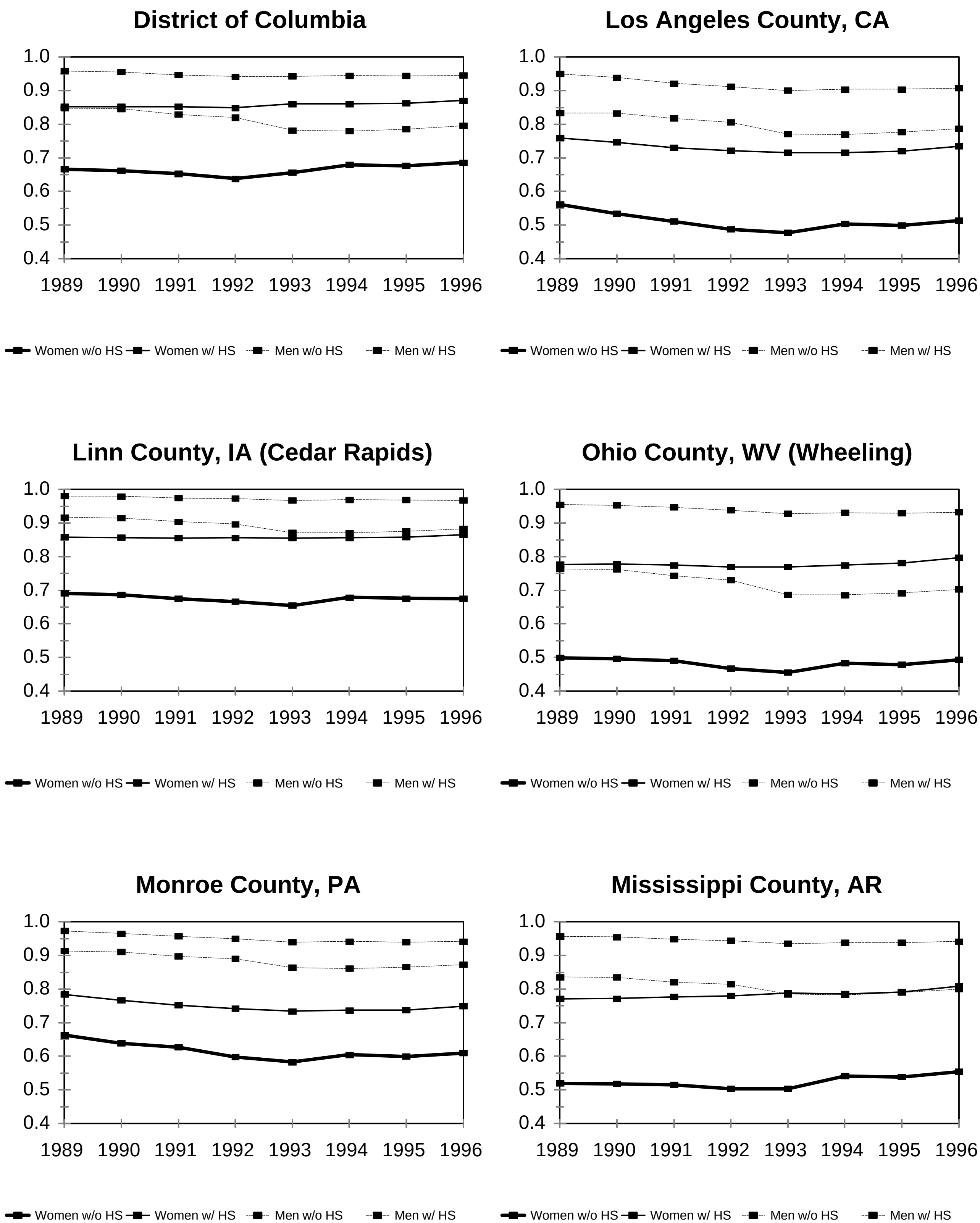
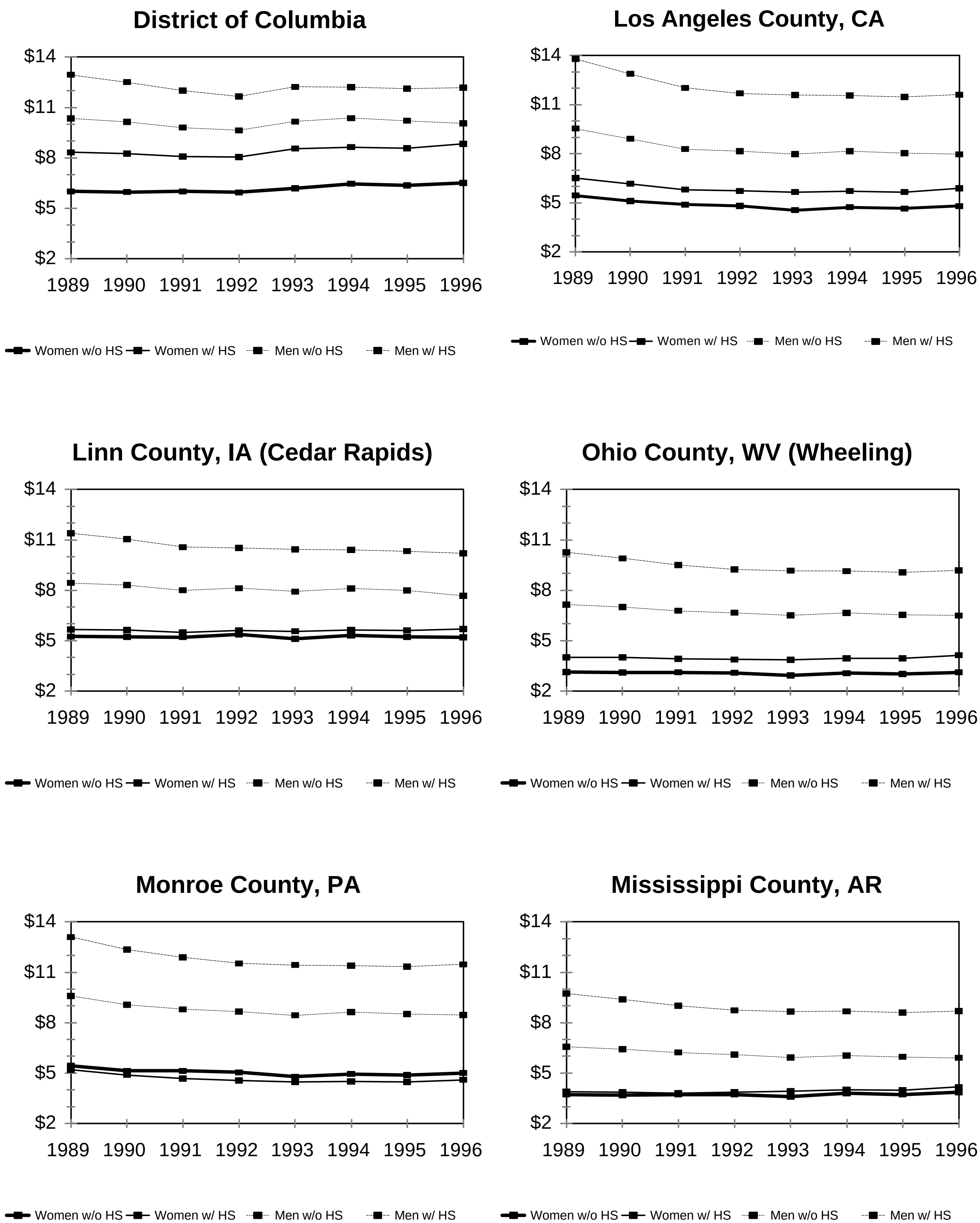


