Essays on the Youth and Low-Skilled Labor Market

by

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B.S., Industrial and Labor Relations, Cornell University (2003)

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Abstract

This dissertation consists of three chapters on the youth and low-skilled labor markets.

In Chapter 1, I show that teen employment is significantly more responsive than adult employment to immigration, and that growth in low-skilled immigration appears to be a partial explanation for recent declines in teen employment rates. Using variation in immigrant shares across metropolitan areas between 1980 and 2000, I demonstrate that the impact of immigration on youth employment is at least twice as large as the impact on adults, and that immigration affects school enrollment decisions and the type of jobs held by native youth. These effects are strongest for black youth and youth from poorer and less educated families. The estimates suggest that a 10 percentage point increase in the immigrant share of a city's low-skilled population reduces the teen employment rate by 5 percentage points, implying that between one-third and one-half of the fall in teen employment between 1990 and 2005 can be explained by increased immigration.

In Chapter 2, co-authored with David H. Autor and Alan Manning, we offer a fresh analysis of the effect of state and federal minimum wages on earnings inequality over 1979 to 2007, exploiting substantially longer state-level wage panels than were available to earlier analyses as well as a proliferation of recent state minimum wage laws. We obtain identification using cross-state and over-time variation in the 'bite' of federal and applicable state minimum wages, as per influential studies by Lee (1999) and Teulings (2000, 2003). Distinct from this work, we use statutory minimum wages as instrumental variables for the bite of the minimum wage, thereby purging simultaneity bias stemming from errors-in-variables, which we hypothesize causes upward bias in prior OLS estimates. While we uphold the finding that the minimum wage reduces inequality in the lower tail of the wage distribution, we estimate that earlier OLS models overestimate this impact greatly—by 150 to 450 percent. Models purged of simultaneity bias indicate that the minimum wage explains at most one-third of the rapid rise in inequality during the 1980s, and a comparable share of the more modest subsequent rise. These impacts are still larger than would be implied by a simple mechanical application of the minimum to the distribution, suggesting spillovers. We identify these spillovers by structurally estimating the latent wage distribution, calculating the mechanical effect of the minimum wage through truncation, and inferring spillovers by comparison of the mechanical and observed distributions. Spillovers account for one-third to one-half of the minimum's modest impact on percentiles in the lower tail of the wage distribution. Their magnitude has declined in parallel with the direct effects of the minimum, though their share of the total effect has risen.

In Chapter 3, I explore the extent to which polarization in the adult labor market—i.e. a gradual increase in the share of adults working in the highest and lowest paying occupations, caused by technology-induced (computers) changes in labor demand—has impacted youth employment. I show that, since 1980, teen employment rates fell more in states and commuting zones for which the share of adults in low-paying occupations increased the most. I also find that this measure of polarization is strongly associated with lower teen and low-skilled adult wages, and more weakly associated with lower employment rates for low-skilled adults. These results can be rationalized in a model of local labor markets for which a reduction in the price of computing capital reduces labor demand for middle-income, routine-task intensive (manufacturing) jobs, pushing these workers into lower-paying service jobs. This chapter therefore provides evidence that a portion of the recent decline in youth employment is attributable to a reduction in labor demand for youth, due to an increase in the supply of substituable labor (i.e. the gradual movement of less-educated adults from middle-paying to lower-paying occupations).

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Chapter 1

"Dude, Where's My Job?" The Impact of Immigration on the Youth Labor Market

1.1 Introduction

The summer employment rate for high school-aged teenagers fell by over ten percentage points between the early 1990s and 2005. No other age group experienced such a dramatic decline in employment over this period. Declining teen employment rates have frequently been discussed by the press and policy communities[1], but there is little research exploring the causes of this trend. Potential explanations for this decline include growth in the use of high stakes testing and exit exam requirements (Smith 2008), greater labor market competition from other less-skilled workers such as immigrants and single mothers, and increased emphasis on high school and college education (Aaronson, Park and Sullivan 2006). Understanding why youth are less likely to work is important because some explanations (increased schooling) suggest that lost work experience is replaced with other forms of human capital, while other explanations (greater competition from low-skilled workers) do not necessarily have this implication.

The recent, large influx of less-educated and younger adult immigrants might seem to offer

[1] For example, Bureau of Labor Statistics 2002 and Sudeep Reddy, "Teen Behavior Offers Clue To Why Jobless Rate Stays Low Despite Slowing Growth", *The Wall Street Journal,* June 18, 2007.

a potential explanation, but previous research generally estimates a small to modest impact of immigration on native adult low-skilled employment (Altonji and Card 1991 and Card 2001). Extrapolating from this existing evidence, one might conclude that the effect of immigration on teen employment is also minimal. Nevertheless, the actual youth employment response may be quite different than the adult response. On one hand, since adult low-skilled immigrants typically have more work experience than native teens, they may work in jobs that are less common among youth—so immigration may have an even smaller effect on teen employment than it does on adult employment. If there is some degree of labor market competition between immigrants and teens, however, youth labor supply may be more responsive to immigration because teens have fewer financial constraints that necessitate their labor income, teens can substitute time from labor to schooling and class work in addition to leisure, and teens' job search is more geographically constrained.

This paper analyzes the effects of immigration on teen employment outcomes and the type of jobs held by youth, and considers why these effects may differ between teens and adults, and within the youth population. Using Census microdata, I identify the impact of low-skill immigration on labor market outcomes for youth age 16 and 17 using variation in immigrant concentration across 100 Metropolitan Statistical Areas (MSAs) between 1980 and 2000. I compare these estimates to similar estimates for adults. To overcome the potential endogeneity of immigrant geographic concentration, I implement an empirical strategy commonly used in the literature by instrumenting the immigrant share of the city's population with a measure of predicted immigrant shares, where predicted shares are based on the geographic distribution of pre-existing immigrant stocks in 1970.

The paper has two key findings. First, I show that low-skilled immigration has a stronger effect on the employment rate of teens than on the employment rate of less educated adults: a 10 percentage point increase in the immigrant share of the low-skilled population (which is slightly larger than the average increase across cities between 1990 and 2000) reduces the percentage of teens employed in the reference week by 4.8 percentage points. This is over three times the percentage point effect for adults, and the difference is even larger relative to baseline employment rates. I estimate that the number of employed low-skill native adults falls by 12 and the number of employed native youth falls by 4 for every 100 low-skilled immigrants that enter an MSA, so excluding youth from the analysis significantly underestimates the employment impact of immigration. Employment effects of this magnitude explain some—but not all—of the fall in teen employment since the mid-1990s. Differences in labor supply elasticities can partially explain why immigration effects are larger for youth than adults.

The second major finding is that immigration has larger disemployment effects relative to baseline employment rates on native youth who come from poorer families or are minorities. These are populations with traditionally low employment rates, and a considerable amount of research attention has been devoted to documenting and explaining lower employment for black youth in particular (Freeman and Holzer 1986; Ihlanfeldt and Sjoquist 1998). I show that the employment effects of immigration are proportionately larger for these youth partially because they are more likely to live in urban centers, which is also where low-skilled immigrants are most concentrated. I also demonstrate that school enrollment rates for these populations increase slightly in response to immigration.

Only two recent studies examine the effect of immigration on youth outcomes. Aaronson, Park and Sullivan (2006) consider an extensive set of explanations for recent declines in youth employment. They test immigration as a cause by extending the Mariel boatlift analysis from Card (1990) to the youth labor market, and find that teen employment rates in Miami increased *more* than they did in comparable cities after the arrival of many low-skilled Cuban immigrants. Although this evidence is suggestive, it comes from a single case study, and average immigration effects across all cities may be different. Sum, Harrington, and Kathiwada (2006) uses 2003 American Community Survey data to estimate the cross-state relationship between the relative size of immigrant inflows into a state and employment rates for young natives (age 16-24). They find that a 1 percentage point increase in a state's population due to immigration is associated with a 1.2 percentage point reduction in the employment rate for young adults. Since this is a point-in-time relationship, it may not represent a causal estimate of immigration effects in a state over time.

The paper proceeds as follows. Section 1.2 describes the data I use for this analysis, and provides a brief description of trends in teen employment. Section 1.3 demonstrates that youth employment is more responsive than adult employment to immigration, and shows that larger labor supply elasticities for teens in combination with a binding minimum wage can explain the sizeable employment effects. Section 1.4 demonstrates that employment effects are proportionally larger for youth from less advantaged backgrounds, and tests explanations for this finding. Section 1.5 concludes by estimating the contribution of immigration to recent youth employment trends, and discussing welfare consequences of immigration on the youth population.

1.2 Data

My empirical analysis uses 1970, 1980, 1990, and 2000 Public Use Microdata Samples (PUMS) from the Decennial Census. Immigrant shares for an MSA are derived from the 1980, 1990, and 2000 5 percent samples. Following the literature, an individual is categorized as an immigrant if he or she reports being born abroad and being either a naturalized citizen or a non-citizen. Natives are all other individuals, regardless of their parents' citizenship status. Throughout most of the analysis, I instrument immigrant shares in 1980, 1990, and 2000 with a measure of predicted immigrant shares, where predicted shares are based on native and immigrant stocks in 1970 (as explained further in section 1.3.2). Immigrant and native stocks in 1970 are derived from the 1 percent Form 1 Metro and State samples. For some specifications, I also include the 2005 American Community Survey (ACS)[2].

Natives age 16 and 17 are the primary population of interest in this analysis. A key reason to focus on this population is that the fall in employment since 1990 is largest for this age group (Figure 1.1). Younger ages cannot be included, since employment status in the Census is not asked of individuals less than 16 years old. I exclude 18 year olds, because the primary focus of this research is on the labor market impact of immigration for those still in school and some 18 year olds may have graduated (or have been eligible to do so) by the time of the Census. The data appendix provides further details on sample selection and the construction of wage measures from the Census.

Figure 1.1 displays trends in the average annual employment rate for teen and low-skilled adults. Until the mid-1990s, youth and adult employment rates trended together, and adult

[2]The ACS has been administered annually by the Census Bureau since 2000, and generally asks the same questions as the Census Long Form. However, the survey is administered throughout the year, and public use data does not include a monthly identifier. As a result, I do not pool Decennial Census and ACS data in my primary specifications when considering outcomes with seasonal variability, such as employment or school enrollment probabilities in the previous week. I include 2005 ACS data in some robustness checks.

employment rates exceeded youth rates by about 30 percentage points. The tight labor market of the late-1990s was characterized by rising adult employment, yet over these years teen employment rates remained stable at about 35 percent. Hence, teen employment began falling relative to adult employment in the mid-1990s. Although youth employment participation is highly seasonal, declining employment occurred during both the summer and non-summer months (Figure 1.2). Employment participation and wages are higher for non-blacks and teens from more highly educated or wealthier families (Appendix Table 1.A1), though trends in the employment-population rate are comparable across all categories of youth over this period[3].

Throughout this paper, immigration effects are estimated using variation in immigrant concentration across 100 Metropolitan Statistical Areas (MSAs). Individuals from the 100 MSAs with the largest average population size between 1970 and 2005 and which are consistently coded over all decades are included in the analysis. Immigrants are highly clustered in cities: over 70 percent of all low-skilled immigrants live in these MSAs. Table 1.1 displays low skilled immigrant shares for the included MSAs that have the highest and lowest immigrant shares in 1980. Two facts stand out. First, by 2000 immigrants make up over half of the low skilled adult population for the majority of the high immigrant MSAs. Second, the locational pattern of immigration changes across decades. Between 1980 and 1990, new immigrants tended to go where old immigrants had already settled, and so the immigrant share in high immigrant MSAs increased more than it did in areas that had fewer immigrants. After 1990, immigrants began settling in different areas - for instance, the low skilled immigrant share increased from 1.5 to 10 percent in Greensboro between 1990 and 2000.

The younger and less educated immigrant population has grown substantially in size since 1990 (Figure 1.3). Given somewhat similar levels of education and work experience, it is plausible that this group of immigrants may compete with native youth in the labor market. As shown in Table 1.2, there is some overlap in occupations common among low-skilled immigrants and youth. Male youth and low skilled adult immigrants tend to be cooks, stock handlers, and janitors, while female youth and adult immigrants tend to be cashiers and saleswomen.

[3] Graphs available upon request.

1.3 Labor Market Impact of Immigration

1.3.1 Empirical Strategy and OLS Estimates

To estimate the impact of immigration on natives, I regress labor market outcomes for natives on a measure of low-skilled immigrant concentration for MSA c in year t, individual-level controls, and MSA and year fixed effects. Potential measures of immigrant concentration include the log of the low-skilled immigrant stock, the ratio of low-skilled immigrants to natives, and the immigrant share of the low-skilled population. Converted into the impact of one more immigrant into an MSA on the number of employed natives, the immigration effects that I estimate are similar regardless of how immigrant concentration is measured. Following much of the literature (Altonji and Card 1990; Borjas 2003, 2005; Ottaviano and Peri 2006), I use immigrant shares as the primary regressor of interest, where shares are defined as $\frac{I_{ct}}{I_{ct}+N_{ct}}$ and I_{ct} and N_{ct} are low-skilled immigrant and native adult stocks, respectively[4].

Figures 1.4A and 1.4B illustrate the main empirical result of this section. There is a strong negative relationship between changes in the low-skilled immigrant share of an MSA and changes in the youth employment rate of an MSA between 1980 and 2000. The relationship between changes in low-skilled immigrant shares and adult employment rates is much weaker.

The primary empirical specification for this analysis is:

$$y_{ict} = \gamma P_{ct} + \beta X_i + \alpha_c + \alpha_t + \varepsilon_{ict} \tag{1.1}$$

The regressor of interest, P_{ct}, is the immigrant share of the low skilled population in MSA c and year t as defined above. The dependent variable y_{ict} is one outcome from a set of labor market outcomes reported in the Census, including a dummy for employed last year, a dummy for employed last week, and hours worked in the last year (defined as weeks worked multiplied by usual hours worked per week). Individual-level controls (X_i) are age, age squared, race dummies, and gender dummies. Results from OLS estimates of γ in equation (1.1), separately

[4]Borjas (2003) and (2005) argue that estimated immigration effects tend to be larger when using national variation in immigrant concentration within education-experience groups, and that estimates are smaller in magnitude when geographic variation is also introduced. Since teens represent a single education-experience group, I am unable to estimate immigration effects using only national-level variation. However, the employment effects that I estimate for low-skilled adults using geographic and time variation are quite similar to what Borjas finds for this population using only variation in immigrant concentration in national experience cells over time.

for native teens and low-skilled adults, are shown in Table 1.3.

OLS estimates of (1.1) suggest that immigration has a large negative effect on teen employment outcomes. A 10 percentage point increase in the low-skilled immigrant share of the population is estimated to reduce the proportion of teens employed in the reference week by 4.6 percent, the proportion employed in the last year by 5.2 percent, and annual hours worked (unconditional on employment) by 33. For comparison, the low-skilled immigrant share of an MSA increased on average by 8 percentage points between 1990 and 2000. The estimated magnitude of these effects is at least three times as large as adult estimates, depending on the outcome variable considered.

1.3.2 Instrumental Variables Estimates

Empirical Strategy

OLS estimates of γ might not represent a causal effect of immigration on native outcomes if immigrant concentration is endogenous to native labor market conditions. In particular, if immigrants decide to settle in areas that experience positive local labor market shocks, and if the true γ is negative, then $\hat{\gamma}$ will be biased towards zero and OLS estimates will be smaller in magnitude than the causal effects.

As a solution to bias from endogenous immigrant migration, I instrument immigrant shares with a measure of predicted shares ($\hat{P}$). Predicted shares are derived by predicting immigrant inflows to an MSA from the geographic concentration of immigrants in 1970, which is a commonly used instrument for immigration stocks[5], and from predictions of native stocks absent interstate migration.

The prediction of immigrant inflows is based on the idea that immigrants tend to settle in areas where a larger share of their ethnic group (home country) have previously settled. Let $\hat{F}_{ct,1970}$ represent the predicted low skill immigrant inflows into MSA c between years 1970 and t (where $t \geq 1980$). Then:

$$\hat{F}_{ct,1970} = \sum_{o} F^{o}_{t,1970} \frac{I^{o}_{c,1970}}{I^{o}_{1970}} \tag{1.2}$$

[5] A variant of this instrumental variable strategy was proposed in (Altonji and Card 1991), and has been implemented in (Card 2001), (Lewis 2003), (Cortes 2006a), (Lewis 2006), and (Peri and Sparber 2007), among others.

where $F^o_{t,1970}$ is the flow of all low-skilled immigrants into the United States from originating country o between 1970 and t, and $\frac{I^o_{c,1970}}{I^o_{1970}}$ is the share of all immigrants from country o that lived in MSA c in 1970[6]. Hence, $\hat{F}$ assigns incoming low-skilled immigrants from a specific country into a city based on the geographic density of immigrants in 1970. Predicted low-skilled immigrant stocks in MSA c at time t are then:

$$\hat{I}_{ct} = I_{c,1970} + \hat{F}_{ct,1970} \tag{1.3}$$

where $I_{c,1970}$ is the actual stock of immigrants in 1970.

To form an estimate for native stocks that is purged of migration responses to immigration, I define predicted native low skill stocks in the absence of native migration, $\hat{N}_{ct}$, in the following way:

$$\hat{N}_{ct} = \sum_{64}^{a=18} N^{a-(t-1970)}_{c,1970} \frac{N^a_t}{N^{a-(t-1970)}_{1970}} \frac{LS^a_t}{N^a_t} \tag{1.4}$$

where $N^a_{c,t}$ is the native stock (unconditional on education) of age a in state c in year t. LS^a_t is the size of the low skill native population age a in t. The first term inside the summation represents the size in 1970 of the cohort that is age a in MSA c in t. The second term inside the summation represents the national change in population size between 1970 and t for the cohort that was age a in t (i.e. the survival rate between 1970 and t). The last term is the national share of the cohort age a in t that is low-skilled. $\hat{N}_{ct}$ is the predicted size of the native low skill state adult population in year t if there had been no out of city migration, if the survival rate for each age cohort within an MSA followed the national survival rate, and if the native population did not adjust educational attainment in response to MSA-specific factors (i.e. constraining the low-skilled share of the native labor force to be constant across MSAs)[7].

[6] I divide the set of all possible originating countries into 15 country groups based on geography (group categories available upon request).

[7] This formula is not implemented exactly as written, since age cohorts less than 20 in 1990 and 30 in 2000 were not alive in 1970. To compensate, cohorts of age a for which stocks cannot be predicted in year t are assigned population sizes based on the size of the population aged $a - 10$ in $t - 10$ multiplied by the national survival rate between t and $t - 10$ for the age cohort. For instance, 18 and 19 year olds in 1990 were not alive in 1970, so to predict their population size absent migration, the size of the 8 and 9 year old MSA cohorts in 1980 is multiplied by the national empirical survival rate for this age cohort between 1980 and 1990.

Predicted immigrant shares are then:

$$\hat{P}_{ct} = \frac{\hat{I}_{ct}}{\hat{I}_{ct} + \hat{N}_{ct}} \tag{1.5}$$

For $\hat{P}_{ct}$ to be a valid instrument, it must be correlated with P_{ct}, and conditional on controls, must affect native labor market outcomes only through its effect on actual immigrant shares. This exclusion restriction will be violated, for instance, if immigrants in 1970 chose their location based on local labor market shocks which took decades to diminish. These shocks would induce city-year specific variation in labor market outcomes after 1970 that would not be absorbed by the separate city and year fixed effects in (1) (and would therefore be contained in ε_{ict}), and would be correlated with $\hat{P}_{ct}$.

If variation in 1970 immigrant dispersion is due to persistent but *stable* differences in local labor market conditions, this will not violate the exclusion restriction because such variation will be absorbed by MSA fixed effects. The exclusion restriction will not be violated if immigrants in 1970 are attracted to areas that experience positive labor market shocks in 1970 which dissipate by 1980. Empirical evidence from (Blanchard and Katz 1992) on the persistence of state-level employment and wage shocks suggests the impact of temporary labor market shocks disappears within about 10 years. Additionally, most results are robust to the inclusion of Census region dummies interacted with year dummies, so the exclusion restriction holds even if immigrants are attracted to *regions* of the country which have positive labor market shocks in 1970 that diminish over time.

Table 1.4 displays estimates from various city-level analogs to the first stage equation of the following form:

$$w_{ct} = \delta \hat{w}_{ct} + \theta_c + \theta_t + v_{ct} \tag{1.6}$$

where w_{ct} and $\hat{w}_{ct}$ represent actual and predicted immigrant stocks (panel A) native stocks (panel B) and immigrant shares (panel C). All estimates are weighted by the size of the low-skilled population, and standard errors are clustered at the MSA level.

The relationship between predicted and actual immigrant stocks, native stocks, and immigrant shares is strong (column 1). Actual immigrant stocks are somewhat underpredicted by the predicted stock variable, actual native stocks are overpredicted by predicted native stocks, and actual immigrant shares are somewhat underpredicted. The strength of the relationship between actual and predicted immigrant stocks implies that the first stage relationship between actual and predicted shares—which is used for 2SLS estimation—is not driven solely by native stocks. The first stage relationship is robust to the exclusion of the earlier and later decade of data (columns 2 and 3), the inclusion of Census region/year fixed effects (column 4), and the inclusion of a large set of time-varying MSA controls[8] (column 5). Excluding the three high-immigrant states has very little effect on the magnitude of the first stage relationship (column 6).

Finally, one would be concerned about the validity of the instrument if the majority of an ethnic group settles in one state, so that national inflows are driven by state inflows for that particular group[9]. Column 7 tests the robustness of the first stage relationship to this concern by constructing $F^{o}_{t,1970}$ as the inflow of immigrants into all areas other than city c, recalculating predicted immigrant stocks, and reestimating (1.6). The strength and magnitude of the first stage is robust to this specification.

As in previous studies (Card 2001 and Cortes 2006a), I find that the size of the native low skilled population in an MSA is relatively unresponsive to changes in immigration. To demonstrate this, I run the following regression at the MSA level using Census data from 1980-2000, instrumenting the log of the low skilled immigrant stock with the log of the predicted low skilled immigrant stock:

$$\log N_{ct} = \beta \log I_{ct} + \alpha_c + \alpha_t + v_{ct} \tag{1.7}$$

β is estimated to be -.04 with a standard error (clustered at the MSA level) of .14. Hence, there is no evidence to suggest that the size of the native low skilled population responds to immigration growth, and so changes in P_{ct} can be interpreted as coming mainly from changes in the size of the immigrant population rather than from a combination of immigrant inflows and native outflows.

[8] These controls are the average age of the native population, and the share of the native population that is: black, male, high school dropouts, and college graduates.

[9] For instance, 27% of Mexican immigrants lived in Los Angeles in 1970. If the L.A. labor market experiences a positive shock between 1970 and 1980 and consequently attracts Mexican immigrants, then predicted Mexican inflows to L.A. will be somewhat driven by actual inflows (this is because inflows to L.A. represent a large share of national inflows). In this case, predicted inflows will be positively related to local labor market conditions, violating the exclusion restriction.

Instrumental Variables Estimates

Table 1.5 presents instrumental variables estimates of (1.1). In all instances, estimated employment effects are larger in magnitude than OLS estimates from Table 1.2, but the difference between OLS and IV results is not large. This suggests that the potential endogeneity of immigrant shares is not a significant source of bias[10]. IV estimates imply that a 10 percentage point increase in the low-skilled immigrant share of the population reduces teen weekly employment rates by 4.8 percentage points, teen annual employment rates by 5.5 percentage points, and the average total number of hours worked in a year by 29. Employment effects for teens remain at least three times as large as estimated adult effects, and the difference is even larger relative to baseline employment rates[11].

How many native adults and teens are displaced from employment for every additional low-skilled immigrant? To answer this question, I convert estimates of the relationship between immigrant shares and native weekly employment rates (column 1 of Table 1.4) into the implied impact of one additional low-skilled immigrant on the number of employed native teens and adults in an MSA[12]. Teens form about 2 percent of the employed native low-skilled population, so if teen displacement from immigration is proportional to the share of teens in the employed native population, and if there is perfect (one-for-one) displacement between immigrants and natives, 100 additional immigrants would reduce the number of employed low-skilled adults by 98 and the number of employed teens by 2. Put differently, 2.04 employed teens would become unemployed for every 100 employed adults who lose their jobs due to immigration.

I estimate that for every additional 100 low-skilled adult immigrants that enter an MSA,

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[10] In specifications that use $\log I_{ct}$, the difference between OLS and IV results is more significant. I show this in section 1.3.3.

[11] Adult employment effects are no larger than previous estimates in the literature. For instance, (Borjas 2003) estimates that a 10 percentage point increase in the immigrant share of the high school dropout population reduces the number of weeks worked in the year by about .4 weeks (weeks worked is the only employment outcome reported in Borjas 2003). In unreported results, I estimate that immigration growth of this size reduces the number of weeks worked for this adult population by .6 weeks and reduces the number of weeks worked for teens by 1.6 weeks.

[12] I use the following calculation: $\frac{\partial L^g_{ct}}{\partial I_{ct}} = n^g_{ct} \frac{\partial EMP^L_{ct}}{\partial P_{ct}} \frac{\partial P_{ct}}{\partial I_{ct}}$, where $\frac{\partial L^g_{ct}}{\partial I_{ct}}$ is the impact of one additional low-skilled immigrant in a city on the number of employed natives of group g (either low-skilled adults or teens), n^g_{ct} is the size of group g in city c in year t, $\frac{\partial EMP^L_{ct}}{\partial P_{ct}}$ is the immigration effect estimated in column 1 of Table 1.4, and $\frac{\partial P_{ct}}{\partial I_{ct}} = \frac{N_{ct}}{(I_{ct}+N_{ct})^2}$. Using estimates of n^g_{ct} and $\frac{N_{ct}}{(I_{ct}+N_{ct})^2}$ from Census data, I calculate $\frac{\partial L^g_{ct}}{\partial I_{ct}}$ for each city-year, and average across cities and years.

the number of teens employed in the last week falls by 4 and the number of adults employed in the last week falls by 12, for a total of 16 displaced natives. Ignoring the effects of immigration on teens would reduce the estimated employment impact by one quarter of the actual impact. These estimates imply that about 33 teens are displaced for every 100 native adults who lose their jobs due to immigration. This is significantly larger than if the effect of immigration on the number of employed youth relative to adults equaled the youth share of the employed low-skilled population.

1.3.3 Robustness of Estimates

This section presents robustness checks of estimated annual employment effects for the teen population (Table 1.6). Panel A displays estimates from testing the robustness of the primary results to different specifications of the immigrant share variable. Estimates from Table 1.2 and 1.4 are repeated in columns 1 and 2 of panel A. Columns 3 and 4 include the immigrant share of the high skilled population as an additional regressor, where the high skilled population is defined over all adults with at least some college experience, and high skilled shares are instrumented with predicted high skilled shares (which are constructed with predicted high skill immigrant and native stocks). Low skilled immigration effects are, if anything, strengthened by the inclusion of high skilled immigrant shares, and the effect of high skilled immigration is imprecisely estimated[13]. Columns 5 and 6 replace the low skilled immigrant share with the log of the number of low-skilled immigrants (controlling for the log of the number of low-skilled natives). A 10 percent increase in the size of the low-skilled immigrant population, conditional on the size of the native low-skilled population, is estimated to reduce the proportion of teens employed in the last year by 1.6 percentage points. Compared to estimates using immigrant shares, these imply somewhat *larger* immigration effects[14].

[13]This is not due to a weak first stage; the coefficient on predicted high skill immigrant shares from the analog to (1.6) is .73 with a standard error of .05.

[14]Between 1980 and 1990, the immigrant share of an MSA increased by 6.5 percentage points on average, and the log of the number of low-skilled immigrants rose by .21 on average — each estimate implying that teen weekly employment rates were about 3.1 percentage points lower than they would have been in the absence of immigration growth regardless of how immigration concentration is measured. Between 1990 and 2000, similar calculations imply that, in the absence of changes in immigrant concentration, teen weekly employment rates would have been 4 percentage points higher. Had log immigrant stocks remained at their 1990 levels, teen employment rates are estimated to have been 9 percentage points higher.

Estimated employment effects remain sizeable in magnitude and precisely estimated when observations from 1980 or 2000 are excluded from the analysis, or when MSAs from the highest immigration states are excluded (panel B). Employment effects are larger in magnitude in the later period (column 2) than the earlier period (column 4). Excluding observations from the high immigration states has little effect on estimated employment effects (column 6).

In panel C, I address concerns that changes in predicted immigrant shares may be correlated with other time-varying MSA characteristics that also affect employment. Columns 1 and 2 add Census region dummies interacted with year dummies. Point estimates are quite similar to those in the original specification. Columns 3 and 4 report estimates from adding 2005 American Community Survey data to the analysis. Columns 5 and 6 add MSA-specific time trends as well. In this specification, a 10 percentage point increase in the low skill immigrant share is estimated to reduce the probability of teen employment by 3.7 percentage points, which, though less precisely estimated, is still an economically significant effect[15].

1.3.4 Immigration Effects by Age

Figure 1.5A provides striking visual evidence that the employment effects of immigration are concentrated among the youth. In this figure, I plot the coefficient on low-skilled immigrant shares, $\hat{\gamma}$, from estimating equation (1.1) independently for each age from 16 to 64. Again, the employment effects of immigration are strongest for the younger ages and diminish rapidly in magnitude through the late teens and early 20s, stabilizing around -.2 for individuals in their mid-20s through 50s, and declining in magnitude for older individuals.

One reason why the employment effects of immigration as estimated from equation (1.1) and presented in Table 1.5 are larger for teens than for 21-64 year olds may be because low-skilled immigrant populations are younger and hence more comparable in terms of work experience with

[15]Both OLS and IV estimates using MSA-specific time trends are smaller in magnitude than those which exclude time trends, though the difference between OLS estimates is larger than the difference between IV estimates. One explanation for this is that, after including time trends, much of the remaining variation in immigrant shares is measurement error. Consistent with this explanation, instrumenting for immigrant shares has a substantial impact on the estimated employment effects of immigration once MSA time trends are included. Point estimates from adding MSA-specific time varying controls (including the average age of the native population, and the share of the native population that is black, male, a high school dropout, and a college graduate) are quite similar to those from the initial specification.

youth[16]. In other words, the relationship between low-skilled immigrant shares and teen employment may be larger in magnitude than that between immigrant shares and the employment rate for 21-64 year olds because the age composition of the low-skilled immigrant population becomes younger between 1980 and 2000, rather than because native youth employment is more responsive to immigration from similarly experienced immigrants.

To test whether employment effects are larger for youth because youth are more responsive to immigration from immigrants of a similar age, I estimate the following for each age a from 16 to 24:

$$y_{ict}^{a} = \gamma^{a} P_{ct}^{a} + \beta X_i + \alpha_c + \alpha_t + \varepsilon_{ict} \tag{1.8}$$

This specification differs from that used to estimate Figure 1.5A since immigrant shares now vary *by age*. For natives of age a, P_{ct}^{a} is constructed as the immigrant share of the entire low-skilled population between ages $a-5$ and $a+5$ in city c and in year t[17], and P_{ct}^{a} is instrumented with predicted immigrant shares for that age group. This incorporates the idea that immigrants and natives with similar amounts of potential work experience should be most substitutable, and addresses the concern that estimated immigration effects on adults 21-64 were small because they aggregated younger adults with older adults who are unlikely to be affected by younger immigrants. I estimate (1.8) for ages 16 to 64 with 2SLS, and present the plot of $\hat{\gamma}^{a}$ by age in Figure 1.5B. Estimating immigration effects in this way only strengthens the conclusion from the previous section: the employment effects of immigration are significantly stronger for teens than for adults, and this is because teen employment is more responsive to immigration, rather than because the immigrant population tends to be more similar in experience to youth than to older workers[18].

[16] The average age of the low-skilled immigrant population of the country is 51 in 1980 and 42 in 2000.

[17] For individuals less than 21 years old, immigrant shares are calculated over ages 16 to 26.

[18] A 10 percentage point increase in the low-skilled immigrant share of one's 10 year experience group in his or her city is estimated to reduce the percent of teens employed in the last week by 8.3 percentage points and the percent of adults 21-64 employed in the last week by .5 percentage points.

1.3.5 Impact of Immigration on Type of Occupation

Native disemployment in response to immigration should be greater in occupations that are more common among immigrants. As an additional robustness check to my measure of immigrant concentration, in this section I test whether disemployment effects are smaller in occupations for which natives have a comparative advantage over immigrants—such as jobs that rely more heavily on English language skills, and verbal and interpersonal skills and abilities[19].

To define the level of English language skills, and communication skills and abilities required for a job, I use the US Department of Labor's Occupational Information Network (O*NET), which classifies the level (on a 1-7 scale) and importance (on a 1-5 scale) of various skills, abilities, activities, and required knowledge for over 800 occupations (of which around 300 can be matched with Census occupations). For each occupation, I define a communication skills index based on the normalized sum of the level and importance scores for a large set of relevant skills and abilities[20]. I then calculate each occupation's communication index percentile (ranging from 0 to 1) in the population-weighted distribution of all jobs, using the occupation distribution in 2000 and most recent skills classification from O*NET. As evidence that low-skilled immigrants are less likely to work in occupations that require stronger communication skills, the coefficient on communication percentile from an occupation-level regression of the 1980 share of immigrants in an occupation on communication percentile is -.37 and is significant at the 1 percent level. Occupations that have a high verbal percentile and are common among youth include secretaries, teacher's aides, and customer service representatives. Common low verbal percentile jobs for teens include gardeners, farm workers, and construction laborers.

[19] This is similar to analysis from (Cortes 2006b) and (Peri and Sparber 2007) for the native adult population. (Cortes 2006b) demonstrates that immigrants tend to work in occupations which require fewer verbal skills, and in response to immigration, the immigrant share of an occupation increases by more in jobs that are less English-intensive. She also shows that immigration has a more negative effect on the wages of natives in less English-intensive occupations. (Peri and Sparber 2007) shows that native labor supplied to manual tasks relative to native labor supplied to more interactive tasks (directing, controlling, planning) falls in response to low-skilled immigration within a state, suggesting that natives adapt to immigration by specializing in jobs for which they have a comparative advantage over immigrants.

[20] The communication index aggregates the level and importance scores for the abilities "oral comprehension," "oral expression," "written comprehension," "written expression," "speech clarity," and "speech recognition"; for the skills "speaking" and "active listening"; and for "knowledge of the English language." For each occupation, the level at which the skill is required is scored on a scale of 1-7, and the importance of the skill for the job is scored on a scale of 1-5. I normalize each level and importance score to 1, and for each occupation sum the level and importance scores for all 9 categories. The occupation's raw verbal score is this sum, and ranges from 0-18.

I estimate the following equation at the occupation-city-year level:

$$\log(\#\ employed)_{oct} = \gamma P_{ct} + \delta P_{ct} \cdot comm\ pctile_o + \theta_o + \theta_c + \theta_t + \varepsilon_{oct} \tag{1.9}$$

The dependent variable, $\log(\#\ employed)_{oct}$, is the log number of employed teens or employed low-skilled native adults in occupation o in MSA c in year t. Occupation o's rank in the communication skills and abilities distribution of all jobs, as described above, is $comm\ pctile_o$ and ranges from 0 to 1. The potentially endogenous variables in (1.9) are P_{ct} and $P_{ct} \cdot comm\ pctile_o$. I instrument for P_{ct} as before, and instrument for $P_{ct} \cdot comm\ pctile_o$ using $\hat{P}_{ct}$ and its interaction with $comm\ pctile_o$. Growth in the immigrant concentration of an MSA reduces employment in occupation o if $\gamma + \delta comm\ pctile_o < 0$, while $\gamma + \delta comm\ pctile_o > 0$ indicates that immigration growth causes employment *growth* in occupation o. If $\delta > 0$, employment declines are smaller (or employment gains are larger) in occupations which require more communication skills and abilities.

The number of employed teens in the least communication-intensive occupations ($comm\ pctile_o = 0$) are estimated to fall by up to 8.5 percent in response to a 10 percentage point increase in the low-skilled immigrant share of an MSA (Table 1.7). The number of employed native adults in these occupations is estimated to fall by 24 percent. Since $\hat{\delta} > 0$, employment declines are smaller in more communication-intensive jobs, and teen employment is estimated to *increase* in the most communication-intensive jobs in response to immigration. Growth in the immigrant concentration of 10 percentage points is estimated to increase the number of teens employed in the most communication-intensive occupations by about 1 percent[21]. Since native disemployment in response to immigration is smaller in occupations for which natives have a comparative advantage, this is additional evidence that native employment responds to changes in immigrant concentration.

[21] Although adult employment is estimated to fall more in percentage terms than teen employment for a given occupation, the overall employment effects on youth are still estimated to be larger. This is because a greater share of native teens are employed in jobs which require few communication skills.

1.3.6 Effect of Immigration on Wages

OLS and 2SLS Estimates of Immigration Effects on Wages

Why are the employment effects of immigration so much larger for teens than for adults? One explanation for this finding is that immigration reduces native wages and that teen labor supply is more responsive to changes in the wage. Reasons for this may include that teens have fewer financial constraints which necessitate their income[22], that teens have higher disutility of labor, and that teens can more readily substitute from labor to schooling as well as from labor to leisure.

To assess whether teens are more responsive to changes in the wage, I first estimate (1.1) with OLS and 2SLS for teens and low-skilled adults using log hourly wages as the dependent variable[23]. These estimates are presented in columns 1, 2, 4 and 5 of Table 1.7. A 10 percentage point increase in the low-skilled immigrant share of the population is estimated to reduce teen wages by 1.4 percent, and adult wages by .6 percent. These estimates are small in magnitude and imprecisely estimated—a common finding in studies that identify immigration effects from geographic variation in immigrant concentration (Card 2001, Cortes 2006). Combining these estimates with estimated employment effects from Table 1.5 implies implausibly large employment participation elasticities (over 3 for adults and over 8 for teens)[24].

Recent research provides some explanations for why the impact of immigration on the average adult wages in a local labor market is small. (Lewis 2006) and (2003) demonstrate that the choice of production techniques within industries—particularly, technology choice—is especially responsive to the size of the low skilled population. Thus, endogenous production decisions (i.e. heavier use of manufacturing techniques that more efficiently utilize low skilled labor) may mitigate the wage effects of immigration. However, these studies mainly focus on adjustments in manufacturing industries, which are smaller employers of youth than of low-

[22] Johnson and Lino 2000 provides evidence that a teen's labor income is used primary for his or her own personal use, rather than for contributing to household expenses.

[23] For these regressions, I also include the log of the state minimum wage and the following city level controls: the average age of the native population, and the share of the native population that is black, male, a high school dropout, and a college graduate.

[24] For instance, a 10 percentage point increase in the low-skilled immigrant share of the population reduces teen employment in the previous week by 4.82 percentage points from an average of 31.7 percent — or, by 15 percent. From 2SLS estimates, an immigration increase of this magnitude reduces teen wages by 1.4 percent. The ratio of these two effects (10.6) is an estimate of employment responsiveness to a change in the wage.

skilled adults or immigrants[25]. Peri and Sparber (2007) demonstrate that natives respond to immigration by moving to occupations for which they have a comparative advantage (such as jobs which require stronger verbal or interpersonal communication skills), and (Cortes 2006b) shows that the wage effects of immigration are smallest for natives who work in occupations for which verbal skills are more important. Hence, the observed effect of immigration on adult wages is mitigated because adults partially respond to immigration growth by moving to occupations that face less immigrant competition. Although this is a potential explanation for the small estimated impact of immigration on adult wages, there is little difference in the impact of immigration on teen wages across occupations[26].

Two additional explanations for small wage effects are relevant for the youth labor market. First, since immigration substantially affects youth employment, selection bias is a significant concern. If immigration has larger employment effects on teens with lower earnings ability, then the estimated impact of immigration on observed wages confounds the effect of immigration on the offered wage with the effect of immigration on the composition of the employed youth population. Second, the minimum wage is more binding for youth wages than for adult wages, and a strongly binding minimum wage will mitigate wage adjustment from immigration. I next address each of these explanations.

Selection Bias

If teens with lower earning ability are more likely to drop out of the labor force in response to immigration, then the observed immigration effect is a combination of two effects: the impact of immigration on the offered wage of teens, and compositional effects (selection bias) because individuals with higher earnings ability are more likely to remain employed. Although it is not possible to directly examine whether the underlying earnings ability of those who are

[25] 8 percent of employed teens in the 1980 Census (2 percent in the 2000 Census) were employed in manufacturing industries. 25 and 33 percent of low-skilled native adults and immigrants were employed in manufacturing in 1980, respectively (19 and 21 percent in the 2000 Census).

[26] To test this, I have estimated the following regression at the individual level:

$$\log wage_{ict} = \gamma P_{ct} + \delta P_{ct} \cdot comm\ pctile_o + \xi comm\ pctile_o + \beta X_i + \varphi W_{ct} + \alpha_c + \alpha_t + \varepsilon_{ict}$$

Given the likelihood of selection into employment and into occupations, however, these estimates are only suggestive. For teens, I find that $\hat{\gamma} = -.145$ (.094) and $\hat{\delta} = .006$ (.050). For adults, $\hat{\gamma} = -.315$ (.156) and $\hat{\delta} = .571$ (.066). The wage impact of immigration is uniform across occupations for teens, while it is less negative for more communication-intensive occupations for adults.

employed exceeds that for those who experience disemployment, I demonstrate changes in the composition of observed characteristics for the employed teen population by estimating the following equation:

$$\frac{\#\ employed\ educated_{ct}}{\#\ employed\ less\ educated_{ct}} = \psi P_{ct} + \beta \frac{\#\ educated_{ct}}{\#\ less\ educated_{ct}} + \theta_c + \theta_t + \nu_{ct} \tag{1.10}$$

The dependent variable proxies as a measure of the skill composition of the employed teen population of MSA c in year t. It represents the ratio of employed youth with more educated parents to employed youth with less educated parents, where youth from less educated parents are defined as those with at least one parent who is a high school dropout, and those with educated parents are defined as all other youth. In 2000, the average wage for teens with more educated parents was \$7.72 and the average wage for other teens was \$7.57—so this ratio is a summary measure of the observed earnings ability composition for the employed youth population. To control for the composition of the entire youth population (i.e. unconditional on employment), I include $\frac{\#\ educated_{ct}}{\#\ less\ educated_{ct}}$. If the share of the employed population from more educated families increases due to immigration growth, then $\psi > 0$. The OLS estimate of ψ is 21.0 (with standard error of 12.5), and the 2SLS estimate of ψ is 33.6 (with standard error of 18.1). A 10 percentage point increase in the low-skilled immigrant share is predicted to increase the ratio of employed youth with more educated parents to those with less educated parents by 3.4 (for comparison, the average across MSAs is 6.5). This is suggestive evidence that immigration growth causes the average earnings potential of the employed youth population to increase due to compositional changes. Although the observed difference in earnings potential between youth from different family backgrounds is not large (an hourly wage difference of \$.20 in 2000), selection on observable characteristics suggests that selection on unobserved characteristics may also be present. Hence, the observed effect of immigration on wages is its effect on offered wages (which is assumed to be negative) combined with its effect on the composition of the employed youth population (which is likely to be positively related to the wage). The impact of immigration on observed wages will therefore be more positive than the impact of immigration on offered wages.

Selection bias in wage equations has traditionally been modeled by assuming linear offer wage and reservation wage equations, and making distributional assumptions about the error terms in both equations (Heckman 1979). Since the immigrant share is potentially endogenous and affects both selection and the wage, I am unable to implement a standard Heckman selection correction procedure. Assuming that an individual's log offered wage is $w_{ict} = \gamma P_{ct} + \beta X_i + \alpha_c + \alpha_t + \varepsilon_{ict}$, that individuals work only if their offered wage exceeds their reservation wage w^*_{ict} where $w^*_{ict} = \delta X_i + \zeta_c + \zeta_t + u_{ict}$, and that u_{ict} and ε_{ict} have a bivariate normal distribution, then a simple solution motivated by the Heckman-type correction and as used in (Card 2001) is to note that the effect of immigration on observed wages can be expressed as: $\frac{\partial E[w_{ict}|w_{ict}>w^*_{ict}]}{\partial P_{ct}} = \gamma + \rho\sigma_\varepsilon \frac{\partial\lambda(\pi_{ct})}{\partial\pi_{ct}}\frac{\partial\pi_{ct}}{\partial P_{ct}}$.

In this expression, w_{ict} is individual i's offered wage, w^*_{ict} is i's reservation wage, $\lambda(\pi_{ct})$ is the Inverse Mills Ratio (IMR) expressed as a function of the annual employment rate of MSA c in year t (π_{ct}), ρ is the correlation between errors in the offered wage and selection equations, σ_ε is the standard deviation of residuals in the offered wage equation, γ is the effect of P_{ct} on offered wages, and $\frac{\partial\pi_{ct}}{\partial P_{ct}}$ is the effect of immigrant concentration on annual employment probabilities. I use IV estimates of $\frac{\partial\pi_{ct}}{\partial P_{ct}}$ and $\frac{\partial E[w_{ict}|w_{ict}>w^*_{ict}]}{\partial P_{ct}}$ from Tables 1.4 and 1.6, I estimate the slope of the IMR at the average value of π_{ct} for teens and adults, and I estimate σ_ε from the data. I assume moderate correlation between residual earnings ability and employment likelihood and set $\rho = .5$. The effect of immigration on offered wages is $\frac{\partial E[w_{ict}|w_{ict}>w^*_{ict}]}{\partial P_{ct}} - \rho\sigma_\varepsilon \frac{\partial\lambda(\pi_{ct})}{\partial\pi_{ct}}\frac{\partial\pi_{ct}}{\partial P_{ct}}$. These estimates are presented in columns 3 and 6 of Table 1.6. Wage effects are negative and larger in magnitude than 2SLS estimates: a 10 percentage point increase in the low-skilled immigrant share reduces teen wages by 3.6% and adult wages by 1.1%.

The combination of employment effects estimated in Table 1.5, and selection-corrected wage effects imply that the teen weekly employment participation elasticity (the responsiveness of employment in the reference week to changes in the wage) is 4.2, and that the annual employment participation elasticity is 3.3. These estimates are larger than the implied labor supply elasticities for low-skilled adults, and to my knowledge these are the first estimates of teen labor supply elasticities. Elasticities for adults, though imprecise, are somewhat larger than most previous estimates. For example, (Meyer and Rosenbaum 2001) uses the expansion of the EITC in the 1980s and 1990s to estimate employment participation elasticities for single low income mothers, and find weekly employment elasticities of .83 and annual employment elasticities of 1.07. Using immigration-induced wage and employment changes, (Borjas, Grogger and Hanson 2006) estimates annual participation elasticities of .8 for low-skilled black males, and .2 for low-skilled white males.

Youth Wages and the Minimum Wage

A potential explanation for the combination of large youth employment effects and small youth wage effects from immigration (which together imply large youth labor supply elasticities) is that a binding minimum wage prevents further downward wage adjustment while still permitting teen employment to decline. As shown in Figure 1.6, if the minimum wage is binding or is nearly binding for teens, and an increase in immigration reduces demand for teen labor (from D to D') enough that the minimum wage binds, then there will be an excess supply of teen labor. The resulting wage-employment outcome will not be on the teen labor supply curve, and the labor supply elasticity estimated from wage and employment changes will be an overestimate of the true labor supply elasticity[27].

There is some suggestive evidence that a binding minimum wage inhibits wage adjustment from immigration for teens. Imputed hourly wages for a large proportion of the youth population are no greater than the minimum wage, although the share of the employed youth population earning more than the minimum wage has risen as the real value of the minimum wage has fallen. In 1980, the federal minimum wage exceeded the national median hourly teen wage as calculated in the Census. The federal minimum wage gradually became less binding over the next two decades: it was \$3.80 in 1990 while the median wage for teens was \$4.00, and it was \$5.15 in 2000 while the median wage was \$5.71. In 1980, the federal or state minimum wage exceeded the median youth wage in every state. In 2000, this was true for only 7 states. Nonetheless, between 1980 and 2000, minimum wages were binding for a significant fraction of

[27] The initial equilibrium amount of youth labor is L^*, and the equilibrium wage is w^*. If low-skilled immigrants and teens are somewhat substitutable, then immigration growth will reduce the demand for teens, shifting the demand curve from D to D'. For a given wage, if employers prefer immigrants over native youth (since immigrants may be willing to work longer hours in more difficult work conditions, or may be more willing to remain employed throughout the school year), then youth employment may fall to a point such as L^{min}. The new wage-labor outcome is $\{w^{min}, L^{min}\}$, which is not on the youth labor supply curve. From observed wage and employment changes, the estimated labor supply elasticity would be $\frac{(L* - L^{min})}{L*} / \frac{(w* - w^{min})}{w*}$, which is larger in magnitude than the actual labor supply elasticity at $\{w^*, L^*\}$.

the youth population.

If a binding minimum wage supported the teen wage distribution and mitigated the wage effects of immigration, then the wage impact of immigration should be smaller in states for which the minimum wage is more binding (i.e. states where the wage has less room to adjust). 2SLS estimates suggest that this is true for the impact of immigration on youth wages, but not for the impact on adult wages. Estimates are not sufficiently precise to draw firm conclusions, however[28].

1.4 Immigration Effects for Minority and Less Advantaged Youth

1.4.1 Employment Effects of Immigration

An extensive body of research has documented that employment rates for youth from less advantaged backgrounds—black youth in particular—are lower than those for other groups (Ihlanfeldt and Sjoquist 1990). One explanation that has received some empirical support is the spatial mismatch hypothesis, which argues that suburbanization of jobs combined with blacks' lack of mobility from the inner city to the suburbs is a primary cause of black joblessness (Ihlanfeldt and Sjoquist 1998; Raphael 1998; Weinberg 2000). Since low-skilled immigrants are more concentrated in the urban center of an MSA than in the suburbs of an MSA[29] and minority youth or youth from poorer families (in the bottom qartile of the family income distribution) are also more likely to live in the urban center of an MSA[30], the effects of low-skilled immigration

[28] I estimate the following: $y_{ict} = \gamma P_{ct} + \delta P_{ct} \cdot bind_{ct} + \xi bind_{ct} + \beta X_i + \xi W_{ct} + \alpha_c + \alpha_t + \varepsilon_{ict}$, where $bind_{ct}$=log(*median teen wage*)$_{ct}$ − log(*min wage*)$_{ct}$, and W_{ct} are the city level controls included in the wage equations estimated in Table 1.6. In this specification, $bind_{ct}$ is a measure of state wage levels relative to the state or federal minimum wage. This is a commonly used measure of the bindingness of the minimum wage — see Lee 1999, for instance. A larger (more positive) value indicates that the minimum wage is less binding. IV estimates of this equation yield $\gamma = .163(.124)$ and $\delta = -.469(.421)$. Although these estimates are quite imprecise, they suggest that areas with less binding minimum wages (higher values of $bind_{ct}$) experience larger wage declines in response to immigration growth. This is consistent with a binding minimum wage that mitigates wage effects. Since the minimum wage is less binding for native adults (the median wage for low-skilled natives always exceeds the state and federal minimum), there is no a priori reason to expect the effect of immigration on adult wages to be larger in states for which the minimum wage is more binding relative to adult wage levels. Estimating a similar equation for native low-skilled adults finds $\gamma = .049(.107)$ and $\delta = .144(.102)$. The impact of immigration on adult wages is *smaller* in areas with less binding minimum wages.

[29] In 2000 for instance, the low-skilled immigrant share of an MSA's center city was 33% on average, and was 28% on average outside of the center city. 57% of low-skilled immigrants in an MSA lived in its center city, on average.

[30] In 2000, 61 percent of black teens versus 23 percent of non-black teens lived in the center city of an MSA, and 51 percent of teens from poorer families versus 25 percent of other teens lived in the center city of an MSA.

into an MSA may be particularly strong for these youth.

I begin by showing that employment effects are proportionately greater for these populations. The primary estimation equation for this section is:

$$y_{ict} = \psi P_{ct} \cdot d_i + \pi P_{ct} \cdot (1 - d_i) + \varphi d_i + \sigma X_i + \phi_c + \phi_t + \nu_{ict} \tag{1.11}$$

Immigrant shares are interacted with d_i and $(1 - d_i)$, which are dummy variables indicating whether the youth is black, from a poorer family (their family is in the bottom quartile of the household income distribution), or lives in the center city of an MSA. P_{ct} is the low skilled immigrant share of the population, and the interactions between P_{ct} and d_i, and P_{ct} and $(1-d_i)$ are instrumented with the interactions between $\hat{P}_{ct}$ and d_i, and $\hat{P}_{ct}$ and $(1 - d_i)$.