Figure 8. Trends in imputed wages for selected counties



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Appendix A. Means and standard deviations of analysis variables

	Women		Men	
Variable	without HS	with HS	without HS	with HS
Hourly earnings [A]	9.293	10.860	13.298	15.639
	(9.820)	(9.139)	(11.620)	(11.284)
Weekly earnings [A]	322.349	386.403	538.595	658.902
	(331.531)	(311.254)	(436.483)	(441.101)
Employed last year?	0.433	0.666	0.718	0.884
	(0.496)	(0.472)	(0.450)	(0.320)
Estimated skill-specific employment	0.053	0.124	0.085	0.133
in county ($\hat{M}(s,r,t)$)	(0.016)	(0.030)	(0.032)	(0.042)
Employment per working age	0.802	0.805	0.802	0.803
adult in county (unadjusted)	(0.241)	(0.211)	(0.233)	(0.207)
Maximum AFDC benefits for family	495.417	501.867	499.393	503.146
of 3 with no other income in state	(216.138)	(193.088)	(214.661)	(192.870)
Minimum wage in state	4.644	4.615	4.647	4.618
	(0.425)	(0.377)	(0.425)	(0.378)
Age	41.820	39.388	40.515	37.387
	(14.377)	(13.077)	(14.537)	(12.688)
African origin	0.163	0.099	0.139	0.092
	(0.370)	(0.298)	(0.346)	(0.289)
Hispanic origin	0.193	0.058	0.197	0.061
	(0.395)	(0.233)	(0.397)	(0.240)
Other non-white origin	0.139	0.048	0.132	0.049
	(0.346)	(0.215)	(0.338)	(0.216)
Observations	930,276	1,805,308	884,160	1,497,090

Note: Data from combined SEDF and CPS files. Standard deviations appear in parentheses. Estimates use files' sampling weights.

[A] Calculated only for workers.