Table 1.9A presents 2SLS estimates of this equation, separately for male and female teens (columns 1 and 2), where y_{ict} indicates whether individual i was employed in the reference week. Panel A compares the impact of immigration on black youth to other youth, panel B compares the impact on youth from poorer families to other youth, and panel C compares the impact on youth from urban areas (living in the center city of an MSA) to all other youth. Black youth, youth from poorer families, and urban youth have lower employment rates on average (at least 10 percentage points below all other youth), so an equal percentage point impact of immigration on employment represents a larger immigration effect, relative to baseline rates, for these populations. To scale the impact of immigration by baseline employment rates, I divide the effect of a 10 percentage point increase in the low-skilled immigrant share by the average employment rate for each group (reported in brackets to the right of the mean).

The magnitude of immigration effects on employment rates is greater for white youth, youth from wealthier families, and youth who do not live in the center city of an MSA. The effect of immigration on employment rates relative to average employment rates, however, is larger for youth with lower overall employment rates[31]. For instance, a 10 percentage point increase in low-skilled immigrant shares is estimated to reduce the employment rate of black males by about 23 percent (4.0 percentage points) and the employment rate of non-black males by 16 percent (5.7 percentage points). There is little difference in employment effects by gender.

[31]The same conclusion holds if immigration effects are estimated with an IV probit model rather than a 2SLS linear probability model.

Since employment effects are proportionately larger for urban youth (panel C), the impact of immigration on black youth employment may be particularly large because black youth are also more likely to live in the center city of an MSA. To test the plausibility of this explanation, columns 1 and 2 of Table 1.9B (panel D) present estimates of immigration effects on the employment of urban youth and other youth, conditional on being black. Although employment rates are lower, on average, for black urban youth compared to all other black youth, the magnitude of immigration effects on employment are larger for urban youth. Conditional on living in the center of a city, immigration employment effects are not proportionately larger for black youth (panel E), as they are in the unconditional estimates. This is suggestive evidence that one reason why low-skilled immigration has a proportionately large impact on black youth employment is that black youth are more likely to live in the center city of an MSA, and that the employment effects of immigration are larger for urban youth.

Another potential reason why the employment effects of immigration are proportionately larger for youth from less advantaged backgrounds is that these youth are more likely to work in occupations that are prevalent among immigrants. Youth tend to work in similar occupations regardless of family background or minority status, however, so differential immigration effects are unlikely due to differences in the youth occupational distribution[32].

1.4.2 Immigration and School Enrollment

Since disadvantaged youth are more likely to drop out of high school than other youth (Appendix Table 1.A1), and they are more likely to report being employed and not in school, they can more realistically substitute from labor to schooling as well as to leisure. This added dimension of substitutability provides an additional channel through which immigration may differentially impact the less advantaged population.

Column 3 and 4 of Table 1.9A present estimates of (1.11), where y_{ict} is a dummy indicating

[32] For each category of youth (based on family background or race), I calculate the employed share of that group in each occupation. For instance, 10.5 percent of employed black teens in 1970 were janitors. I make the same calculations for low-skilled adult immigrants. I compare occupational distributions by calculating the correlation in these shares between any two groups. The occupational distribution of teens is quite similar, regardless of which groups are considered. For instance, the correlation between the distribution for youth from lower income families in an occupation and for all other youth is .91, and the correlation between blacks and whites is .92. The correlation between the share of low-skilled adult immigrants and youth in an occupation ranges from .49 to .57 depending on which category of the family income level or race of the youth is considered.

whether an individual reported being enrolled in school at any point in the two months prior to the Census reference week. Immigration is estimated to significantly increase enrollment rates among youth from poorer families and urban youth: a 10 percentage point increase in the low-skilled immigrant share of the population increases the proportion of these youth that are enrolled in school by 1 to 1.3 percentage points, relative to average enrollment rates of around 90 percent. These enrollment effects may be coming through two channels. First, since immigration reduces offered wages in the youth labor market, school enrollment may rise due to a reduction in the opportunity costs of attending school. Second, to the extent that youth perceive a reduction in job opportunities in the low-skilled adult labor market due to immigration, low-skilled immigration growth may increase the perceived returns to education. My analysis is unable to disentangle the two effects. These estimates mirror findings from the minimum wage literature. For instance, Neumark and Wascher (1995a, 1995b, 2003) find that reported youth enrollment falls in response to an increase in the minimum wage.

1.5 Conclusion

Previous research on the labor market impact of immigration generally concludes that immigration has little displacement effect on adult natives, particularly for low-skilled adults. My paper confirms this finding, but demonstrates that focusing only on the adult labor market ignores a segment of the population—high school age youth—that experiences substantial disemployment from immigration. I estimate that a 10 percentage point increase in the share of the low skilled population that is immigrant reduces the proportion of teens employed in the Census reference week by 4.8 percentage points, and the proportion employed in the previous year by 5.3 percentage points. Given average employment rates of 32% and 47%, respectively, these effects are large.

How much of the decline in teen summer employment since the early 1990s can be explained by rising low skill immigration? To answer this question, I estimate the impact of immigration on summer youth employment using CPS data from 1979-81, 1989-91, 1999-2001, and 2004-05. A 10 percentage point increase in the low-skilled immigrant share of a state is estimated to reduce the number of teens who report being employed in the previous week (during the summer) by 6.0 percent. To estimate a counterfactual national 2005 summer employment rate for teens in the absence of changes to immigrant concentrations since 1990, I adjust each state's 2005 teen summer employment rate by the estimated immigration effect on employment multiplied by the actual change in immigrant shares over this period[33]. Between 1990 and 2005, the summer employment rate fell from 43% to 32%. The counterfactual employment rate in 2005 is 37%, suggesting that in the absence of immigration growth, the teen employment rate would have fallen by 6 percentage points instead of 11 percentage points. Teen summer employment rates are about 5 percentage points lower than they would be had immigrant concentrations remained unchanged since 1990, and this difference is equivalent to almost half of the actual decline in the employment rate over this period.

Much of the difference between actual and counterfactual employment rates is due to significant immigration growth between 1990 and 2000. During this period, teen employment rates remained stable despite rising adult employment rates (Figure 1.1), so one interpretation of this analysis is that in the absence of immigration, teen employment rates would have trended up with low-skilled adult employment rates. However, it is not accurate to claim that half of the decline in teen employment between 2000 and 2005—the period of especially strong declining youth employment—is attributable to immigration growth. Across all states, immigrant shares increased by 2 percentage points on average between 2000 and 2005, and the number of low-skilled immigrants increased by about 20 percent on average. Combining these changes with the estimated effects of changes in immigrant shares and stocks on teen employment, immigration growth between 2000 and 2005 can explain 15-25 percent of the observed decline in teen employment in this 5-year period. Some have argued that teens have reduced their labor force participation recently because of supply-side factors such as increasing emphasis on high school and college education and growth in Hope-type scholarships (Aaronson, Park and Sullivan 2006). One implication of this view is that alternative human capital investments are replacing youth employment experience, which may result in long-run gains to these cohorts. Since immigration effects are substantial, however, demand-side factors are also significant—and

[33] Since only 40 MSAs are identified in earlier CPS data, I use variation in the immigrant share of a state rather than an MSA. Counterfactual state employment rates in 2005 are: $emp_{s,2005} + .60 * (P_{s,2005} - P_{s,1990})$. Immigrant shares in 2005 are calculated using the 2005 American Community Survey. State counterfactual employment rates are used to estimate the counterfactual number of employed youth by state, which are aggregated to calculate the national counterfactual rate.

the long-run implications of falling employment are less certain.

This is particularly true for black youth, youth from poorer families, and urban youth, as the employment effects of immigration relative to average employment rates are larger for these populations. Ignoring the general equilibrium effects of immigration (including lower product prices due to cheaper labor), disemployment due to immigration would generally suggest that affected natives are worse off. For these less advantaged youth, however, this conclusion is less certain because poorer youth and urban teens also respond to immigration by increasing high school enrollment. Estimates of the returns to education from compulsory schooling laws suggest that, for reasonable discount rates, the monetary returns from graduating high school significantly outweigh the opportunity costs of lost wages from dropping out early (Oreopoulos 2002). Behavioral explanations such as distaste for school, uncertainty regarding individual returns to education, myopia, or peer pressure may be better explanations for dropout behavior. To the extent that these other explanations contribute to the dropout decision for at risk youth, positive enrollment effects from immigration may be welfare enhancing in the long run[34]. The long run impact of the immigration-induced reduction in teen employment remains an open and important research question.

[34] Fully understanding the long-run welfare implications of lower youth employment requires better knowledge of the effects of youth employment on academic performance and later life outcomes. However, there is little consensus on whether school year employment affects academic achievement or post-graduation labor market outcomes. See (Tyler 2003) and (DeSimone 2006) for estimates of employment effects on grades and test scores; see (Ruhm 1997) and (Hotz, Xu, Ienda and Ahituv 2002) for conflicting estimates of employment effects on later life labor market outcomes.

Data appendix

Data sources and variable definitions

The primary Census regression results are estimated from pooled 5 percent microdata samples for 1980, 1990, and 2000, as provided by *IPUMS* (Ruggles 2004). Estimates in Tables 1.9A and 1.9B that use indicators for whether individuals live in the center city of an MSA include the 1 percent 1990 sample (rather than 5 percent) because center city status is not reported in the 5 percent sample for 1990. Immigrants are defined as individuals who were born abroad and are either non-citizens or naturalized citizens. The adult sample is comprised of individuals 21-64. Low skill immigrant shares refer to the immigrant share of the 21-64 population without a college degree. Hourly wages in the Census are defined as annual wage income divided by the product of usual weekly hours worked and usual weeks worked in a year. Individuals are coded as having worked in the previous year if they report positive weeks worked in the previous year. Individuals are reported as having worked in the previous week if their reported employment status at the time of the Census is "at work" or "has job, not working." School enrollment is determined from individuals' responses to a Census question which asks whether they were enrolled in school at any time over the last two months.

Annual wage income is top coded at $999,999. No values are top coded for teens. I multiply adult top coded values by 1.5. Given the imprecision of wage imputation, there are a number of implausible wage values for teens in particular, which arise mainly from individuals who report high annual wage incomes with few weeks or hours worked. It seems likely that these responses are significant mismeasurements of actual wages. Similarly, there are some implausibly low wage estimates due to low reported annual wages but high weeks or usual hours worked. I correct for this by assigning the 10th percentile of the wage distribution (by decade) to those youth with wages below the value, and I assign the 90th percentile to youth with wages above that amount. This seems less of a concern for adults, but given the likelihood that the wage imputation procedure results in some implausible values, I assign the 5th wage percentile to adults with wages less than that value, and the 95th percentile to adults with wages greater than that value. Wage regression results are largely robust to these corrections, but the correction helps summary statistics for the Census sample correspond more closely to those from the CPS.

I use immigrant shares calculated in the Census as the primary regressor of interest in regressions on CPS data. Since CPS samples are much smaller in size, I pool 1979-1981, 1989-1991, 1999-2001, and 2004-05 for the CPS regression used for the counterfactual summer employment rate estimation in section 1.5. Immigrant shares calculated from the Census are assigned to the appropriate range of years.

Table 1.1 - Low-skilled immigrant shares in select MSAs

	1980	1990	2000
	(1)	(2)	(3)
A. High Immigration MSAs			
Miami, FL	0.448	0.608	0.692
El Paso, TX	0.339	0.430	0.492
Los Angeles, CA	0.306	0.539	0.632
Jersey City, NJ	0.279	0.391	0.514
New York City, NY	0.255	0.374	0.512
Ventura-Oxnard-Simi Valley, CA	0.193	0.320	0.443
San Francisco, CA	0.189	0.473	0.584
Honolulu, HI	0.184	0.244	0.305
Bergen-Passaic, NJ	0.177	0.250	0.395
San Jose, CA	0.176	0.360	0.534
B. Low Immigration MSAs			
Mobile, AL	0.014	0.015	0.027
Indianapolis, IN	0.013	0.016	0.046
Memphis, TN	0.012	0.014	0.052
York, PA	0.012	0.021	0.034
Greensboro, NC	0.011	0.015	0.103
Louisville, KY	0.011	0.011	0.034
Nashville, TN	0.011	0.018	0.076
Chattanooga, TN	0.009	0.011	0.030
Birmingham, AL	0.009	0.010	0.032
Knoxville, TN	0.007	0.008	0.017

Notes: Calculations are estimates of the immigrant share of the adult population that has no more than a high school degree (i.e. no college experience). High and low immigration MSAs are those with the 10 highest and lowest low-skilled immigrant shares in 1980.

Table 1.2 - Employment shares in the five most common occupations for native teens and low-skill adult immigrants, 1980 and 2000

A. Native male teens				B. Native female teens			
1980		2000		1980		2000	
ght, stock, and material dlers	0.204	Food prep / misc. restaurant workers	0.148	Waiter/waitresses	0.138	Cashiers	0.224
d prep / misc. aurant workers	0.128	Freight, stock, and material handlers	0.107	Cashiers	0.135	Salespeople	0.117
ks	0.087	Cooks	0.101	Salespeople	0.125	Food prep / misc. restaurant workers	0.115
tors	0.080	Cashiers	0.090	Food prep / misc. restaurant workers	0.106	Waiter/waitress	0.094
n workers	0.070	Salespeople	0.072	Child care workers	0.045	Child care workers	0.050

C. Low-skill male immigrants				D. Low-skilled female immigrants			
1980		2000		1980		2000	
ght, stock, and material dlers	0.060	Truck, delivery, and tractor drivers	0.058	Textile sewing machine operators	0.096	Housekeepers, maids, butlers	0.089
chine operators	0.054	Cooks	0.057	Assemblers of electrical equipment	0.053	Nursing aides, orderlies, and attendants	0.056
c. managers and ninistrators	0.044	Construction laborers	0.056	Secretaries	0.049	Cashiers	0.049
tors	0.041	Freight, stock, and material handlers	0.051	Salesperson	0.047	Textile sewing machine operators	0.042
m workers	0.040	Gardeners and groundskeepers	0.042	Machine operators	0.046	Freight, stock, and material handlers	0.042

es: Estimates are the share of the employed population in the given occupation. Low-skilled immigrants are non-citizens born outside of the United States
o have no greater education than a high school degree. Occupation shares are calculated from Census IPUMS samples. Consistent occupation titles across
rs are formed using the IPUMS consistent 1990 occupational coding.

Table 1.3 - OLS estimates of immigration effects on native outcomes

	Employed last week	Employed last year	Annual hours
	(1)	(2)	(3)
A. Natives age 16 and 17			
Immig. share of low-skilled pop.	-0.458	-0.524	-329.2
	(0.036)	(0.064)	(43.8)
N	526,151	526,151	526,151
Mean (1980)	0.320	0.469	228.7
Mean (2000)	0.309	0.437	199.6
Mean (All years)	0.317	0.466	217.7
B. Natives age 21-64 without a high school degree			
Immig. share of low-skilled pop.	-0.142	-0.102	-139.1
	(0.044)	(0.031)	(74.8)
N	1,263,407	1,263,407	1,263,407
Mean (1980)	0.561	0.639	1109.1
Mean (2000)	0.498	0.612	1062.3
Mean (All years)	0.536	0.626	1078.9

Notes: Estimates are coefficients on the immigrant share of the adult population with no more than a high school degree. Standard errors clustered at the MSA level are reported in parentheses. All regressions include MSA and year fixed effects and the following individual-level controls: age, age squared, race dummies, and a dummy indicating whether the respondent is male. Regressions are weighted by the reported Census person weight. All regressions use pooled Census data from 1980, 1990, and 2000.

Table 1.4 - Instrumental variable components and first stage results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	A. Dependent Variable: Low skill immigrant stocks						
Predicted low skill immigrant stocks	0.386	0.652	0.248	0.395	0.330	0.351	0.455
	(0.030)	(0.260)	(0.063)	(0.025)	(0.028)	(0.029)	(0.016)
N	300	200	200	300	300	234	300
	B. Dependent Variable: Low skill native stocks						
Predicted low skill native stocks	1.278	1.497	0.749	1.312	1.202	1.323	1.278
	(0.055)	(0.163)	(0.265)	(0.056)	(0.057)	(0.055)	(0.055)
N	300	200	200	300	300	234	300
	C. Dependent Variable: Low skill immigrant shares						
Predicted low skill immigrant shares	0.811	1.174	0.442	0.760	0.539	0.818	0.824
	(0.067)	(0.134)	(0.123)	(0.117)	(0.079)	(0.083)	(0.076)
N	300	200	200	300	300	234	300
Included years	1980-2000	1980-1990	1990-2000	1980-2000	1980-2000	1980-2000	1980-2000
Census region/year fixed effects				X			
MSA-level controls					X		
Excluding California, New York, Texas						X	
Excluding own-state inflows (see text)							X

Notes: All regressions include MSA and year fixed effects. Standard errors clustered at the MSA level are reported in parentheses. Regressions are weighted by the number of individuals age 18-64 with reported education no greater than a high school degree. MSA-level controls in column 5 include the average age of the native population, and the share of the native population that is: black, male, high school dropouts, and college graduates.

Table 1.5 - 2SLS estimates of immigration effects on native outcomes

	Employed last week	Employed last year	Annual hours
	(1)	(2)	(3)
A. Natives age 16 and 17			
Immig. share of low-skilled pop.	-0.482	-0.553	-287.8
	(0.054)	(0.096)	(55.6)
N	526,151	526,151	526,151
Mean (1980)	0.320	0.469	228.7
Mean (2000)	0.309	0.437	199.6
Mean (All years)	0.317	0.466	217.7
B. Natives age 21-64 without a high school degree			
Immig. share of low-skilled pop.	-0.157	-0.124	-248.9
	(0.061)	(0.048)	(98.7)
N	1,263,407	1,263,407	1,263,407
Mean (1980)	0.561	0.639	1109.1
Mean (2000)	0.498	0.612	1062.3
Mean (All years)	0.536	0.626	1078.9

Notes: Estimates are coefficients on the immigrant share of the adult population with no more than a high school degree. Standard errors clustered at the MSA level are reported in parentheses. All regressions include MSA and year fixed effects and the following individual-level controls: age, age squared, race dummies, and a dummy indicating whether the respondent is male. Regressions are weighted by the reported Census person weight. All regressions use pooled Census data from 1980, 1990, and 2000.

Table 1.6 - Robustness of the effect of immigration on teen employment, 1980-2005 (2SLS)

	Dependent variable: employed last year					
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Robustness to immigrant concentration variable					
Immig. share of low-skilled pop.	-0.524 (0.064)	-0.553 (0.096)	-0.594 (0.128)	-0.978 (0.199)		
Immig. share of high-skilled pop.			0.172 (0.298)	0.915 (0.521)		
Log number of low-skilled immigrants					-0.058 (0.011)	-0.156 (0.037)
N	526,151	526,151	526,151	526,151	526,151	526,151
	B. Robustness to sample selection					
Immig. share of low-skilled pop.	-0.432 (0.108)	-0.853 (0.335)	-0.428 (0.101)	-0.359 (0.108)	-0.584 (0.073)	-0.625 (0.115)
N	318,413	318,413	348,848	348,848	361,416	361,416
Excluding 1980	X	X				
Excluding 2000			X	X		
No CA., TX., NY MSAs					X	X
	C. Robustness to controls					
Immig. share of low-skilled pop.	-0.472 (0.079)	-0.505 (0.158)	-0.544 (0.060)	-0.573 (0.105)	-0.223 (0.105)	-0.377 (0.239)
N	526,151	526,151	565,884	565,884	565,884	565,884
Census region/year fixed effects	X	X				
Including 2005 (ACS)			X	X	X	X
MSA specific time trends					X	X

Notes: Estimates are coefficients on the immigrant share of the adult population with no more than a high school degree. Standard errors clustered at the MSA level are reported in parentheses. All regressions include MSA and year fixed effects and the following individual-level controls: age, age squared, race dummies, and a dummy indicating whether the respondent is male. Columns 5 and 6 of Panel A also control for the log of the number of low-skilled natives. Regressions are weighted by the reported Census person weight. All regressions use pooled Census data from 1980, 1990, and 2000. Estimates in columns 3-6 of Panel C include 2005 ACS data.

Table 1.7 - Differential impact of immigration on occupation-level employment by communication skills required in the occupation (2SLS)

Dependent variable: log number of employed natives in occupation *o*	Native teens	Low-skilled native adults
	(1)	(2)
Low-skilled immig. share$_{ct}$	-0.853	-2.421
	(0.210)	(0.683)
(Low-skilled immig. share)$_{ct}$ x (job's percentile in distribution of communication skills)$_{o}$	0.953	1.840
	(0.157)	(0.261)
Average communication percentile of job (all years)	0.346	0.542
N	98,700	98,700

Notes: Estimates are coefficients from occupation-MSA-year level 2SLS regressions of the log number of teens or native adults employed in occupation *o* on low skill immigrant shares, and immigrant shares interacted with communication percentile. The number of employed individuals in a cell is set equal to 1 if there are no observations for the particular occupation-year-city. Standard errors clustered at the MSA level are reported in parenthesis. See text for description of communication percentile. Communication percentile is measured from 0 to 1.

Table 1.8 - Estimated wage impact of immigration and implied employment participation elasticities

	Dependent variable: log hourly wage					
	Natives age 16 and 17			Natives age 21-64 without a high school degree		
	OLS	IV	Selection-corrected	OLS	IV	Selection-corrected
	(1)	(2)	(3)	(4)	(5)	(6)
Immig. share of low-skilled pop.	-0.127	-0.143	-0.366	0.144	-0.062	-0.112
	(0.052)	(0.086)		(0.087)	(0.166)	
		N=238,063			N=722,357	
Implied weekly employment participation elasticity	12.0	10.6	4.2	-	4.7	2.6
Implied annual employment participation elasticity	9.5	8.4	3.3	-	3.2	1.8

Notes: Estimates in columns 1, 2, 4, and 5 are coefficients on the immigrant share of the adult population with no more than a high school degree. Selection-corrected wage estimates in columns 3 and 6 are calculated as described in the text. Standard errors clustered at the MSA level are reported in parentheses. All regressions include MSA and year fixed effects, the log of the maximum of the state and federal minimum wage, city-level controls (the average age of the native population, and the share of the native population that is: black, male, high school dropouts, and college graduates) and individual-level controls (age, age squared, race dummies, and a dummy indicating whether the respondent is male). Regressions are weighted by the reported Census person weight. All regressions use pooled Census data from 1980, 1990, and 2000.

Table 1.9A: 2SLS estimates of immigration effects for subsamples of the youth population

	Dependent variable: Employed last week		Dependent variable: In school	
	Males	Females	Males	Females
	(1)	(2)	(3)	(4)
A. Comparison of immigration effects for black youth and all other youth				
Low-skilled immigrant share (black youth)	-0.404	-0.447	0.028	0.049
	(0.077)	(0.069)	(0.024)	(0.022)
Low-skilled immigrant share (other youth)	-0.567	-0.638	0.043	0.045
	(0.050)	(0.059)	(0.021)	(0.019)
N	209,485	205,454	209,485	205,454
Mean, all years [immigration impact relative to mean]				
Black youth	0.175 [-.231]	0.182 [-.245]	0.910 [.003]	0.912 [.005]
All other youth	0.347 [-.164]	0.352 [-.181]	0.925 [.005]	0.921 [.005]
B. Comparison of immigration effects for youth from poorer families and all other youth				
Low-skilled immigrant share (youth from poorer families)	-0.415	-0.487	0.135	0.135
	(0.046)	(0.063)	(0.021)	(0.019)
Low-skilled immigrant share (other youth)	-0.536	-0.594	0.035	0.041
	(0.046)	(0.055)	(0.017)	(0.016)
N	198,893	191,033	198,893	191,033
Mean, all years [immigration impact relative to mean]				
Youth from poorer families	0.216 [-.192]	0.230 [-.212]	0.871 [.015]	0.886 [.015]
All other youth	0.346 [-.155]	0.353 [-.168]	0.947 [.004]	0.954 [.004]
C. Comparison of immigration effects for urban youth and all other youth				
Low-skilled immigrant share (urban youth)	-0.496	-0.518	0.072	0.105
	(0.059)	(0.064)	(0.022)	(0.025)
Low-skilled immigrant share (other youth)	-0.531	-0.579	0.041	0.026
	(0.084)	(0.086)	(0.026)	(0.018)
N	167,422	163,918	167,422	163,918
Mean, all years [immigration impact relative to mean]				
Urban youth	0.236 [-.211]	0.240 [-.216]	0.896 [.008]	0.892 [.012]
All other youth	0.346 [-.154]	0.353 [-.164]	0.936 [.004]	0.933 [.003]

Notes: Estimates are coefficients on the immigrant share of the low-skilled adult population interacted with dummies for various subgroups of youth. Standard errors clustered at the MSA level are reported in parentheses. The mean of the dependent variable is reported for various subgroups, and the impact of a 10 percentage point increase in the low-skilled immigrant share relative to this mean is reported in brackets. All regressions include MSA and year fixed effects and the following individual-level controls: age, age squared, race dummies, and a dummy indicating whether the respondent is male. Regressions are weighted by the reported Census person weight. All regressions use pooled Census data from 1980, 1990, and 2000. Panel B only includes individuals with at least one matched parent in the Census. Panel C uses the 1990 one percent sample in place of the five percent sample (see data appendix for details).

Table 1.9B: 2SLS estimates of immigration effects for subsamples of the youth population (cont.)

	Dependent variable: Employed last week		Dependent variable: In school	
	Males	Females	Males	Females
	(1)	(2)	(3)	(4)
D. Comparison of immigration effects for urban youth and all other youth, conditional on being black				
Low-skilled immigrant share (urban youth)	-0.386	-0.475	-0.013	0.031
	(0.088)	(0.087)	(0.060)	(0.034)
Low-skilled immigrant share (other youth)	-0.326	-0.391	-0.019	0.031
	(0.085)	(0.107)	(0.062)	(0.040)
N	30,006	30,848	30,006	30,848
Mean, all years [immigration impact relative to mean]				
Urban youth	0.152 [-.253]	0.160 [-.296]	0.902 [-.001]	0.900 [.003]
All other youth	0.195 [-.168]	0.214 [-.182]	0.932 [-.002]	0.932 [.003]
E. Comparison of immigration effects for black youth and all other youth, conditional on living in the center city of an MSA				
Low-skilled immigrant share (black youth)	-0.161	-0.293	-0.010	0.017
	(0.145)	(0.179)	(0.045)	(0.042)
Low-skilled immigrant share (other youth)	-0.387	-0.503	0.097	0.088
	(0.107)	(0.145)	(0.049)	(0.030)
N	53,719	54,026	53,719	54,026
Mean, all years [immigration impact relative to mean]				
Black youth	0.152 [-.106]	0.160 [-.182]	0.902 [-.001]	0.900 [.002]
All other youth	0.288 [-.135]	0.293 [-.172]	0.892 [.011]	0.887 [.010]

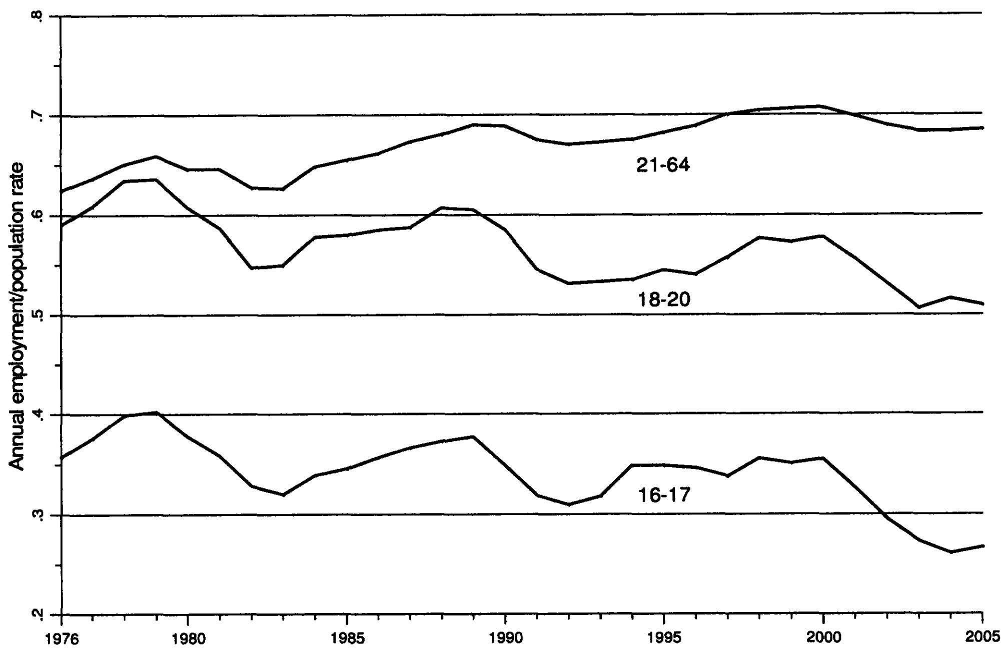
Notes: Estimates are coefficients on the immigrant share of the low-skilled adult population interacted with dummies for various subgroups of youth. Standard errors clustered at the MSA level are reported in parentheses. The mean of the dependent variable is reported for various subgroups, and the impact of a 10 percentage point increase in the low-skilled immigrant share relative to this mean is reported in brackets. All regressions include MSA and year fixed effects and the following individual-level controls: age, age squared, race dummies, and a dummy indicating whether the respondent is male. Regressions are weighted by the reported Census person weight. All regressions use pooled Census data from 1980, 1990, and 2000. Panels D and E use the 1990 one percent sample in place of the five percent sample (see data appendix for details).

Table 1.A1 - Means of teen labor market outcomes, Census

	Hourly wage		Employed last year		Employed last week		Fraction weeks worked		In school	
	1980	2000	1980	2000	1980	2000	1980	2000	1980	2000
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. All teens										
	8.61	7.74	0.47	0.44	0.31	0.31	0.20	0.20	0.89	0.94
B. Gender (natives)										
Males	8.78	7.81	0.51	0.45	0.33	0.31	0.23	0.20	0.89	0.94
Females	8.38	7.59	0.43	0.45	0.29	0.33	0.18	0.20	0.89	0.95
C. Race (natives)										
Black	8.96	7.60	0.27	0.31	0.15	0.20	0.09	0.12	0.89	0.94
Non-black	8.58	7.75	0.50	0.46	0.34	0.33	0.22	0.21	0.89	0.94
D. Parental education (natives)										
At least one parent does not have a HS degree	8.57	7.57	0.39	0.34	0.26	0.25	0.16	0.15	0.86	0.90
At least one parent has a HS degree	8.63	7.73	0.52	0.47	0.35	0.33	0.23	0.21	0.95	0.97
E. Family income (natives)										
Family is below the 25th percentile of the income distribution	8.39	7.41	0.36	0.34	0.23	0.24	0.14	0.14	0.84	0.92
Family is above the 25th percentile of the income distribution	8.67	7.78	0.50	0.48	0.34	0.34	0.22	0.21	0.94	0.97

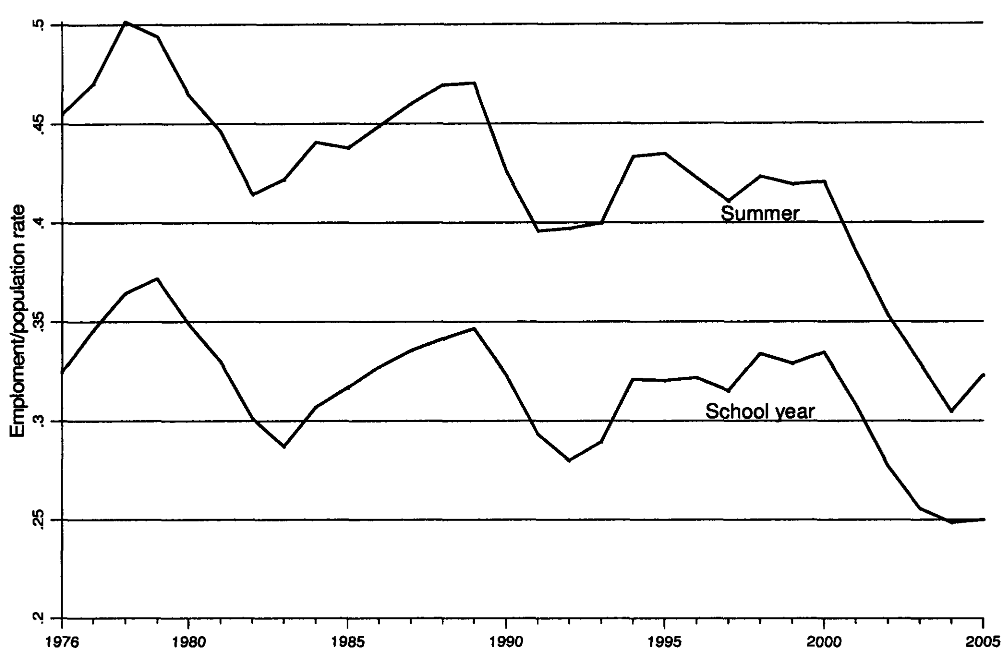
Notes: Hourly wages are calculated only over those who report positive wages. All other variables are calculated over the entire given subpopulation. Estimates are averages weighted by Census person weights. Wages are reported in 2006 dollars. See data appendix for a description of how hourly wages are calculated.

Figure 1.1: Trends in annual employment/population rates by age



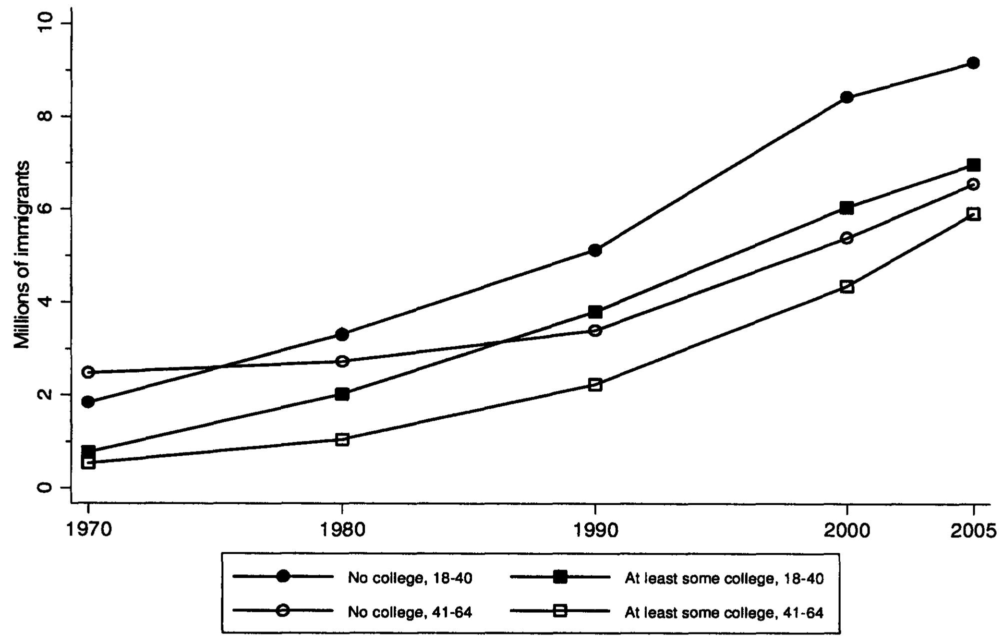
Note: Data is from NBER monthly CPS extracts. Rates are for indicated age groups with no more than a high school degree.

Figure 1.2: Trends in teen summer and school-year employment/population rates



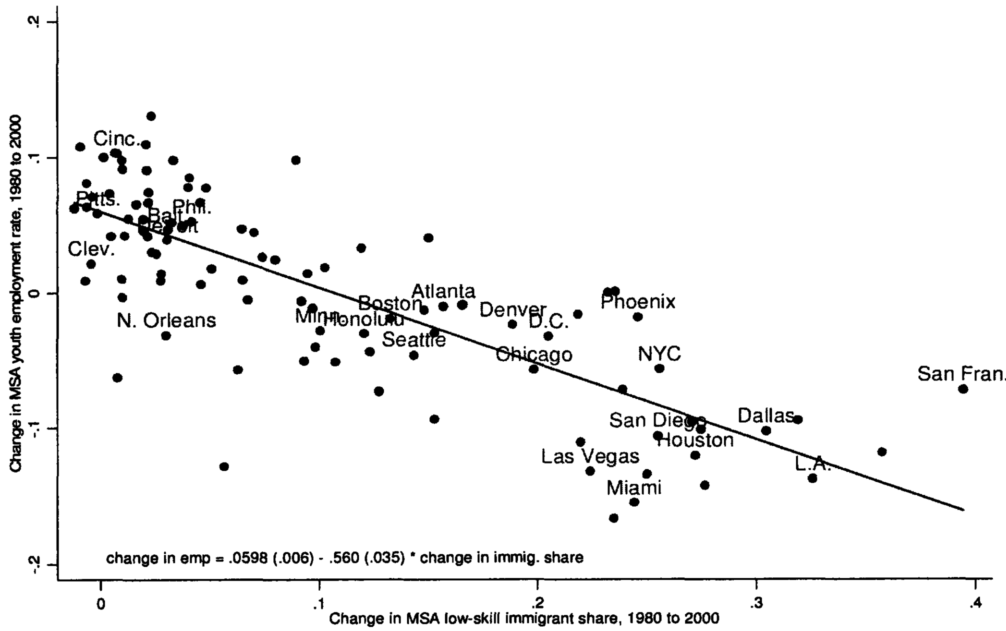
Note: Data is from NBER monthly CPS extracts. Summer months are June-August. School year months are all other months.

Figure 1.3: Trends in immigrant shares, by age and education groups



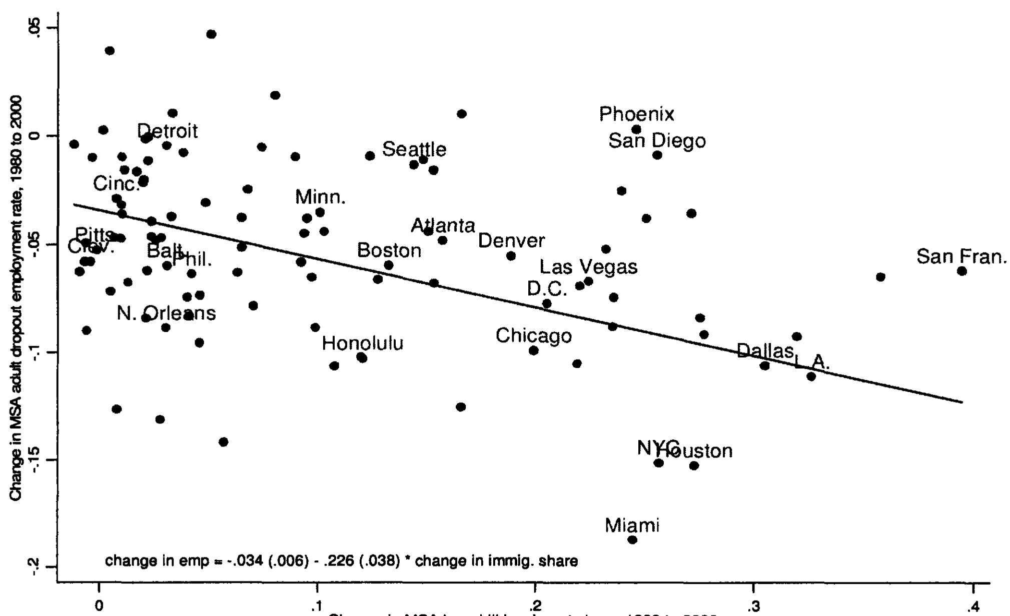
Note: 1970-2000 estimates are from Census microdata. 2005 estimate is from ACS microdata. Estimates are for all non-natives.

Figure 1.4A: Relationship between changes in MSA teen employment rate and low-skill immigrant shares, 1980-2000



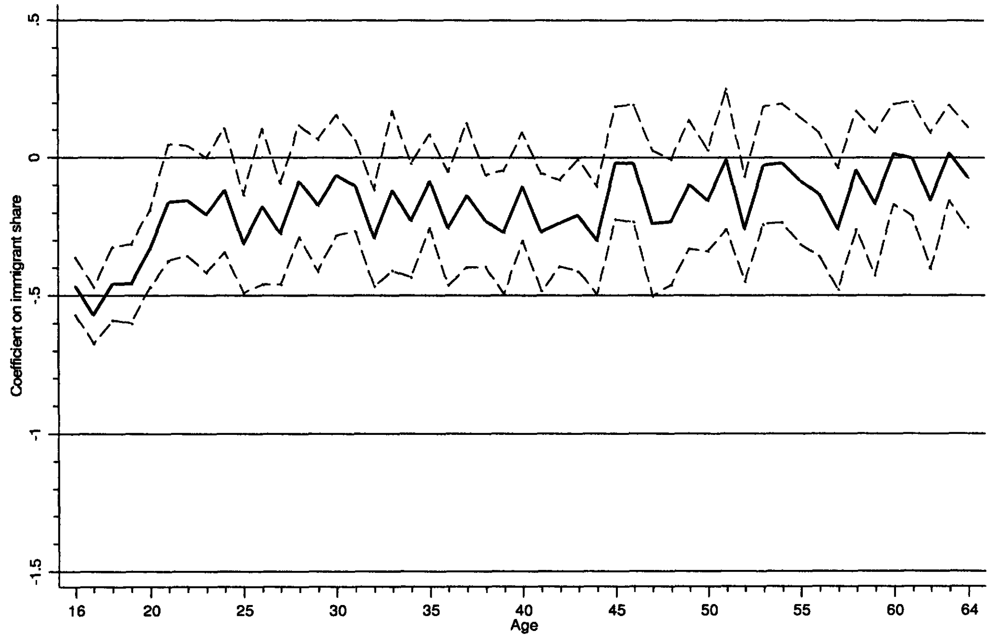
Immigrant shares are calculated over the population without college experience. Regression line is weighted by the size of the 16-17 year old MSA population in 2000.

Figure 1.4B: Relationship between changes in MSA adult dropout employment rate and low-skill immigrant shares, 1980-2000



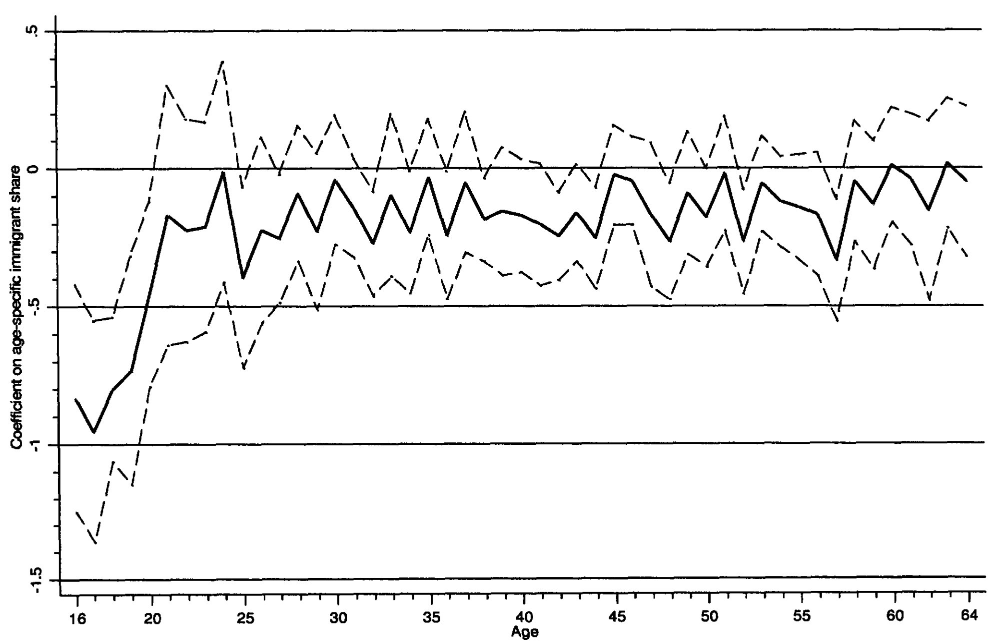
Notes: Immigrant shares are calculated over the population without college experience. Employment rates are calculated over the adult (18-64) high school dropout population. Regression line is weighted by the size of the adult dropout MSA population in 2000.

Figure 1.5A: Coefficient on immigrant share (IV estimates), by age
Dependent variable: employed in the last week



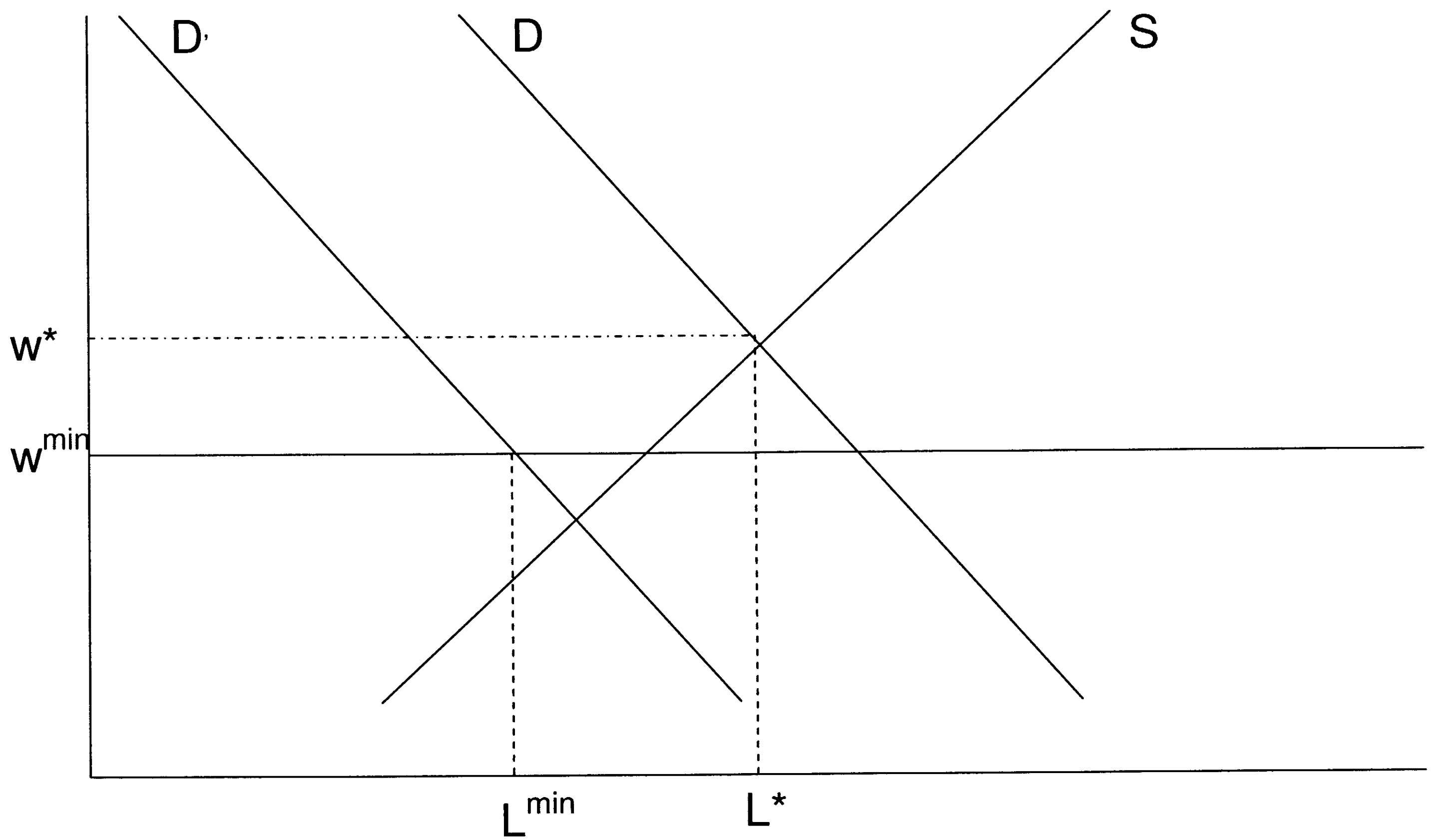
Sample limited to those without a high school degree, both sexes

Figure 1.5B: Coefficient on age-specific immigrant share (IV estimates), by age
Dependent variable: employed in the last week



Sample limited to those without a high school degree, both sexes

Figure 1.6: Immigration effects on youth wages in a labor market with a binding minimum wage



Note: In this model, immigration reduces demand for teen labor from D to D'. Teen wages fall from w* to wmin, and the number of employed teens falls from L* to Lmin.

Chapter 2

Minimal Impact: The Minimum Wage's Role in the Evolution of U.S. Wage Inequality over Three Decades (with David Autor and Alan Manning)

2.1 Introduction

While economists have vigorously debated the effect of the minimum wage on employment levels for at least six decades (cf. Stigler, 1946), its contribution to the evolution of earnings inequality—that is, the shape of the earnings distribution—was largely overlooked prior to the seminal 1996 contribution of DiNardo, Fortin and Lemieux (DFL hereafter). Using kernel density techniques, DFL produced overwhelming visual evidence that the minimum wage substantially 'held up' the lower tail of the US earnings distribution in 1979, yielding a pronounced spike in hourly earnings at the nominal minimum value, particularly for females. By 1988, however, this spike had virtually disappeared. Simultaneously, the inequality of hourly earnings increased markedly in both the upper and lower halves of the wage distribution. Most relevant to this paper, the female 10/50 ('lower tail') log hourly earnings ratio expanded by 23 log points (two thirds) between 1979 and 1988, while male and pooled-gender 10/50 ratios grew by 5.7 and 10.5 log points in the same interval (Table 2.1). To assess the causes of this rise, DFL constructed counterfactual wage distributions that potentially account for the impact of changing worker characteristics, labor demand, union penetration, and minimum wages on the shape of the wage distribution. Comparing counterfactual with observed wage densities, DFL conclude that the erosion of the federal minimum wage—which declined in real terms by 30 log points between 1979 and 1988—was the predominant cause of rising lower tail inequality between 1979 and 1988, explaining two-thirds of the growth of the 10/50 for both males and females.[1]

Though striking, a well-understood limitation of the DFL findings is that the counterfactual wage distributions derive exclusively from reweighting of observed wage densities rather than controlled comparisons. As such, the DFL exercise is closer in spirit to simulation than inference. Cognizant of this limitation, DFL highlight in their conclusion that the expansion of lower tail inequality during 1979 to 1988 was noticeably more pronounced in 'low-wage' than 'high-wage states,' consistent with the hypothesis that the falling federal minimum caused a differential increase in lower tail equality in states where the minimum wage was initially more binding. Building on this observation, Lee (1999) exploits cross-state variation in the gap between state median wages and the applicable federal or state minimum wage (the 'effective minimum') to estimate what the share of the observed rise wage inequality during 1979 through 1991 was due to the falling minimum rather than changes in underlying ('latent') wage inequality. Amplifying the conclusions of DFL, Lee estimates that more than the entire rise of lower tail earnings inequality between 1979 and 1989 was due to the falling federal minimum wage; had the minimum been constant throughout this period, observed wage inequality would have fallen.[2]

These influential findings present a number of puzzles. First, the rise in lower tail inequality during the 1980s was accompanied by an equally pronounced increase in dispersion in the upper-half (90/50) of the distribution (Figure 2.1b), an area where the minimum is unlikely

[1]DFL attribute 62 percent of the growth of the female 10/50 and 65 percent of the growth of the male 10/50 to the declining value of the minimum wage (Table III).

[2]Using cross-region rather than cross-state variation in the 'bindingness' of minimum wages, Teulings (2000 and 2003) reaches similar conclusions. See also Mishel, Bernstein and Allegretto (2006, chapter 3)(Mishel, Bernstein and Allegretto 2006) for an assessment of the minimum wage's effect on wage inequality.

to be relevant. Though the contemporaneous rises in upper and lower tail inequality need not have identical causes, it would be surprising if they had no causes in common. Second, at no time between 1979 and 2007 were more than eight percent of male hours paid at or below the federal (or applicable state) minimum wage (Table 2.1). If the falling minimum wage explains the bulk of the rise in male wage inequality, this implies extremely large spillovers from the minimum wage to non-covered workers. Finally, the Lee analysis uncovers, and scrupulously reports, a number of puzzling results that cast some doubt on the validity of the exercise.[3] Most surprisingly, the main estimates imply that the declining federal minimum wage substantially reduced the growth of upper-tail inequality in both the male and pooled-gender wage distributions during 1979 to 1991, a finding that appears implausible on a priori grounds.[4]

Spurred by these puzzles, we offer a fresh analysis of the impact of state and federal minimum wages on the shape of the US earnings distribution. Our work benefits from substantially longer state-level wage panels than were available to earlier studies, and from a proliferation of state minimum wage laws enacted after 2000 that generate usable state variation in wage floors.[5] Our statistical approach follows closely the model of Lee and Teulings; we obtain identification by using cross-state and over-time variation in the 'bindingness' of federal and applicable state minimum wages. The main advance of our approach is in estimation. Because the impact of the minimum wage will in part depend upon where in the wage distribution the statutory minimum falls, it is necessary to scale the statutory minimum by some measure of expected 'bindingness.' Lee (1999) proposes a natural scaling: the gap between the log state minimum and log state median wage, which Lee labels the 'effective minimum.' This approach introduces a potential confound, however, which is that the median wage appears on both sides of the estimating equation (in the effective minimum wage and in the 10/50 earnings ratio, and other inequality metrics). This is problematic inasmuch as sampling variation in the median wage measure may generate simultaneity bias in OLS models that leads to inflated estimates of the effect of the minimum on state wage distributions.[6] Cognizant of the possibility of simultaneity

[3] These results are presented with admirable candor, and discussed in detail, by the author.

[4] See Lee (1999) Table II. The large, positive and highly significant coefficients in this table imply that a 1 log point in the effective minimum wage (defined as the difference between the log state minimum wage and the log state median wage), reduces male and pooled-gender 90/50 log wage inequality by 0.16 to 0.44 log points.

[5] As of 2007, 30 states had established state minimum wages that exceeded the federal level (Table 2.1).

[6] This problem is exacerbated when state fixed effects are included as more of the remaining variation in the

bias, Lee takes a number of steps to minimize its impact. These steps do not appear to fully resolve the problem, as we show below.

In this paper, we apply the canonical (Durbin, 1954) technique to purge simultaneity bias induced by errors-in-variables: we instrument the error-ridden effective minimum wage variable with a variable that does not contain correlated measurement error, the statutory minimum wage. This instrumental variable approach, first used by Card, Katz and Krueger (1993) in their reanalysis of the employment effects of minimum wage laws, fixes simultaneity bias so long as the statutory minimum is exogenous.[7] For purposes of comparison to these 2SLS estimates, we also replicate Lee's (1999) OLS models and extend them to 2007.

Our main results are as follows. In partial confirmation of prior work, we find that the minimum wage significantly affects the shape of the US wage distribution during the 1980s, particularly for females. However, simultaneity bias causes OLS estimates to substantially overestimate the contribution of the minimum wage to inequality. This problem is most severe for the male and pooled-gender wage distributions, but is also pronounced for the female distribution.[8] During the period of 1979 through 1988, when the erosion of the minimum wage was most rapid, OLS models appear to overstate the contribution of the minimum wage to rising inequality by 450 percent for males, 240 percent for both sexes combined, and 160 percent for females. After accounting for the decompressing effect of the falling minimum wage, OLS estimates suggest that latent wage inequality decreased during 1979 to 1988. By contrast, 2SLS models indicate that the minimum wage explains at most one-third of the substantial increase in inequality during this period. Graphical comparisons of OLS and 2SLS estimates reinforce the conclusion that OLS estimates are unlikely to be reliable.

To benchmark the generality of these findings, we calculate the contribution of the minimum wage to inequality during two subsequent periods of minimum wage erosion, 1991 to 1996 and 1998 to 2006. In these two time intervals, the employment-weighted average of state minimum wages fell by 12.7 log points and 10.1 log points, respectively. 2SLS estimates indicate that the

effective minimum wage is the result of sampling variation.

[7]If it is not exogenous, the OLS approach is also invalid. We provide some evidence of the validity of this assumption by documenting that essentially all changes in wage structure accompanying changes in the minimum occur within one calendar quarter of the law change, and not in the surrounding quarters before or thereafter.

[8]The problem is likely more severe for the male and the pooled distributions because the minimum wage is largely non-binding in these samples, so identification of OLS models is primarily driven by simultaneity bias rather than statutory variation in the minimum wage.

falling minimum contributed negligibly (no more than 2 log points) to male and pooled-gender wage inequality during both periods. 2SLS estimate for females are only are only slightly larger. By contrast, OLS models suggest that the declining minimum masked substantial compressions of (latent) female and pooled-gender inequality in both periods—a result that likely derives from simultaneity bias.

The modest effects of the minimum on inequality that we identify may arise through two channels: a direct (mechanical) impact whereby wages below the minimum are increased[9]; and an indirect (spillover) effect whereby earnings above the minimum are also pushed upward (due perhaps to incentive or equity considerations). While our 2SLS models capture the net of these two effects, it is also of interest to analyze their separate contributions since any usable forecast of the effect of the minimum on wage inequality must account for spillovers (if present). Identifying these spillovers requires an empirical model of the full latent distribution of wages (or at least its lower tail), purged of both direct and indirect minimum wage effects. We model each states' latent wage distribution as log-normal. We estimate the parameters of these distributions using wage observations from higher percentiles of the distribution, where the minimum wage is unlikely to be relevant. We calculate the mechanical impact of the minimum wage by truncating the lower tail of the (estimated) latent distribution, and we infer spillovers by comparing the 'mechanical' distribution with the observed distribution.

Though the minimum wage had only a modest effect on inequality over 1979 to 2007, spillovers were a significant component of this impact. At its highest level (in 1979), the minimum wage mechanically raised percentiles in the female distribution by 4 log points on average, and spillovers raised percentiles by an additional 2 log points on average. Both the direct and spillover effects were considerably smaller for males and for the pooled distribution. As the real minimum eroded between 1979 and 2007, both direct effects and spillovers fell by more than half. Notably, spillovers appear to account for a somewhat larger share—approximately half—of the minimum wage's (modest) impact in 1997 than in 1979, when the spillover contribution was one-third of the total effect.

The remainder of the paper proceeds as follows. Section 2.2 describes the data and presents

[9]We assume no disemployment effects at the modest minimum wage levels mandated in the US, an assumption that is supported by a large recent literature.

simple, reduced-form estimates of the relationship between the statutory minimum wage and inequality throughout the distribution. Section 2.3 presents more fully parameterized models that, like Lee (1999), explicitly account for the bite of the minimum wage in estimating its effect on the wage distribution. This section compares parameterized OLS and 2SLS models, and documents the pitfalls that arise in the OLS estimation. Section 2.4 summarizes two sets of counterfactual exercises. The first exercises, following Lee, uses point estimates from the main regression models to calculate counterfactual changes in wage inequality holding the real minimum wage constant. The second analysis uses parametric estimates of the latent wage distribution to provide a full accounting of mechanical and spillover effects. The final section concludes.

2.2 Change in the federal minimum wage and variation in state minimum wages

The Federal minimum wage remained constant in nominal terms over the nine-year period between 1981 and 1990. Similarly, the Federal minimum wage remained at $5.15 between September 1997 and July 2007, and by July 2007, the real value of the Federal minimum was lower than it had been at any point in the past fifty years (Figure 2.1). The difference between the two periods is that by the late 1980s, only 15 states minimum wages exceeded the federal minimum wage; by 2007, 30 state minimum wages did. As a result, the average real value of the minimum wage applicable to workers in 2007 was not much lower than it was in 1997, and was significantly higher than if states had not enacted their own minimum wages. Appendix Table 2.1 illustrates the extent of state minimum wage variation between 1979 and 2007.

We use these differences in minimum wages across states and over time as one source of variation for identifying the impact of the minimum wage on the wage distribution. As an additional form of variation, we use the notion that the wage distribution of lower wage states should be more affected for a given value of the real minimum wage. Table 2.1 provides examples of this. For each year, there is significant variation in the percentile of the state wage distribution where the state or federal minimum wage "binds." For instance, in 1979 the minimum wage was equal to the 6^{th} percentile of the female wage distribution in Alaska, Connecticut, and

Washington, equal to the 30^{th} percentile in Mississippi, and the median percentile at which it bound, across all states, was around the 13^{th} percentile. In 1979, this variation in the "bite" or "bindingness" of the minimum wage is due mainly to cross-state differences in wage levels, since only Alaska had a state minimum wage that exceeded the federal minimum. In later years—particularly 2000 and after—this variation is also due to differences in the value of state minimum wages.

2.2.1 Sample and variable construction

Our analysis uses the percentiles of states' annual wage distributions as the primary outcomes of interest. We form these by pooling all individual responses from the Current Population Survey Merged Outgoing Rotation Group (CPS MORG) for each year. An individual's wage is taken to be his reported hourly wage, if the individual reports being paid by the hour, and is otherwise calculated as weekly earnings divided by weekly hours worked. We limit the sample to individuals age 18 through 64, and we multiply top-coded values by 1.5. We make no adjustment for individuals with particularly low wages (i.e. sub-minimum wages). We then take these individual wage data and calculate all percentiles of the male, female, and pooled state wage distributions for 1979-2007, weighting individual observations by their CPS sampling weight multiplied by their weekly hours worked.

Our primary analysis is at the state-year level. However, minimum wages often change during the middle of a year. We resolve this by assigning the value of the minimum wage that was in effect the longest throughout the calendar year to the state-year observation. For those states and years in which a different minimum wage was in effect for six months in the year, the maximum of the two is used. Alternatively, we have tried assigning the maximum of the minimum wage within a year as the applicable minimum wage, and this leaves our conclusions unchanged.

2.2.2 Initial evidence on the impact of the minimum wage on the wage distribution: Reduced form estimates

We begin by describing the empirical relationship between median-scaled percentiles of the male, female, and pooled wage distributions and functions of the real value of the minimum wage. In particular, we estimate the following first-differenced equation:

$$[w_{st}(p) - w_{st}(.5)] - [w_{st-1}(p) - w_{st-1}(.5)] = \alpha_t + f(w_{st}^m) - f(w_{st-1}^m) + \varepsilon_{st} \tag{2.1}$$

where $w_{st}(p)$ is the log wage at the p^{th} percentile in state s at time t and w_{st}^m is the log of the applicable nominal minimum wage (i.e. the maximum of the federal and state minimum wages). We take $f(w_{st}^m)$ to be:

$$f(w_{st}^m) = \beta_p^1 w_{st}^m + \beta_p^2 (w_{st}^m)^2 \tag{2.2}$$

For now, we view this specification as a way to succinctly demonstrate the relationship between states' minimum wages and all percentiles of states' wage distributions. This is not our primary specification since the minimum wage is not properly scaled; in order to make predictions about the effects of changes in the minimum wage, $f(w_{st}^m)$ must scale the minimum by some measure of its bindingness in the wage distribution (i.e. by the wage level of the state). This is the approach we use in the following section, and it leads us to an instrumental variables estimation strategy for which equation 1 is the reduced form. We allow a quadratic term in the log of the minimum wage so as to allow the effect of the minimum wage to vary based on its level.

We estimate equation 1 over the 1^{st} through 99^{th} percentiles of the male, female, and pooled state wage distributions using annual data from 1979 to 2007. We include all 50 states, and weight our regressions by the sum of individuals' sample weights multiplied by hours worked per week. When reporting regression estimates, we exclude the lowest 5 percentiles since these often represent wages significantly below the minimum wage, and it seems likely that these are highly misreported. We exclude the upper 5 percentiles since the level at which wages are top-coded changes over our sample period. Figures 2.2a and 2.2b display estimates of the marginal effect of the log minimum wage when evaluated at its weighted average across states and years. Table 2.2 displays estimates of β_p^1 and β_p^2, as well as the marginal effects of the log minimum wage, for various percentiles.

For the female wage distribution, there is a positive and statistically significant association between the median-scaled value of log wage percentiles and the log of the minimum wage through at least the 15th percentile. This is well beyond where the minimum wage tends to be binding; referring back to table 1, the median percentile at which the minimum was binding in 1979 was around the 13th percentile, and in 2007 it was the 4th percentile. A 10 log point increase in the minimum wage is associated with a 3 log point reduction in log(p5)-log(p50), and a 1 point reduction in log(p10)-log(p50). For males, a statistically significant relationship appears to exist only up to the 10th percentile, and the magnitude of this association at lower percentiles is significantly less than for females, although the magnitude of the association is positive (though statistically insignificant) throughout the distribution. For both males and females, the relationship between upper tail percentiles and the minimum wage is statistically indistinguishable from zero.

Appendix Figures 2.1a and 2.1b provide estimates of equation (2.1), estimated at the quarterly level rather than the annual level, additionally including one lead and lag of the minimum wage and its square. The figures plot the marginal effects for the lead, lag, and contemporaneous change in the minimum, evaluated at the average of the log minimum wage across all states and years. Circles indicate where the marginal effects are statistically significant at the 5 percent level.

For the female wage distribution, there is a strong and significant relationship between increases in lower tail percentiles and changes in the minimum wage in the quarter that the legislated minimum changes. There is some evidence of a continued relationship between increases in lower tail percentiles and changes in the minimum wage in the previous quarter, suggesting that wage distribution adjustment may take at least one quarter. Estimates for the male wage distribution are less precise, and suggest, if anything, that changes in lower tail percentiles are negatively associated with changes in the minimum wage in the previous quarter. However, for both the male and female wage distribution there is no evidence of an association between changes in lower tail percentiles and changes in the minimum wage that occur in the subsequent quarter. This suggests against the possibility of anticipation effects or that the observed relationship in Figures 2.2a and 2.2b is because changes in the legislated value of state minimum wage occur in states that were already experiencing lower tail contraction prior to the minimum wage change. We consider this evidence in support of using legislated changes in the minimum wage as an instrument for changes in the "effective minimum," which we discuss in further detail in the subsequent section.

These results constitute our initial evidence that there appears to be a strong and positive relationship between changes in the value of the minimum wage and changes in lower percentiles of the wage distribution, that this relationship is stronger for the female wage distribution, and that there is little association between changes in the minimum wage and changes in upper tail percentiles. These estimates provide meaningful correlations of the relationship between changes in wage percentiles and changes in the minimum wage, but do not provide parameter estimates that can be used to predict how state wage distributions' would respond to changes in the minimum wage. The next section considers an alternative specification that can be used to do so by specifying and estimating a model that scales the minimum wage by a measure of the state's wage level.

2.3 Parametric estimation

The previous section has shown that there seems to be an impact of the minimum wage on the wage distribution beyond the point at which the minimum wage binds. That raises the possibility that the contribution of the minimum wage to the evolution of wage inequality is larger than one might have expected given the fraction of workers paid the minimum wage. However, the reduced form specifications we have estimated so far are not well-suited to evaluating this claim because of problems with the assumptions about the way in which the minimum wage affects the wage distribution. To see this, consider (2.1). In this specification the impact of a change in the minimum wage on the wage distribution depends only on the level of the real minimum wage—it does not depend on any other feature of the wage distribution. That is implausible—it is intuitively appealing that the impact should depend on the level of the minimum wage relative to the general level of wages. Although these reduced form estimates will have some internal validity—they can be interpreted loosely as average effects within our sample—we are hesitant to claim any external validity as would be required to answer questions like 'what would have been the evolution of wage inequality if minimum wages had not changed relative to average earnings?'

This problem was recognized by Lee (1999) who used the log of the minimum relative to the median as his measure of the 'bite' of the minimum wage. We will also use this measure and refer to it as the effective minimum.[10]

Use of the effective minimum can be justified in the following way, which fleshes out the arguments used by Lee (1999). Denote by $w^*_{st}(p)$ the log wage in state s at time t for percentile p in the absence of the minimum wage—call this the latent wage distribution. With a minimum wage, denoted in log form by w^m_{st}, the actual log wage at percentile p, which we will denote by $w_{st}(p)$ will deviate from the latent distribution for at least some percentiles. If, for example, the minimum wage had no effect on employment rates, and no spill-overs then we would have the relationship:

$$w_{st}(p) = \max[w^*_{st}(p), w^m_{st}] \tag{2.3}$$

However, if there are spill-overs or some employment effects then the minimum wage will have an effect on percentiles above where it binds (see Lee, 1999, for more discussion of these arguments, or Teulings, 2000, for an explicit supply and demand model with this feature). So, let us generalize (2.3) to the form:

$$w_{st}(p) = \phi[w^*_{st}(p), w^m_{st}] \tag{2.4}$$

What are plausible restrictions on the function $\phi[.,.]$? We would expect it to be increasing in both its arguments and also that it satisfies a homogeneity property—that if the latent percentile and the minimum wages both rise in the same proportion, the actual percentile also rises in that proportion. As the model is expressed in logs this restriction can be written as:

$$\phi[w^*_{st}(p) + a, w^m_{st} + a] = a + \phi[w^*_{st}(p), w^m_{st}] \tag{2.5}$$

Now set $a = -w^*_{st}$ and applying (2.5) to (2.4) we have that:

$$w_{st}(p) = w^*_{st}(p) + \phi[0, w^m_{st} - w^*_{st}(p)] = w^*_{st}(p) + \psi(w^m_{st} - w^*_{st}(p)) \tag{2.6}$$

i.e. that the deviation of the actual percentile from the latent percentile depends on the

[10] The OECD also use the minimum relative to the median as their measure of the bite of the minimum wage.

gap between the minimum and the latent percentile. What are the plausible restrictions on the function $\psi(.)$? We would expect it to be positive everywhere (otherwise the minimum wage would reduce wages at some percentiles) and to have a positive first derivative. In addition, if the minimum wage is very low (or non-existent) we would expect the actual percentile to be very close to the latent percentile so that we have $\psi(-\infty) = 0$. On the other hand, if the minimum wage gets very high we would expect the actual percentile to be very close to the minimum wage so that we have $\lim_{x \longrightarrow \infty} \psi(x) = x$. Graphically, we might expect that the relationship between deviations of the actual from the latent percentile and the difference between the minimum wage and the latent percentile looks something like that presented in Figure 2.3.

This discussion should make it clear that non-linearity is likely to be an important feature of (2.6) so that some thought needs to be given to the functional form of the estimating equation. In what follows, our main specification uses a quadratic approximation (as does Lee, 1999), and we approximate (2.6) by:

$$w_{st}(p) = w^*_{st}(p) + \alpha_0 + \alpha_1(w^m_{st} - w^*_{st}(p)) + \alpha_2(w^m_{st} - w^*_{st}(p))^2 \tag{2.7}$$

However, it should be noted that a quadratic cannot have a shape similar to that drawn above over the whole of its range so that we have to exercise caution in estimating minimum wage effects outside the observed sample. In particular, this specification cannot really be used for an assessment of what the distribution of wages would be like if there was no minimum wage.

To make (2.7) into an estimable equation wage we need to put some additional structure on the form taken by the latent wage distribution. We follow Lee (1999) in assuming that the latent wage distribution can be summarized by 2 parameters – the median and the variance so that we can write:

$$w^*_{st}(p) = \mu_{st} + \sigma_{st} F^{-1}(p) \tag{2.8}$$

Where we have the normalization $F^{-1}(0.5) = 0$ so that μ_{st} is the median log wage in state s at time t. Plugging (2.8) into (2.7) and collecting terms we have that:

$$w_{st}(p) - \mu_{st} = \alpha_0 + \sigma_{st}(1-\alpha_1)F^{-1}(p) + \alpha_2[\sigma_{st}F^{-1}(p)]^2 + [\alpha_1 - 2\alpha_2\sigma_{st}F^{-1}(p)](w_{st}^m - \mu_{st}) + \alpha_2(w_{st}^m - \mu_{st})^2 \tag{2.9}$$

The first two terms are related to the overall evolution of wage inequality and last two terms to the effect of the effective minimum. Note that the coefficients in (2.9) will vary with the percentile, not just because p appears in the linear term of the effective minimum but also because, as pointed out by White (1980), the coefficients α will vary with the data. Intuitively we would expect that a rise in latent wage inequality leads to a larger impact on lower percentiles for a given effective minimum.

For (2.9) to be estimable one also needs models for the median and variance. There are a number of options here and we start our discussion with the choices made by Lee. Lee replaces μ_{st} by the observed median, σ_{st} by a set of time dummies and assumes that any cross-state variation in latent wage inequality is uncorrelated with the median and can therefore be subsumed into the error without causing bias in the estimated impact of the minimum wage. Hence, the Lee equation can be written as:

$$w_{st}(p) - w_{st}(0.5) = \alpha_t + \beta_1(w_{st}^m - w_{st}(0.5)) + \beta_2(w_{st}^m - w_{st}(0.5))^2 \tag{2.10}$$

In the first three columns of Table 2.3 we present estimates of β_1 and β_2 from equation (10) for our sample period 1979-2007 for selected percentiles, as well as marginal effects when estimated at the weighted average of the effective minimum over all states and years in our sample. If we look at the lower percentiles, we find, as Lee did, large significant effects of the minimum wage reaching the 30^{th} percentile for men and the 40^{th} percentile for women. However, there are good reasons to be skeptical of these estimates as one also finds large significant effects for men at the top of the distribution. This is even more apparent when one plots the estimated marginal effects of the minimum wage (evaluated at is weighted average across states for the period 1979-2007), as in figures 2.4a, 2.5a, and 2.6a. The implausibility of the male estimates is especially clear.

One possible form of misspecification is that the identifying assumption that state latent wage inequality is uncorrelated with the median is false. Indeed if we regress the log(60)-log(40) on the median (which should be uncorrelated if the density function is symmetric around the median) and time dummies (to capture the controls put in equation (2.8)), the log median has a t-statistic of 17 for females, 2.5 for men and 15 for the combined sample. This suggests that those states with high median wages have high levels of latent wage inequality. Since this seemingly indicates permanent differences in latent wage inequality across states, then one might think of including state fixed effects in (2.10)—Lee also reports this type of specification (Tables II and III), and we have replicated these results as well (unreported). However, this makes the implausibility problem even worse—the estimated impacts of the minimum wage at the top of the distribution are now large and positive for all sets of estimates.

The explanation for this problem is almost certainly a point made by Lee (1999)—the presence of the median in both the dependent and independent variables in (2.10) induces an artificial positive correlation caused by sampling variation. This gets worse when state fixed effects are included as more of the remaining variation is the result of sampling variation.

Lee (1999) is aware of this problem and his preferred solution is to use two different measures of central tendency in the dependent and independent variables. In the dependent variable he continues to use the median but he uses the trimmed mean on the right-hand side (i.e. the mean after excluding the bottom and top 30 percentiles). Although this does reduce the correlation, it does not eliminate it. In fact, one can show that if the latent log wage distribution is normal, the correlation between the trimmed mean and the median will be about 0.93—i.e. not one, but very high (see the derivation in the Appendix). So, this method does not really solve the problem.

Here, we use another method to estimate an equation like (2.10). Instead of estimating by OLS we instrument the effective minimum terms. As instruments we use the minimum wage and its square and the minimum wage interacted with a measure of the average wage in the state. This latter instrument is to give us instruments which differ in their ability to discriminate between the linear and quadratic terms. For the linear and quadratic terms in the effective minimum, the first-stage is simply the reduced forms discussed previously. We also estimate the model in first-differenced form—this will eliminate any permanent differences in wage inequality across states.[11]

The last three columns of Table 2.3 report the results from this specification. There are a number of points to note. First, the estimates are more plausible than the OLS estimates. The estimated impact on the top percentiles is never significantly different from zero while those for the lowest percentile are. But the estimated impacts of the minimum wage at the lower percentiles are all much lower than those estimated in the OLS specifications. Nonetheless they are significantly different from zero and do reach further up the wage distribution than the direct effects, suggesting there are spillovers. In addition both the linear and quadratic terms are generally positive supporting the convexity of the relationship argued for above. However, there is considerable collinearity between the linear and quadratic terms which makes the standard errors of the individual coefficients often appear very large.

Figures 2.4b, 2.5b, and 2.6b plot the estimated marginal effect for each percentile when the log of the effective minimum is evaluated at its sample mean. For men the estimated effect seem to be positive up to the 15^{th} percentile (though is only significantly different from zero up to the 8^{th}).[12] For women there are significant effects up to the 17^{th} but a positive effect would seem to remain almost up to the median. For males and females together the effects seem to reach to the 15^{th} percentile.[13]

2.4 Benchmarking the effect of the minimum wage on the shape of the wage distribution

Our analysis confirms a significant impact of the minimum wage on wage inequality. To develop a precise sense of the size of this contribution, we conduct two sets of analyses. The first, following Lee (1999), uses point estimates from the main models to estimate the changes in wage inequality that would counterfactually have occurred had the minimum wage held constant at

[11] We do not report OLS specifications in first-differenced form. Unsurprisingly, this magnifies the problems caused by sampling variation so that the estimates obtained in this way are implausible.

[12] Because we would expect the impact of the minimum wage to go to zero as we move up the percentiles, there will inevitably be some percentiles with effects that are positive but insignificantly different from zero. So it is not appropriate simply to argue that the minimum wage only effects percentiles where it has a significant effect.

[13] As a robustness check we also estimated models with a cubic in the effective minimum and found similar results. We do not present these results here, but report the robustness of our results to the choice of a quadratic versus cubic specification in our analysis of counterfactual wage distributions in Section 2.4.

a given real level. This analysis provides an estimate of the net contribution of the minimum to wage inequality. It does not distinguish between mechanical and spillover effects, however. The second analysis decomposes these two effects through a more ambitious modeling exercise.

2.4.1 Counterfactual wage inequality estimates with the real minimum held constant

A straightforward approach to gauging the contribution of the minimum wage to inequality trends is to use the earlier regression estimates to calculate counterfactual wage distributions, holding the effective minimum wage constant. Following Lee (1999), we calculate for each observation in the dataset its rank in its respective state wage distribution. We then adjust each wage by the quantity:

$$\Delta w_{st}^{p} = \hat{\beta}_1(\widetilde{m}_{s,\tau 0} - \widetilde{m}_{s,\tau 1}) + \hat{\beta}_2(\widetilde{m}_{s,\tau 0}^2 - \widetilde{m}_{s,\tau 1}^2) \tag{2.11}$$

where $\widetilde{m}_{s,\tau 1}$ is the observed end-of period effective minimum in state s in some year $\tau 1$, $\widetilde{m}_{s,\tau 0}$ is the corresponding beginning-of-period effective minimum in $\tau 0$, and $\hat{\beta}_1$, $\hat{\beta}_2$ are point estimates from the OLS and 2SLS estimates in Table 2.3. We pool these adjusted wage observations to form a counterfactual national wage distribution, and we compare changes in inequality in the simulated distribution to those in the observed distribution.[14] One feature of this simulation procedure bears note: it does not permit estimation the full 'latent' distribution of wages—i.e., in the absence of any minimum wage—since the effective minimum wage measure, equal to the logarithm of the minimum minus the logarithm of the median, is undefined at a minimum wage of zero. This simulation tool is therefore appropriate for estimating the impact of the minimum wage over ranges observed in the data. We address this infirmity in the subsequent sub-section.

Panel A of Table 2.4 shows that the female 10/50 log wage ratio increased by 23.2 log points between 1979 and 1988. Applying the OLS point estimates from Table 2.3, we calculate that the 10/50 would counterfactually have risen by only 2.1 log points over this period had the 1988 effective minimum been in places in 1979. Thus, consistent with Lee (1999), OLS estimates

[14] Also distinct from Lee, we use states' observed median wages when calculating $\widetilde{m}$ rather than the national median deflated by the price index. This choice has no substantive effect on the results, but appears most consistent with the identifying assumptions.

imply that the minimum wage can account for the bulk (21.1 of 23.2 log points) of the observed expansion of lower tail female wage inequality in this period.[15] The next two rows of the table present analogous counterfactuals using the 2SLS in lieu of OLS point estimates. Here we find that the falling minimum wage explains no more than 8 of 23 log points of the expansion of the female lower tail, and this result is similar across quadratic and cubic specifications. When these calculations are repeated for the male and pooled-gender wage distributions (panels B and C), the contrast between OLS and 2SLS estimates is even shaper. OLS models imply that the falling minimum explains more than all of the 5.7 and 10.5 log point expansions of the male and pooled-gender distributions between 1979 and 1988. 2SLS estimates instead suggest that the minimum explains no more than one-third of the total expansion of the 10/50 of either distribution in either period.

How robust are these findings across time periods and specifications? In panels B and C of Table 2.4, we calculate identical regression-based counterfactuals for two subsequent time periods during which the real minimum dropped rapidly: 1991 to 1996, when it fell by 12.7 log points, and 1998 to 2006, when it fell by 10.1 log points.[16] While expansion of lower tail inequality was much smaller during these intervals, the pattern of counterfactuals is quite similar. OLS estimates imply in nearly all cases that, were the effective minimum held at its end of period level throughout, inequality would either decreased or remained stable during these time intervals.[17] 2SLS estimates instead suggest that the falling minimum had at best a modest effect on inequality. Similar to our findings for 1979 to 1988, we estimate that the minimum accounts for one-third to one half of the rise in female lower tail inequality, and one-fifth to one-third of the rise in male and pooled-gender inequality. The discrepancy between OLS and 2SLS results is therefore not specific to the extensively studied 1979 through 1988 interval.

The above simulations are calculated by applying point estimates from models fit to the full

[15] Lee (Table IV) estimates that the female 10/50 rose by 18.6 log points between 1979 and 1989, and that the falling minimum accounts for all but 4.5 log points of this increase. We focus on the interval of 1979 to 1988 rather than 1979 to 1989 because wage lower tail wage inequality for males had already begun to reverse course by 1989. If we instead focus on 1979 to 1989, our results are substantively identical.

[16] Since state and federal minimum wages begin to diverge meaningfully after 1997, we report the hours-weighted average of minimum wages faced by US workers. We study the period to 2006 because the state minimums make a large jump in 2007, reversing the drop that informs the counterfactual.

[17] An exception is male inequality during 1991 to 1996, where the OLS model implies that the minimum had no effect.

1979 through 2007 sample to specific sub-periods of the data. Since our primary inference concerns sub-periods in which the minimum wage was declining most rapidly, a second robustness test is to compare models fit using only data from the years of interest for each counterfactual calculation. A complementary approach is to fit models using only out of sample years for each counterfactual, applying the point estimates to the years of interest.

Appendix Table 2.2 summarizes results of these alternative approaches. Comparison of columns (1) through (3) with columns (4) through (6) of the table shows that counterfactuals based on only in-sample estimates for the years of interest (1979 to 1988, 1991 to 1996, or 1998 to 2006) are closely comparable to those based on full-sample estimation. This pattern suggests that point estimates obtained from sub-intervals of the data are reasonably comparable to those obtained from the full sample. Columns (6) through (9) present calculations in which we use out-of-sample data to form point estimates, and these are used to form counterfactuals for in-sample years. These results again prove comparable to the primary estimates, with the exception of 1991 to 1996, in which results are a bit less stable than other time periods. In net, these simple, regression-based simulation results suggest a consistent, modest effect of the declining minimum wage on the evolution of lower tail wage inequality. The minimum accounts for about one-third of the rise in female inequality, and a smaller share for males and for the pooled distribution.

2.4.2 Decomposing the direct and spillover effects of the minimum wage

One intriguing implication of the results so far is that the minimum wage must have spillovers. To see this, note that that even at its most binding, the minimum wage was never above the 12^{th} percentile of the male wage distribution in any state, and was always below the 10^{th} percentile after 1981 (Table 2.1). Yet, the main estimates imply that the minimum wage compressed the male 10/50 ratio modestly, even in the late 1990s. Thus, the minimum must have had spillovers onto higher percentiles. A natural question then arises as to the relative size of the direct and spillover effects on the wage distribution. To infer these effects requires an estimate of the latent wage distribution in all parts of the distribution, even those percentiles that are always below where the minimum binds. It also requires extrapolation of the effect of the minimum wage on the earnings distribution to the case where the minimum wage did not bind. Inferring these effects requires more structure, and thus more stringent assumptions, than we have previously imposed. There is some unavoidable extrapolation in this exercise, although we will attempt to verify that the assumptions are not violated in the regions of the data that we observe.

To model the effect of the minimum on the actual distribution we need to use a functional form that has the shape shown in Figure 2.3. We follow Lee (1999) in using the following version of (2.6):

$$w_{st}(p) = w^*_{st}(p) + \frac{w^m_{st} - w^*_{st}(p)}{1 - e^{-\frac{1}{\rho}[w^m_{st} - w^*_{st}(p)]}} \tag{2.12}$$

where $\rho \geq 0$ is a parameter that measures the size of the spill-over effect. If $\rho = 0$ the model of (2.12) reduces to one where those with $w^*(p) < w^m$ have their wage raised to the minimum but there are no spillovers. Higher values of ρ imply higher spillovers. With this functional form, the spillover effects are largest for those just affected by the minimum wage (i.e. those for whom $w^*(p) = w^m$) and, for these workers, the increase in log wages is equal to ρ.

To estimate the model, we also need some assumption about the latent log wage distribution. We assume this is normal—i.e., we use the model of (2.8) with F having the standard normal form. We use a two-step estimation procedure—first we estimate the latent wage distribution using parts of the wage distribution where we think the minimum has no effect, and we use between the 40^{th} and 60^{th} percentiles for this purpose. We model both μ_{st} and σ_{st} of (2.8) as additive year and state dummies, that is, we allow both mean and variance to vary across state and time . With these estimates we can then estimate the latent wage distribution for all percentiles. So in other words, we are assuming that the wage distribution is relatively unaffected by the minimum wage between the 40th and 60th percentiles, and using information on this part of the distribution to infer the shape of the entire latent wage distribution for each state in each year.

To give some idea of the adequacy of the assumption that the latent wage distribution can be well-approximated by the normal, Figure 2.10 plots the average deviation (across states and years) between the actual observed percentile and the estimated latent distribution for percentiles from the 3^{rd} to the 60^{th}. This is done separately for women, men and the pooled distribution. For all three samples this deviation is very close to zero for all percentiles between the 40^{th} and 60^{th} percentiles—this indicates that the normal distribution is a good approximation for the sample on which the data is estimated (the average deviation must be zero but it could be correlated with the percentile). For the lower percentiles the average deviation is positive, exactly what one would expect if the minimum wage has an impact. For men, the deviation is zero down to about the 20^{th} percentile indicating that normality is a good approximation out of sample. For the women and pooled samples, it is harder to see the validity of the out-of-sample approximation because there seems to be some effect of the minimum wage close to the 40^{th} percentile.

Now consider the relationship between the actual minus the latent and the log minimum minus the latent as implied by the assumptions behind (2.6). This is plotted for the 3 samples in Figure 2.11. Because of the large number of observations this Figure plots the average value of the actual minus the latent for 1 log point bins of the estimated log minimum minus the latent. In all samples one can see the general shape of the relationship between the deviation between the actual and latent and the minimum and latent that is predicted by theory and drawn previously in Figure 2.3. The functional form given in (2.12) has the appropriate shape.

Using our estimated values of latent percentiles in the lower tail of state-year wage distributions, we estimate the model of (2.6) for our three samples using non-linear least squares for a sample including all percentiles at or above the minimum and up to the 30th percentile. The estimated values of are 0.094 for females, 0.097 for males and 0.117 for the combined sample. The estimate of 0.094 for women can be interpreted to mean that those workers with a latent wage equal to their minimum have their pay raised by 9.4%, an estimate that is not enormous but is not small either. The parameter estimates for men and women are similar suggesting that the larger effect of the minimum wage on the female wage distribution is simply a product of the fact that the male wages are generally higher than female wages..

As an indication that the functional form assumed is a good one, we also plot on Figure 2.11 above the predicted values from the non-linear equation. One can see that the fit is extremely good with the exception of some of the lowest percentiles.

Our estimates of the non-linear model give us the total effect of the minimum wage on each percentile. We can then break this total effect up into a direct and a spillover effect of the minimum wage. The direct effect of the minimum wage can be computed as:

$$\max[w_{st}^{m} - w_{st}^{*}, 0] \tag{2.13}$$

The spillover effect is the difference between the total effect and this direct effect.

To give some idea of the magnitudes of the direct and spillover effects we compute the effect on average log wages by averaging the direct and spillover effects across all percentiles. These estimates are reported for each sample and year in Figure 2.12.

There are several points to note. First, the direct effect is generally larger than the spillover effect though they are very similar for men. Secondly, both effects are larger for women than men, as one would expect. Thirdly, there is time variation—both direct and spillover effects were much larger for women in 1979 than they are now. In 1979 the total effect of the minimum wage on average log wages for women is estimated to be about 6% (though heavily concentrated in the lower percentiles)—by 2007 it is more like 3% .

2.5 Conclusion

This paper has provided an updated assessment of the impact of the minimum wage on the wage distribution by using a longer panel (incorporating many additional years of data and including significantly more variation in state minimum wages) and an instrumental variables specification that purges estimates of simultaneity bias stemming from errors in variables. We estimate that up to 35% of growth in lower tail inequality in the female wage distribution between 1979 and 1988—a period of significant expansion in lower tail inequality, as measured by the differential between the log of the 50^{th} and 10^{th} percentiles—is attributable to the decline in the real value of the minimum wage, while up to 25% of the growth in male lower tail inequality over this period could be attributed to the minimum wage. These estimates imply that the minimum wage made a smaller contribution to growth in lower tail inequality than OLS models suggest. Similar calculations suggest that the minimum wage contributed roughly the same amount to growing lower tail inequality between 1991-1996 and 1998-2006, two other periods during which the real value of the minimum wage was also falling.

Nonetheless, we estimate minimum wage effects that extend further up the wage distribution than would be predicted if the minimum wage had a purely mechanical effect on wages (i.e.

raising the wage of all who earned below it). We estimate the shape of the latent distribution with a simple structural estimation technique (by assuming log normality and estimating the mean and variance of the state-year wage distribution using 40^{th} to 60^{th} wage percentiles), and use this to separately infer the direct impact and spillover effects from changes in the minimum wage. While the contribution of direct and spillover effects vary across percentiles, on average, spillovers amount to one-third to one-half of the aggregate impact of the minimum wage on the lower tail of the wage distribution, on average.

This analysis suggests that there was significant expansion in latent lower tail inequality over the 1980s, mirroring the expansion of inequality in the upper tail: while the minimum wage was certainly a contributing factor to widening lower tail inequality—particularly for females—it was not the only one. Our ongoing analysis seeks to confirm our findings by applying instrumental variable quantile regression techniques to the estimation of minimum wage effects on the wage distribution.

2.6 Appendix: The Correlation between the Trimmed Mean and the Median.

Here, we derive the correlation coefficient between the median and a trimmed mean under the assumption that log wages are normally distributed and that we are drawing samples of size N from an underlying identical population. As in the main text, denote by $w(p)$ the log wage at percentile p.

A standard result (not dependent on a normality assumption) is that the covariance between wages at two percentiles is given by:

$$cov[w(p_1), w(p_2)] = \frac{p_1(1-p_2)}{Nf[w(p_1)]f[w(p_2)]}, \quad p_1 \leq p_2 \tag{2.14}$$

where $f[.]$ is the density function. If $p_1 = p_2$, this gives the variance of the wage at a particular percentile so that the variance of the median can be written as:

$$var[w(0.5)] = \frac{1}{4Nf[w(0.5)]^2} \tag{2.15}$$

The trimmed mean between the 30^{th} and 70^{th} percentiles can be written as:

$$\bar{w}^t = \frac{1}{0.4}\int_{0.3}^{0.7} w(p)dp \tag{2.16}$$

So that the covariance between the median and the trimmed mean can be written as:

$$cov[\bar{w}^t, w(0.5)] = \frac{1}{0.4}\int_{0.3}^{0.7} cov[w(p), w(0.5)]dp \tag{2.17}$$

The variance of the trimmed mean can be written as:

$$var(\bar{w}^t) = \frac{1}{0.4^2}\int_{0.3}^{0.7}\int_{0.3}^{0.7} cov[w(p), w(p')]dpdp' \tag{2.18}$$

The formulae in (2.15), (2.17) and (2.18) can be used to compute the correlation coefficient between the median and trimmed mean. Note that this correlation does not depend on the sample size N. If the distribution is normal with mean μ and variance σ^2 then the formula for the covariance in (2.14) can be written as:

$$cov[w(p_1), w(p_2)] = \frac{2\pi\sigma^2 p_1(1-p_2)}{Ne^{-\frac{1}{2}[\Phi^{-1}(p_1)]^2}e^{-\frac{1}{2}[\Phi^{-1}(p_2)]^2}}, \quad p_1 \leq p_2 \tag{2.19}$$

where $\Phi^{-1}(p)$ is the inverse of the standard normal cumulative density function. The variance for the median is given by:

$$var[w(0.5)] = \frac{\pi\sigma^2}{2N} \tag{2.20}$$

Note that the correlation coefficient will not depend on either μ or σ.

Table 2.1 - Summary Statistics for Bindingness of State and Federal Minimum Wages

	# states w/higher min.	Min. binding pctile	Med. binding pctile	Female Max. binding pctile	Share of hours at or below min.	Avg. log(50)-log(10)	Min. binding pctile	Med. binding pctile	Male Max. binding pctile	Share of hours at or below min.	Avg. log(50)-log(10)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1979	1	6	12.5	30	0.206	0.382	2	4.0	12	0.076	0.677
1980	1	6	13.0	26	0.186	0.427	3	5.5	12	0.072	0.696
1981	1	5	13.0	25	0.186	0.400	2	6.0	10	0.077	0.693
1982	1	4	10.5	22	0.148	0.496	2	4.0	9	0.069	0.712
1983	1	4	10.0	18	0.136	0.538	2	4.0	9	0.066	0.754
1984	1	2	9.0	16	0.124	0.539	1	4.0	9	0.056	0.763
1985	2	2	8.0	15	0.111	0.580	1	3.0	7	0.051	0.757
1986	5	3	7.0	17	0.100	0.611	1	3.0	7	0.046	0.758
1987	6	2	5.0	9	0.087	0.624	1	2.0	5	0.041	0.799
1988	10	2	4.0	9	0.080	0.614	1	2.0	6	0.039	0.734
1989	12	1	4.0	7	0.071	0.629	1	2.0	5	0.037	0.693
1990	11	2	6.0	16	0.083	0.633	2	3.0	7	0.043	0.742
1991	4	2	7.0	19	0.097	0.616	2	4.0	9	0.052	0.788
1992	7	3	6.0	14	0.093	0.604	1	3.0	7	0.053	0.744
1993	7	2	5.0	11	0.082	0.588	2	3.0	6	0.047	0.722
1994	8	2	5.0	12	0.079	0.588	1	3.0	5	0.043	0.726
1995	9	2	5.0	10	0.069	0.602	1	3.0	6	0.037	0.722
1996	11	3	4.0	8	0.070	0.645	1	3.0	6	0.041	0.693
1997	10	2	5.0	10	0.093	0.635	2	3.0	7	0.056	0.722
1998	7	3	6.0	12	0.085	0.561	2	3.0	9	0.051	0.693
1999	10	3	5.0	12	0.073	0.577	2	3.0	6	0.042	0.673
2000	10	3	4.5	11	0.062	0.595	2	3.0	7	0.036	0.693
2001	10	3	4.0	9	0.055	0.603	1	3.0	6	0.034	0.689
2002	11	2	4.0	9	0.056	0.577	1	3.0	6	0.036	0.693
2003	11	2	4.0	9	0.051	0.580	1	2.0	5	0.033	0.675
2004	12	2	4.0	8	0.049	0.619	1	2.0	6	0.032	0.676
2005	15	2	4.0	9	0.052	0.628	1	2.0	6	0.032	0.693
2006	19	2	3.5	10	0.053	0.644	1	2.0	7	0.033	0.723
2007	30	2	4.0	10	0.068	0.624	1	3.0	6	0.040	0.693

Notes: Column 1 displays the number of states with a minimum that exceeds the federal minimum. Columns (2) and (7) display estimates of the smallest percentile (across states) at which the minimum wage binds. Columns (3) and (8), and (4) and (9) display estimates of the median and largest percentile at which the minimum wage binds across states, respectively. For some states in some years, multiple percentiles in the wage distribution were equal to the value of the minimum wage. For these state/years, the minimum wage is recorded as binding at the highest of these percentiles. Columns (5) and (10) display the share of hours worked for wages at or below the minimum wage. Columns (6) and (11) display the national value of the log(p50)-log(p10) for the male and female wage distributions.

Table 2.1 (cont.) - Summary Statistics for Bindingness of State and Federal Minimum Wages

	Males and Females pooled					
	# states w/higher min.	Min. binding pctile	Med. binding pctile	Max. binding pctile	Share of hours at or below min.	Avg. log(50)-log(10)
	(1)	(2)	(3)	(4)	(5)	(6)
1979	1	3	7.0	19	0.126	0.592
1980	1	4	8.5	17	0.118	0.601
1981	1	3	9.0	16	0.121	0.609
1982	1	3	7.0	14	0.102	0.639
1983	1	3	7.0	13	0.095	0.659
1984	1	2	6.0	12	0.084	0.680
1985	2	2	5.0	10	0.076	0.696
1986	5	2	5.0	11	0.069	0.708
1987	6	2	3.0	7	0.060	0.710
1988	10	2	3.0	7	0.057	0.697
1989	12	1	3.0	6	0.051	0.689
1990	11	2	5.0	10	0.060	0.679
1991	4	2	5.0	13	0.072	0.676
1992	7	2	4.0	10	0.070	0.678
1993	7	2	4.0	8	0.062	0.689
1994	8	2	4.0	8	0.059	0.687
1995	9	2	3.0	6	0.051	0.687
1996	11	2	3.0	7	0.054	0.683
1997	10	2	4.0	8	0.072	0.659
1998	7	2	4.0	8	0.066	0.652
1999	10	2	3.5	8	0.056	0.650
2000	10	2	4.0	8	0.047	0.655
2001	10	2	3.0	7	0.043	0.648
2002	11	2	3.0	8	0.045	0.656
2003	11	2	3.0	7	0.041	0.662
2004	12	2	3.0	7	0.039	0.669
2005	15	2	3.0	7	0.041	0.664
2006	19	1	3.0	8	0.041	0.670
2007	30	2	3.0	8	0.052	0.677

Notes: Column 1 displays the number of states with a minimum that exceeds the federal minimum. Column (2) displays estimates of the smallest percentile (across states) at which the minimum wage binds. Columns (3) and (4) displays estimates of the median and largest percentile at which the minimum wage binds across states, respectively. For some states in some years, multiple percentiles in the wage distribution were equal to the value of the minimum wage. For these state/years, the minimum wage is recorded as binding at the highest of these percentiles. Column (5) displays the share of hours worked for wages at or below the minimum wage. Column (6) displays the weighted average log(p50)-log(p10) across states.

Table 2.2: Reduced form estimates of the relationship between changes in log(p)-log(p50) and changes in log(min) and its square

	Females			Males			Male and female pooled wage distribution		
P	MW	MW^2	Marginal Effect	MW	MW^2	Marginal Effect	MW	MW^2	Marginal Effect
5	1.075	-0.257	0.313	0.344	-0.065	0.154	0.664	-0.162	0.188
	(0.409)	(0.128)	(0.040)	(0.197)	(0.061)	(0.039)	(0.196)	(0.064)	(0.041)
10	0.438	-0.110	0.111	0.641	-0.189	0.085	0.550	-0.140	0.136
	(0.348)	(0.114)	(0.029)	(0.194)	(0.060)	(0.029)	(0.166)	(0.056)	(0.030)
15	0.822	-0.223	0.160	0.406	-0.128	0.031	-0.221	0.061	-0.041
	(0.168)	(0.053)	(0.026)	(0.217)	(0.064)	(0.036)	(0.208)	(0.065)	(0.027)
20	0.264	-0.075	0.042	0.456	-0.131	0.072	0.756	-0.224	0.096
	(0.231)	(0.073)	(0.025)	(0.246)	(0.077)	(0.034)	(0.150)	(0.051)	(0.020)
25	0.285	-0.080	0.048	0.103	-0.030	0.014	0.092	-0.024	0.021
	(0.179)	(0.056)	(0.024)	(0.148)	(0.048)	(0.021)	(0.122)	(0.040)	(0.019)
30	0.171	-0.052	0.018	0.624	-0.189	0.068	0.078	-0.031	-0.014
	(0.153)	(0.047)	(0.027)	(0.214)	(0.065)	(0.035)	(0.130)	(0.043)	(0.018)
35	0.330	-0.107	0.012	0.290	-0.084	0.043	0.293	-0.091	0.025
	(0.083)	(0.026)	(0.019)	(0.153)	(0.048)	(0.022)	(0.179)	(0.055)	(0.027)
40	0.291	-0.086	0.036	0.304	-0.089	0.042	0.252	-0.088	-0.008
	(0.145)	(0.045)	(0.019)	(0.088)	(0.027)	(0.014)	(0.212)	(0.067)	(0.024)
45	0.093	-0.028	0.010	-0.095	0.031	-0.003	0.039	-0.012	0.004
	(0.110)	(0.033)	(0.017)	(0.119)	(0.036)	(0.020)	(0.105)	(0.034)	(0.012)
75	0.047	-0.019	-0.009	0.079	-0.014	0.037	0.018	-0.001	0.017
	(0.221)	(0.069)	(0.032)	(0.156)	(0.051)	(0.020)	(0.148)	(0.048)	(0.019)
90	-0.023	0.018	0.029	0.179	-0.042	0.056	-0.243	0.073	-0.028
	(0.222)	(0.072)	(0.024)	(0.163)	(0.051)	(0.030)	(0.128)	(0.042)	(0.024)

Notes: N=1400. Estimates are the coefficients from regressions of changes in log(p)-log(p50) on changes in log(min) and its square. MW is the coefficient on changes in log(min. wage), and MW^2 is the coefficient on changes in its square. Marginal effect is the marginal effect of changes in log(min. wage), evaluated at the hours-weighted average of log(min. wage) across states and years. Standard errors clustered at the state level are in parenthesis. Regressions are weighted by the sum of individuals' reported weekly hours worked multiplied by CPS sampling weights.

Table 2.3: Relationship between log(p)-log(p50) and log(min. wage)-log(p50), for select percentiles. 1979-2007.

P	OLS quadratic MW-P50	OLS quadratic $(MW\text{-}P50)^2$	OLS quadratic Marg. Effect	2SLS quadratic MW-P50	2SLS quadratic $(MW\text{-}P50)^2$	2SLS quadratic Marg. Effect
			A. Females			
5	0.647	0.056	0.567	1.907	1.029	0.428
	(0.136)	(0.095)	(0.031)	(1.046)	(0.648)	(0.119)
10	1.368	0.651	0.432	0.463	0.237	0.122
	(0.156)	(0.110)	(0.027)	(0.779)	(0.494)	(0.076)
15	0.991	0.475	0.308	1.064	0.597	0.205
	(0.167)	(0.116)	(0.025)	(0.398)	(0.248)	(0.049)
20	0.666	0.311	0.220	0.582	0.346	0.085
	(0.139)	(0.102)	(0.026)	(0.326)	(0.201)	(0.043)
30	0.333	0.152	0.114	0.595	0.364	0.072
	(0.108)	(0.079)	(0.017)	(0.232)	(0.145)	(0.034)
40	0.159	0.073	0.054	0.331	0.198	0.047
	(0.052)	(0.038)	(0.010)	(0.197)	(0.122)	(0.026)
75	-0.046	-0.007	-0.036	0.236	0.154	0.015
	(0.082)	(0.057)	(0.022)	(0.313)	(0.189)	(0.049)
90	0.153	0.107	-0.001	-0.059	-0.057	0.023
	(0.157)	(0.112)	(0.037)	(0.496)	(0.309)	(0.057)
			B. Males			
5	1.786	0.670	0.470	0.580	0.216	0.155
	(0.310)	(0.172)	(0.043)	(0.551)	(0.273)	(0.034)
10	1.058	0.391	0.290	0.541	0.248	0.055
	(0.366)	(0.202)	(0.047)	(0.516)	(0.246)	(0.041)
15	0.751	0.275	0.210	-0.070	-0.029	-0.013
	(0.333)	(0.181)	(0.043)	(0.490)	(0.237)	(0.035)
20	0.542	0.200	0.148	0.278	0.119	0.044
	(0.350)	(0.188)	(0.037)	(0.255)	(0.117)	(0.039)
30	0.335	0.145	0.050	0.051	0.020	0.011
	(0.253)	(0.134)	(0.022)	(0.324)	(0.156)	(0.040)
40	0.114	0.049	0.018	0.193	0.086	0.024
	(0.143)	(0.076)	(0.013)	(0.288)	(0.138)	(0.021)
75	0.615	0.248	0.128	0.598	0.272	0.064
	(0.221)	(0.118)	(0.036)	(0.379)	(0.181)	(0.031)
90	0.808	0.333	0.154	0.557	0.247	0.072
	(0.329)	(0.180)	(0.064)	(0.524)	(0.249)	(0.043)

Notes: N=1450 for the OLS quadratic estimates. N=1400 for the 2SLS quadratic estimates. OLS quadratic are estimates of coefficients from regressions of log(p)-log(p50) on log(min)-log(p50), its square, and year fixed effects. 2SLS quadratic are estimates of coefficients from regressions of changes in log(p)-log(p50) on changes in log(min. wage)-log(p50) and its square, and year fixed effects. MW-P50 is the coefficient on log(min)-log(p50), and $(MW\text{-}P50)^2$ is the coefficient on its square. Marginal effect is the marginal effect of changes in log(min. wage)-log(p50), evaluated at the hours-weighted average of log(min. wage)-log(p50) across states and years. Standard errors clustered at the state level are in parenthesis. Regressions are weighted by the sum of individuals' reported weekly hours worked multiplied by CPS sampling weights.

Table 2.3 (cont.): Relationship between log(p)-log(p50) and log(min. wage)-log(p50), for select percentiles. 1979-2007.

	OLS quadratic			2SLS quadratic		
P	MW-P50	$(\text{MW-P50})^2$	Marg. Effect	MW-P50	$(\text{MW-P50})^2$	Marg. Effect
C. Male and female pooled						
5	1.736	0.685	0.552	1.592	0.773	0.257
	(0.169)	(0.105)	(0.027)	(0.568)	(0.308)	(0.057)
10	1.452	0.634	0.357	0.656	0.300	0.138
	(0.201)	(0.123)	(0.033)	(0.438)	(0.241)	(0.043)
15	0.967	0.427	0.228	0.105	0.067	-0.011
	(0.212)	(0.137)	(0.038)	(0.397)	(0.205)	(0.049)
20	0.688	0.291	0.185	0.388	0.192	0.055
	(0.166)	(0.103)	(0.030)	(0.333)	(0.168)	(0.050)
30	0.451	0.206	0.095	0.350	0.199	0.007
	(0.112)	(0.071)	(0.020)	(0.209)	(0.105)	(0.033)
40	0.195	0.090	0.040	0.161	0.104	-0.019
	(0.067)	(0.043)	(0.012)	(0.316)	(0.166)	(0.035)
75	0.183	0.080	0.044	-0.131	-0.078	0.004
	(0.160)	(0.096)	(0.023)	(0.272)	(0.142)	(0.033)
90	0.627	0.326	0.064	0.526	0.282	0.039
	(0.242)	(0.144)	(0.044)	(0.373)	(0.194)	(0.046)

Notes: N=1450 for the OLS quadratic estimates. N=1400 for the 2SLS quadratic estimates. OLS quadratic are estimates of coefficients from regressions of log(p)-log(p50) on log(min)-log(p50), its square, and year fixed effects. 2SLS quadratic are estimates of coefficients from regressions of changes in log(p)-log(p50) on changes in log(min. wage)-log(p50) and its square, and year fixed effects. MW-P50 is the coefficient on log(min)-log(p50), and $(\text{MW-P50})^2$ is the coefficient on its square. Marginal effect is the marginal effect of changes in log(min. wage)-log(p50), evaluated at the hours-weighted average of log(min. wage)-log(p50) across states and years. Standard errors clustered at the state level are in parenthesis. Regressions are weighted by the sum of individuals' reported weekly hours worked multiplied by CPS sampling weights.

Table 2.4: Actual and counterfactual changes in log(p50)-log(p10) between 1979 and 1988, 1991 and 1996, and 1998 and 2006, after adjusting the effective minimum wage in the earlier year to equal the effective minimum in the later year

Model	1979	1979 to 1988 Change	1979 to 1988 Change in 50/10 Due to Min. Wage	1991	1991 to 1996 Change	1991 to 1996 Change in 50/10 Due to Min. Wage	1998	1998 to 2006 Change	1998 to 2006 Change in 50/10 Due to Min. Wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Females									
Actual	0.382	0.232	-	0.616	0.029	-	0.561	0.084	-
OLS quad.	0.593	0.021	0.211	0.669	-0.024	0.053	0.626	0.019	0.065
2SLS quad.	0.463	0.151	0.081	0.634	0.011	0.018	0.584	0.060	0.024
2SLS cubic	0.455	0.159	0.073	0.631	0.015	0.014	0.581	0.063	0.021
B. Males									
Actual	0.677	0.057	-	0.788	-0.095	-	0.693	0.030	-
OLS quad.	0.752	-0.018	0.075	0.789	-0.096	0.000	0.742	-0.019	0.049
2SLS quad.	0.691	0.043	0.014	0.776	-0.083	-0.013	0.705	0.018	0.012
2SLS cubic	0.678	0.056	0.001	0.769	-0.076	-0.020	0.704	0.019	0.011
C. Male and female pooled									
Actual	0.606	0.105	-	0.691	-0.016	-	0.674	-0.025	-
OLS quad.	0.726	-0.015	0.120	0.741	-0.066	0.050	0.721	-0.072	0.048
2SLS quad.	0.641	0.069	0.035	0.702	-0.028	0.011	0.691	-0.042	0.018
2SLS cubic	0.634	0.077	0.028	0.702	-0.027	0.011	0.690	-0.041	0.016

Note: Columns (1), (4), and (7) are the actual and counterfactual values of the log(p50)-log(p10) in 1979, 1991, and 1998. Columns (2), (5), and (7) are the changes in the actual and counterfactual log(p50)-log(p10) between 1979 and 1988, 1991 and 1996, and 1998-2006. Columns (3), (6), and (9) are the actual change in the log(p50)-log(p10) - the counterfactual change. Counterfactual wage distributions are wage distributions adjusted by the effective minimum wage in the later year of the period, and represent the 50/10 had the effective minimum wage of the earlier year actually been equal to the lower effective minimum wage of the later year. OLS quadratic are counterfactuals formed by adjusting the 1979 and 2007 wage distributions by coefficients from an OLS regression of log(p)-log(p50) on log(min)-log(p50), its square, and year fixed effects. 2SLS quadratic are counterfactuals formed by using coefficients from a 2SLS regression of yearly changes in log(p)-log(p50) on changes in log(min)-log(p50) and its square, and year fixed effects. 2SLS cubic are counterfactuals from a similar regression that includes the difference in the cube of log(min)-log(p

Appendix Table 2.1 - Variation in State Minimum Wages

	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993
Federal min. wage	2.90	3.10	3.35	3.35	3.35	3.35	3.35	3.35	3.35	3.35	3.35	3.80	4.25	4.25	4.25
Alabama															
Alaska	3.40	3.60	3.85	3.85	3.85	3.85	3.85	3.85	3.85	3.85	3.85	4.30	4.75	4.75	4.75
Arizona															
Arkansas															
California										4.25	4.25	4.25			
Colorado															
Connecticut										3.75	4.25	4.25	4.27	4.27	4.27
Delaware															
Florida															
Georgia															
Hawaii															
Idaho										3.85	3.85	3.85		4.75	5.25
Illinois															
Indiana															
Iowa															
Kansas												3.85		4.65	4.65
Kentucky															
Louisiana															
Maine															
Maryland							3.45	3.55	3.65	3.65	3.75	3.85			
Massachusetts															
Michigan								3.65	3.65	3.75	3.75				
Minnesota															
Mississippi										3.55	3.85	3.95			
Missouri															
Montana															
Nebraska															
Nevada															
New Hampshire															
New Jersey									3.45	3.55	3.65				
New Mexico														5.05	5.05
New York															
North Carolina															
North Dakota															
Ohio															
Oklahoma															
Oregon															
Pennsylvania												4.25	4.75	4.75	4.75
Rhode Island															
South Carolina								3.55	3.65	4.00	4.25	4.25	4.45	4.45	4.45
South Dakota															
Tennessee															
Texas															
Utah															
Vermont															
Virginia								3.45	3.55	3.65	3.75	3.85			
Washington															
West Virginia											3.85	3.85			
Wisconsin															
Wyoming											3.65				

Note: Table indicates years in which each state had a state minimum wage that exceeded the federal minimum wage for at least 6 months of the year.

Appendix Table 2.1 - Variation in State Minimum Wages, cont.

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Federal min. wage	4.25	4.25	4.25	4.75	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15
Alabama														
Alaska	4.75	4.75	4.75	5.25	5.65	5.65	5.65	5.65	5.65	7.15	7.15	7.15	7.15	7.15
Arizona														6.75
Arkansas														6.25
California				5.00	5.75	5.75	5.75	6.25	6.75	6.75	6.75	6.75	6.75	7.50
Colorado														6.85
Connecticut	4.27	4.27	4.27	4.77	5.18	5.65	6.15	6.40	6.70	6.90	7.10	7.10	7.40	7.65
Delaware			4.65			5.65	5.65	6.15	6.15	6.15	6.15	6.15	6.15	6.65
Florida														
Georgia												6.15	6.40	6.67
Hawaii														
Idaho	5.25	5.25	5.25	5.25	5.25	5.25	5.25	5.25	5.75	6.25	6.25	6.25	6.75	7.25
Illinois														
Indiana											5.50	6.50	6.50	6.50
Iowa														
Kansas	4.65	4.65	4.65											6.20
Kentucky														
Louisiana														
Maine														
Maryland									5.75	6.25	6.25	6.35	6.50	6.75
Massachusetts													6.15	6.15
Michigan			4.75	5.25	5.25	5.25	6.00	6.75	6.75	6.75	6.75	6.75	6.75	7.50
Minnesota														7.15
Mississippi													6.15	6.15
Missouri														
Montana														6.50
Nebraska														6.15
Nevada														
New Hampshire														6.33
New Jersey														
New Mexico	5.05	5.05	5.05	5.05									6.15	7.15
New York														
North Carolina												6.00	6.75	7.15
North Dakota														6.15
Ohio														
Oklahoma														6.85
Oregon														
Pennsylvania	4.75	4.75	4.75	5.50	6.00	6.50	6.50	6.50	6.50	6.90	7.05	7.25	7.50	7.80
Rhode Island														7.15
South Carolina	4.45	4.45	4.45	5.15		5.65	5.65	6.15	6.15	6.15	6.75	6.75	7.10	7.40
South Dakota														
Tennessee														
Texas														
Utah														
Vermont														
Virginia		4.50	4.75	5.00	5.25	5.25	5.75	6.25	6.25	6.25	6.75	7.00	7.25	7.53
Washington														
West Virginia	4.90	4.90	4.90	4.90		5.70	6.50	6.72	6.90	7.01	7.16	7.35	7.63	7.93
Wisconsin													5.85	6.55
Wyoming												5.70	6.50	6.50

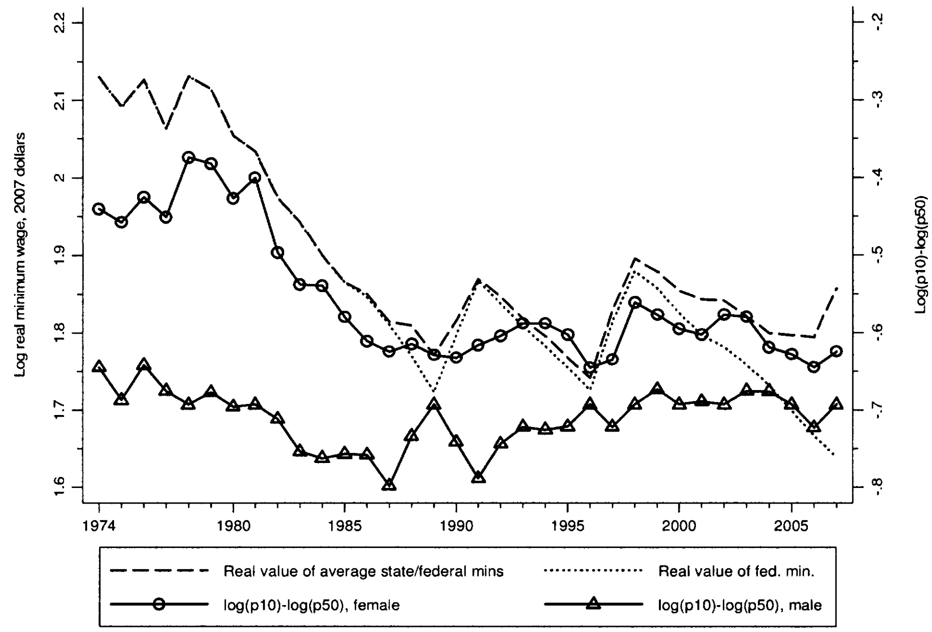
Note: Table indicates years in which each state had a state minimum wage that exceeded the federal minimum wage for at least 6 months of the year.

Appendix Table 2: Actual and counterfactual changes in the log(50)-log(10), using coefficient estimates from the 1979-2007 period, within-sample regression coefficients, and out-of-sample regression coefficients

	Actual log(50)-log(10)		Counterfactual: coefficients from 1979-2007 estimation			Counterfactual: coefficients from "in-sample" estimation			Counterfactual: coefficients from "out-of-sample"		
	Log(50)-log(10), base year	Change, log(50)-log(10)	Log(50)-log(10), base year	Change, log(50)-log(10)	Change due to min.	Log(50)-log(10), base year	Change, log(50)-log(10)	Change due to min.	Log(50)-log(10), base year	Change, log(50)-log(10)	Change due to min.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
A. 1979 adjusted by 1988 effective minimum wage. Base year: 1979. Change: 1979 to 1988.											
Females	0.382	0.232	0.463	0.151	0.081	0.469	0.146	0.086	0.463	0.152	0.080
Males	0.677	0.057	0.691	0.043	0.014	0.697	0.037	0.020	0.681	0.053	0.004
Pooled	0.606	0.105	0.641	0.069	0.035	0.605	0.106	-0.001	0.642	0.069	0.036
B. 1991 adjusted by 1996 effective minimum wage. Base year: 1991. Change: 1991 to 1996.											
Females	0.616	0.029	0.634	0.011	0.018	0.633	0.012	0.017	0.758	-0.113	0.141
Males	0.788	-0.095	0.776	-0.083	-0.013	0.751	-0.058	-0.037	0.780	-0.087	-0.009
Pooled	0.691	-0.016	0.702	-0.028	0.011	0.704	-0.029	0.013	0.750	-0.076	0.059
C. 1998 adjusted by 2006 effective minimum wage. Base year: 1998. Change: 1998 to 2006.											
Females	0.561	0.084	0.584	0.060	0.024	0.570	0.075	0.009	0.593	0.051	0.033
Males	0.693	0.030	0.705	0.018	0.012	0.700	0.023	0.007	0.708	0.015	0.015
Pooled	0.674	-0.025	0.691	-0.042	0.018	0.681	-0.033	0.008	0.695	-0.046	0.021

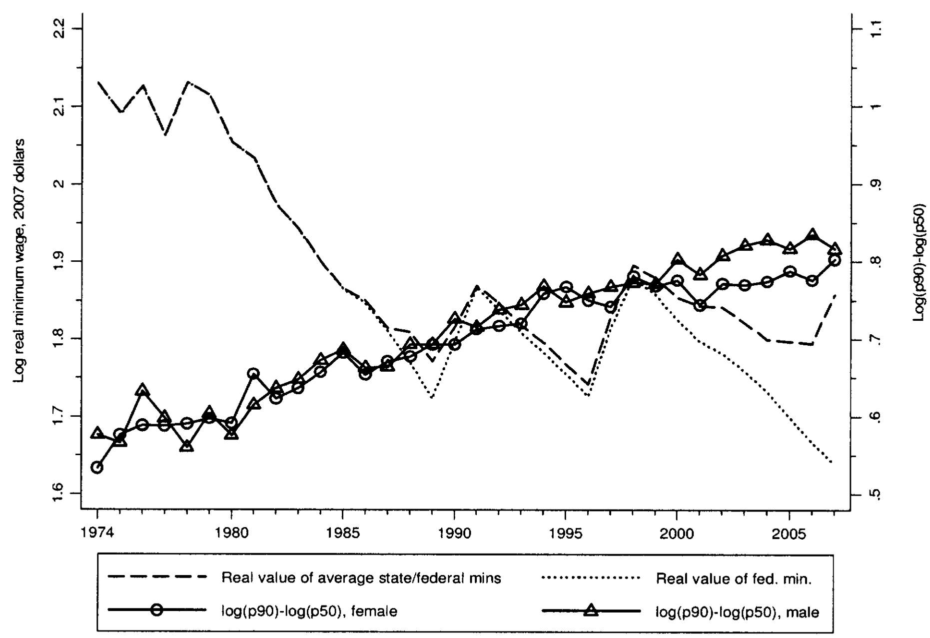
Note: The table presents actual and counterfactual estimates of log(50)-log(10), and changes in log(50)-log(10) between 1979 and 1988 (panel A), 1991 and 1996 (panel B), and 1998 to 2006 (panel C). Columns 3-5 present counterfactual estimates that use coefficients from regressions including all sample years (1979-2007). Columns 6-8 present counterfactual estimates that use coefficients from regressions that only include the years for which the change is computed in the panel, i.e. "in sample" counterfactuals for panel A are constructed using regression coefficients from regressions that use data from 1979-1988. Columns 9-11 present counterfactual estimates that use coefficients from regressions that only include "out-of-sample" years. For panel A, this is 1989-2006. For panel B, this is 1979-1988 and 1998-2006. For panel C, this is 1979-1996. Columns 5, 8, and 11 present the change in log(50)-log(10) attributable to changes in the minimum, i.e. (2)-(4), (2)-(7), and (2)-(10).

Figure 2.1a: Trends in state and federal minimum wages, and log(p10)-log(p50) 1974-2007



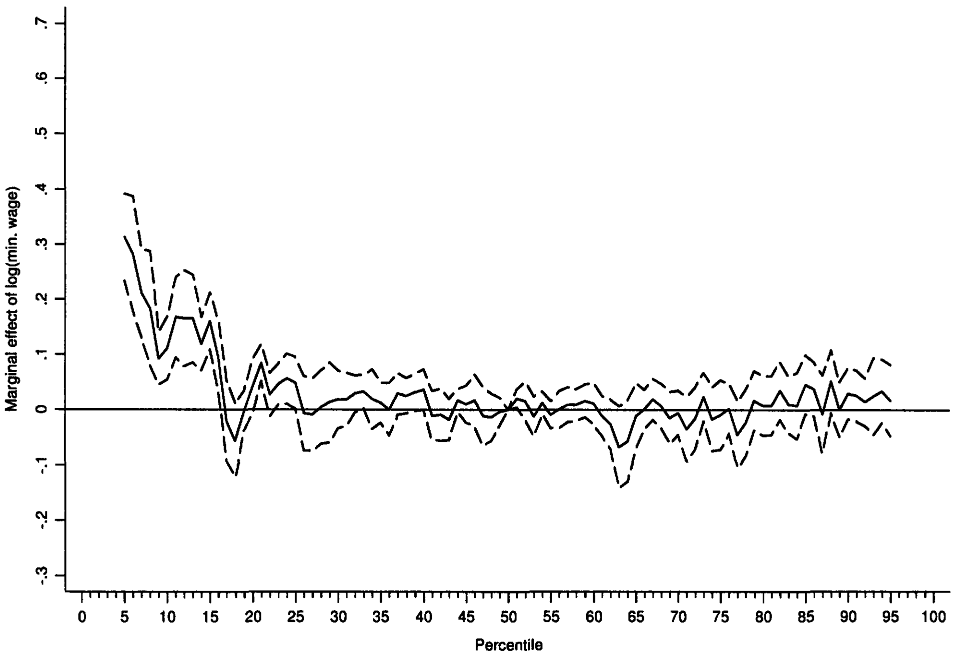
Note: Annual data on state and federal minimum wages and log percentiles. Minimum wages are in 2007 dollars.

Figure 2.1b: Trends in state and federal minimum wages, and log(p90)-log(p50) 1974-2007



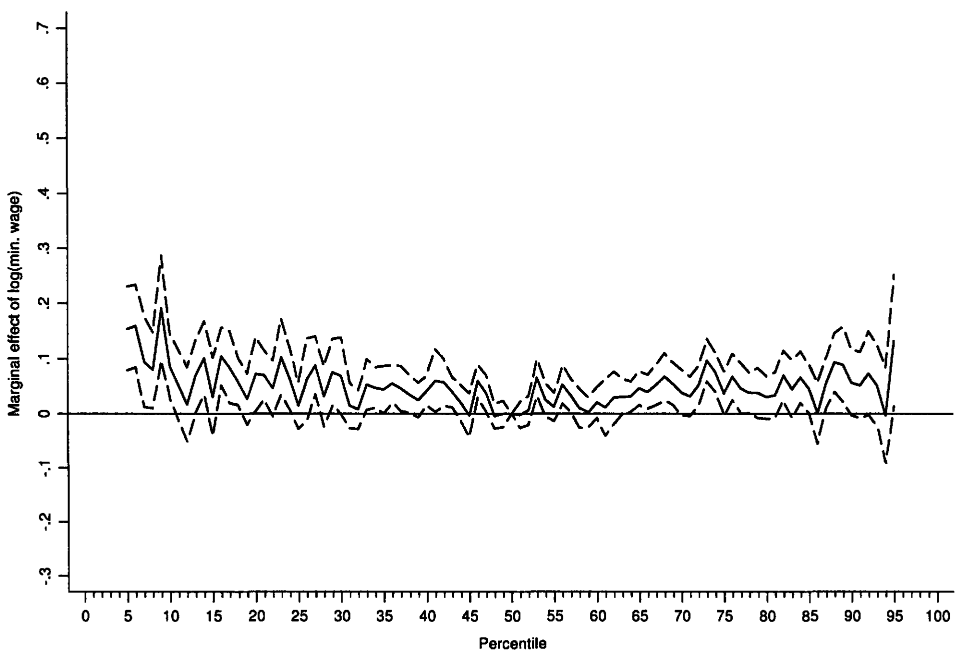
Note: Annual data on state and federal minimum wages and log percentiles. Minimum wages are in 2007 dollars.

Figure 2.21: OLS quadratic model of relationship between log(p)-log(p50) and log(min. wage)
Female wage distribution, 1979-2007



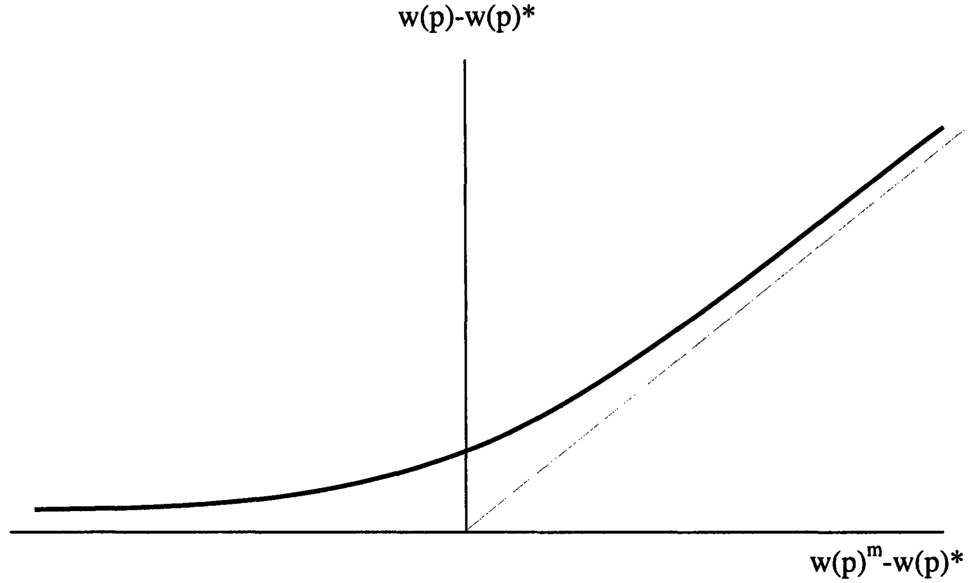
Estimates are from OLS regressions of changes in log(p)-log(p50) on changes in log(min. wage) and its square, and year dummy vars. Observations are state-year observations. Dashed lines indicate the 95% confidence interval.

Figure 2.2b: OLS quadratic model of relationship between log(p)-log(p50) and log(min. wage)
Male wage distribution, 1979-2007



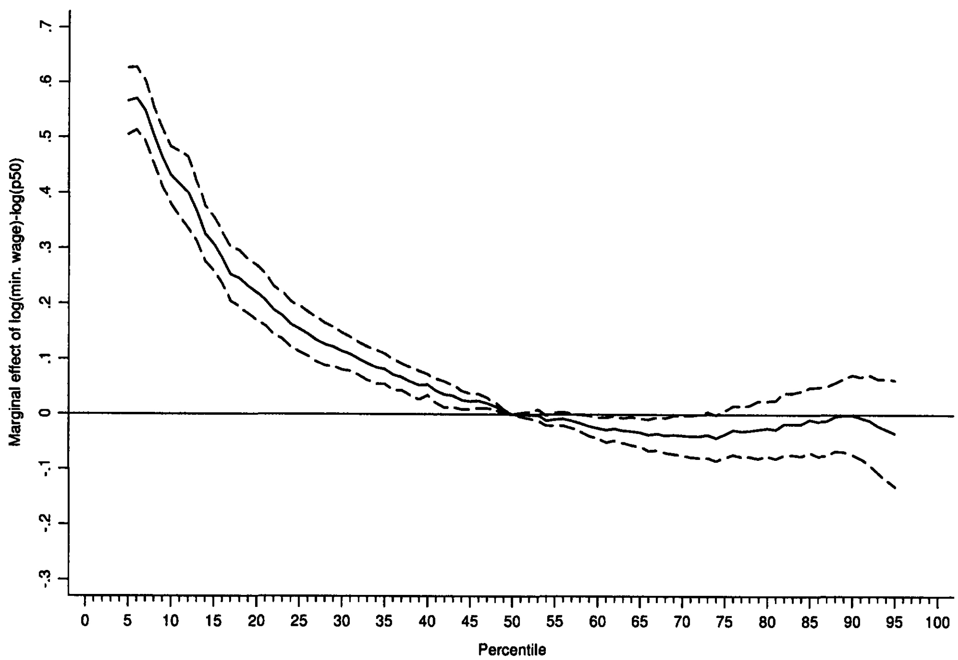
Estimates are from OLS regressions of changes in log(p)-log(p50) on changes in log(min. wage) and its square, and year dummy vars. Observations are state-year observations. Dashed lines indicate the 95% confidence interval.

Figure 2.3: The theoretical relationship between deviations in the minimum and latent wage percentile, and differences between the minimum wage and latent percentile



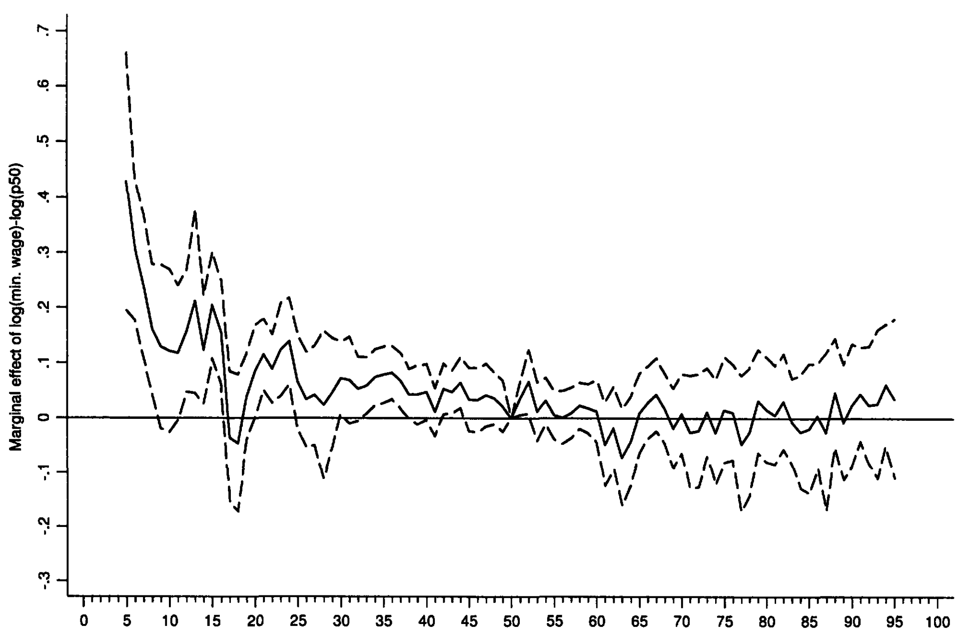
Note: w(p)-w(p)* is the difference between the actual (observed) value of percentile p and the latent value of percentile p (i.e. its value in the absence of a minimum wage). $w(p)^m$-w(p)* is the difference between the minimum and the latent value of percentile p.

Figure 2.4a: OLS quadratic model of relationship between log(p)-log(p50) and log(min.)-log(p50)
Female wage distribution, 1979-2007



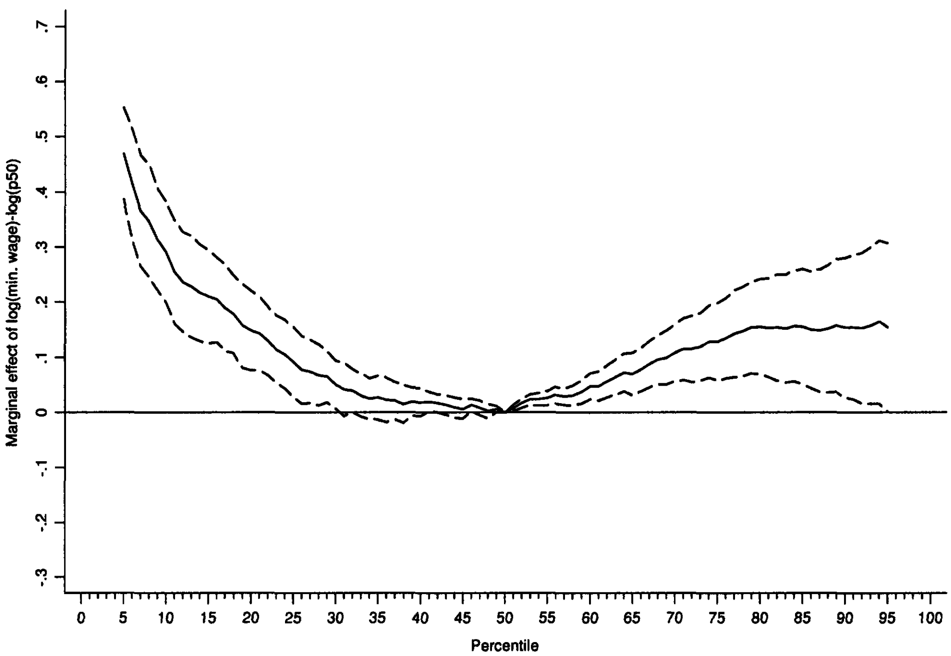
Estimates are from OLS regressions of log(p)-log(p50) on log(min. wage)-log(p50), its square, and year dummy vars. Observations are state-year observations. Dashed lines indicate the 95% confidence interval.

Figure 2.4b: 2SLS quadratic model of relationship between annual changes in log(p)-log(p50) and annual changes in log(min.)-log(p50). Female wage distribution, 1979-2007



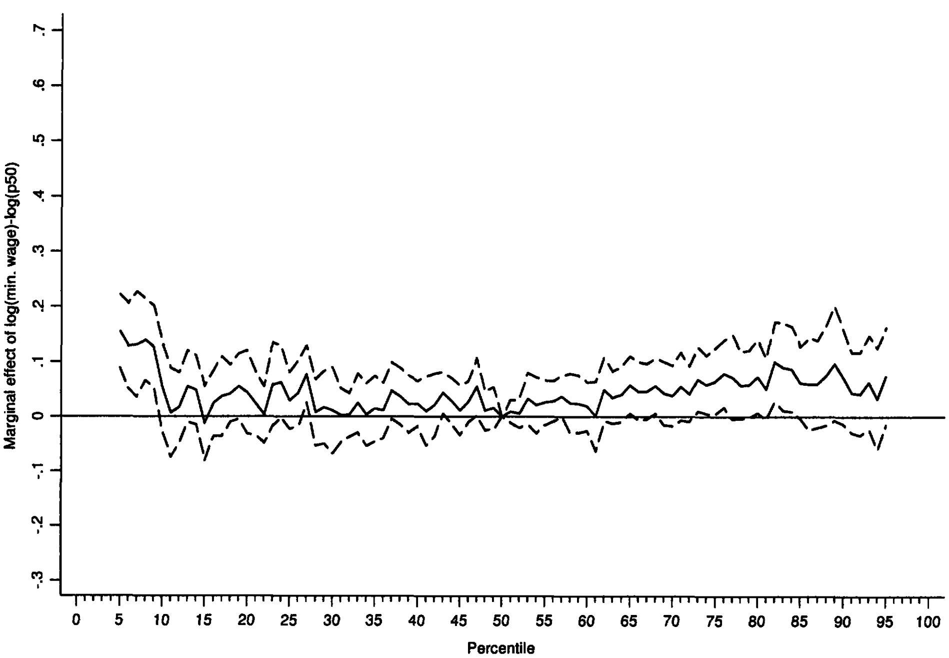
Estimates are from IV regressions of yearly changes in log(p)-log(p50) on changes in log(min. wage)-log(median wage) and its square, and year fixed effects. Dashed lines indicate the 95% confidence interval. Observations are state-year observations.

Figure 2.5a: OLS quadratic model of relationship between log(p)-log(p50) and log(min.)-log(p50)
Male wage distribution, 1979-2007



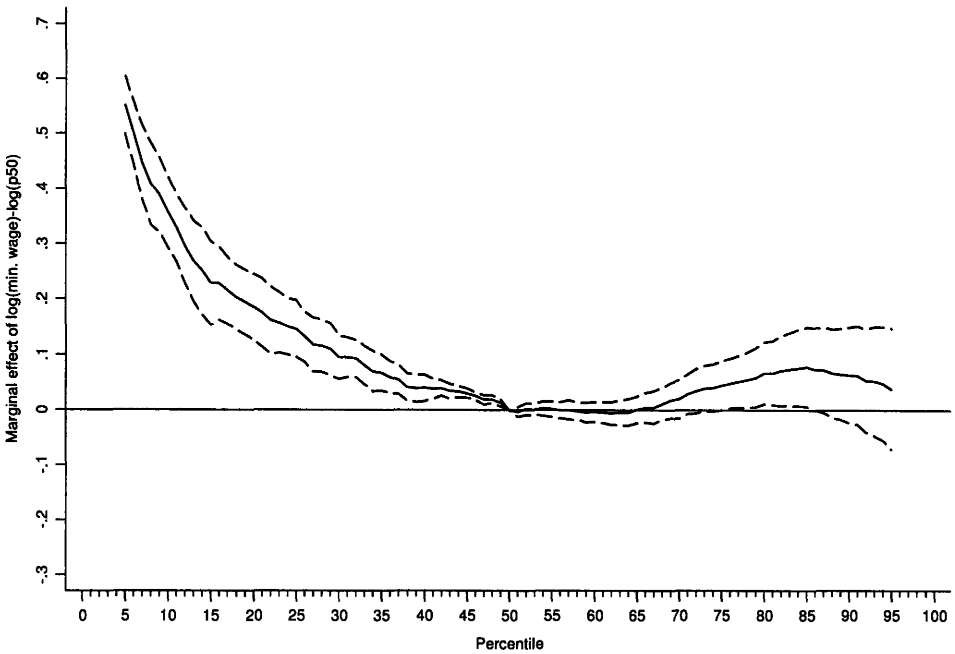
Estimates are from OLS regressions of log(p)-log(p50) on log(min. wage)-log(p50), its square, and year dummy vars. Observations are state-year observations. Dashed lines indicate the 95% confidence interval.

Figure 2.5b: 2SLS quadratic model of relationship between annual changes in log(p)-log(p50) and annual changes in log(min.)-log(p50). Male wage distribution, 1979-2007



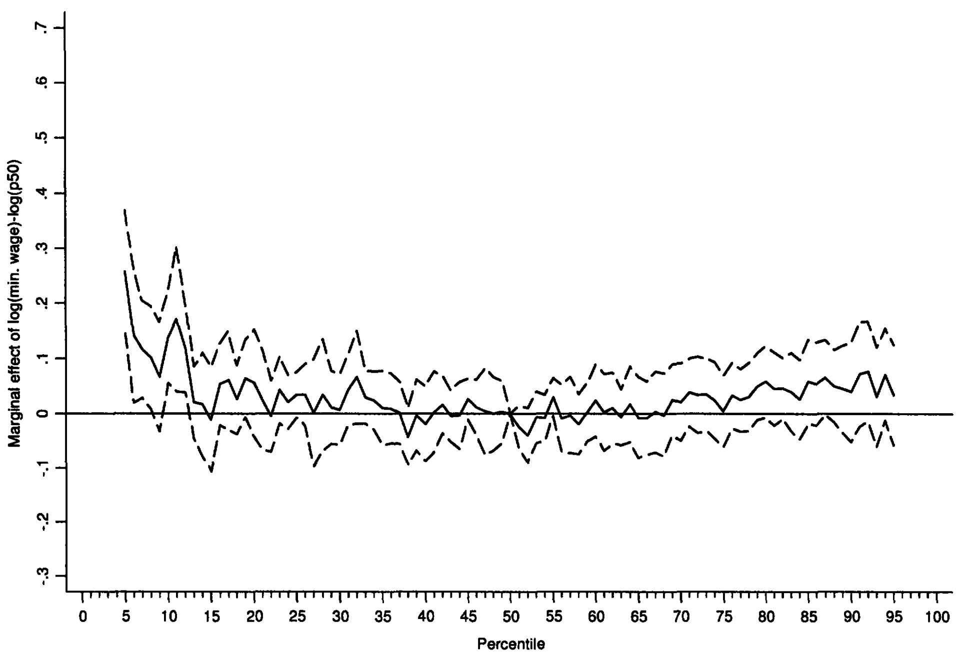
Estimates are from IV regressions of yearly changes in log(p)-log(p50) on changes in log(min. wage)-log(median wage) and its square, and year fixed effects. Dashed lines indicate the 95% confidence interval. Observations are state-year observations.

Figure 2.6a: OLS quadratic model of relationship between log(p)-log(p50) and log(min.)-log(p50)
Male and female pooled wage distribution, 1979-2007



Estimates are from OLS regressions of log(p)-log(p50) on log(min. wage)-log(p50), its square, and year dummy vars. Observations are state-year observations. Dashed lines indicate the 95% confidence interval.

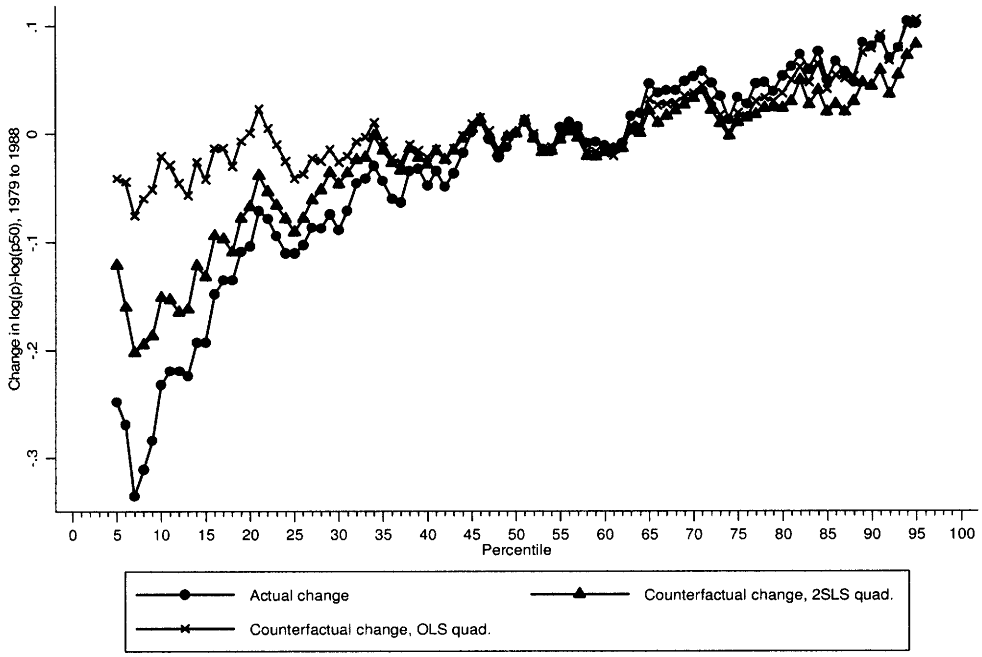
Figure 2.5b: 2SLS quadratic model of relationship between annual changes in log(p)-log(p50) and annual changes in log(min.)-log(p50). Male and female pooled distribution, 1979-2007



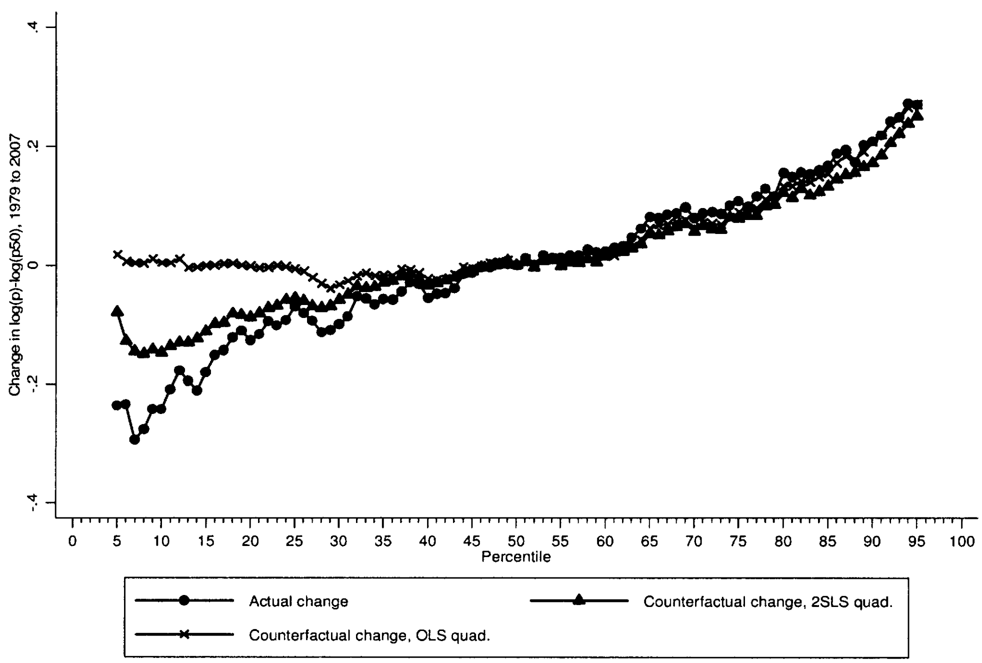
Estimates are from IV regressions of yearly changes in log(p)-log(p50) on changes in log(min. wage)-log(median wage) and its square, and year fixed effects. Dashed lines indicate the 95% confidence interval. Observations are state-year observations.

Figure 2.7: Actual and counterfactual change in log(p)-log(p50)

A. Female wage distribution, 1979 to 1988

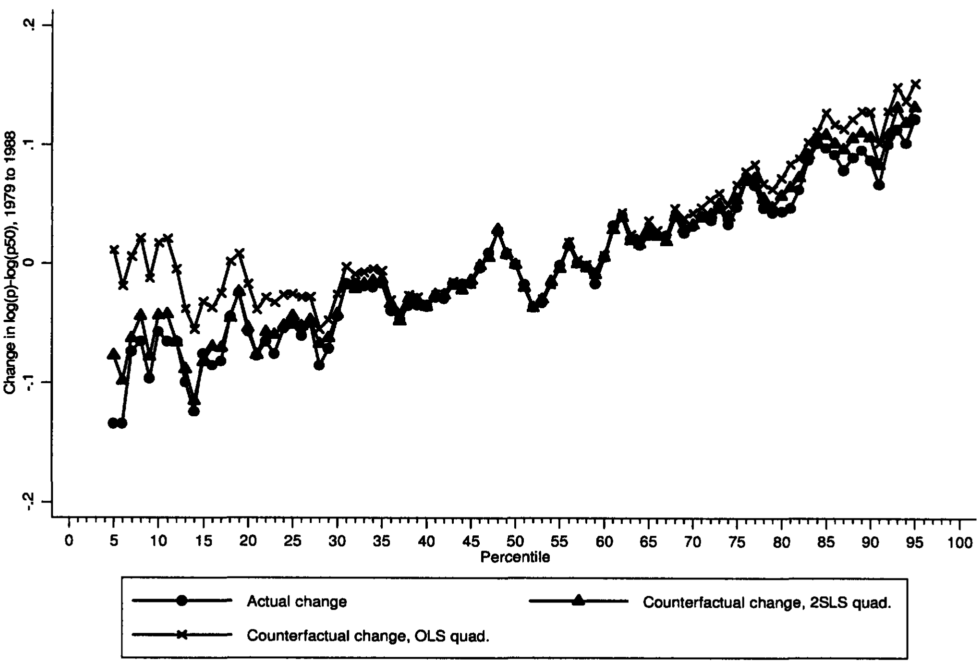


B. Female wage distribution, 1979 to 2007

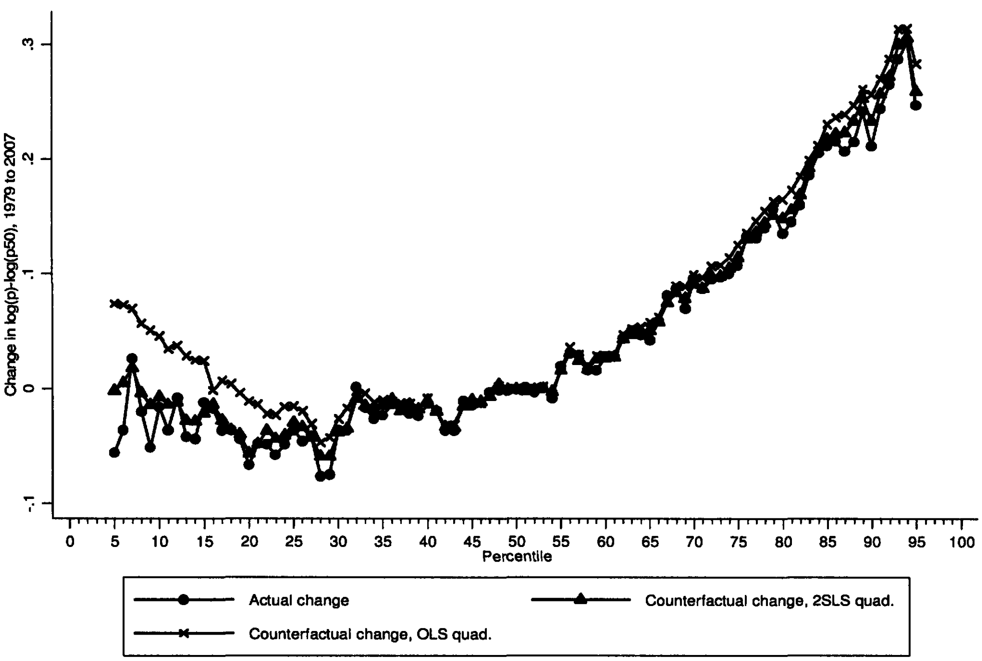


Note: Plots represent the actual and counterfactual changes in the 5th through 95th percentiles of the male wage distribution. Counterfactual changes are calculated by adjusting the 1979 and 2007 wage distributions by states' effective minimum wage in 1988 and coefficients from OLS regressions of log(p)-log(p50) on log(min)-log(p50) and its square, and from 2SLS regressions of the annual change in log(p)-log(p50) on changes in log(min)-log(p50) and its square.

Figure 2.8: Actual and counterfactual change in log(p)-log(p50)
A. Male wage distribution, 1979 to 1988

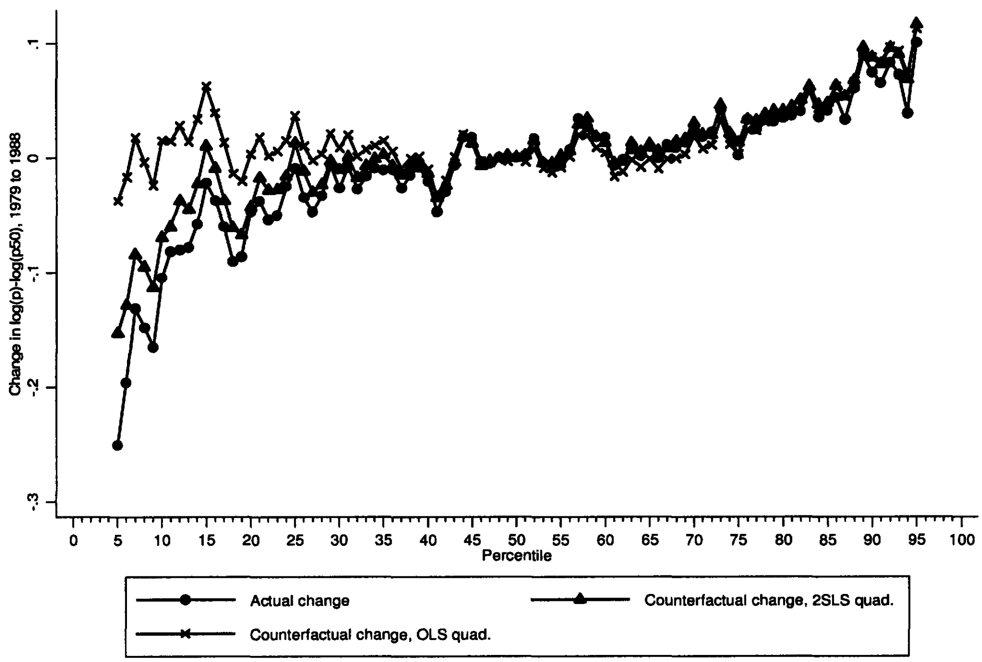


B. Male wage distribution, 1979 to 2007

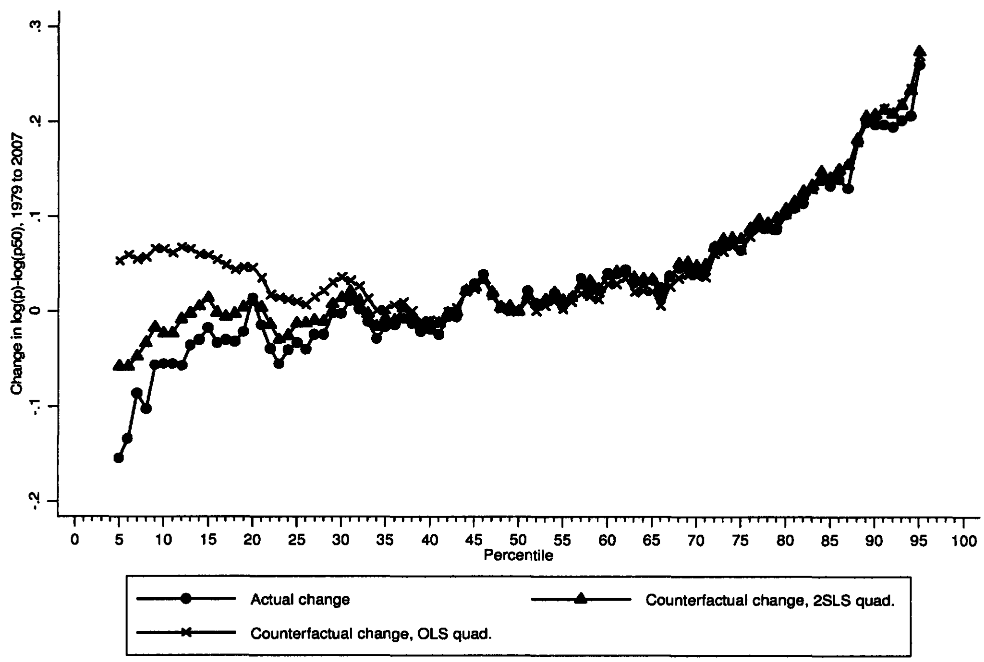


Note: Plots represent the actual and counterfactual changes in the 5th through 95th percentiles of the male wage distribution. Counterfactual changes are calculated by adjusting the 1979 and 2007 wage distributions by states' effective minimum wage in 1988 and coefficients from OLS regressions of log(p)-log(p50) on log(min)-log(p50) and its square, and from 2SLS regressions of the annual change in log(p)-log(p50) on changes in log(min)-log(p50) and its square.

Figure 2.9: Actual and counterfactual change in log(p)-log(p50)
A. Female and male pooled wage distribution, 1979 to 1988

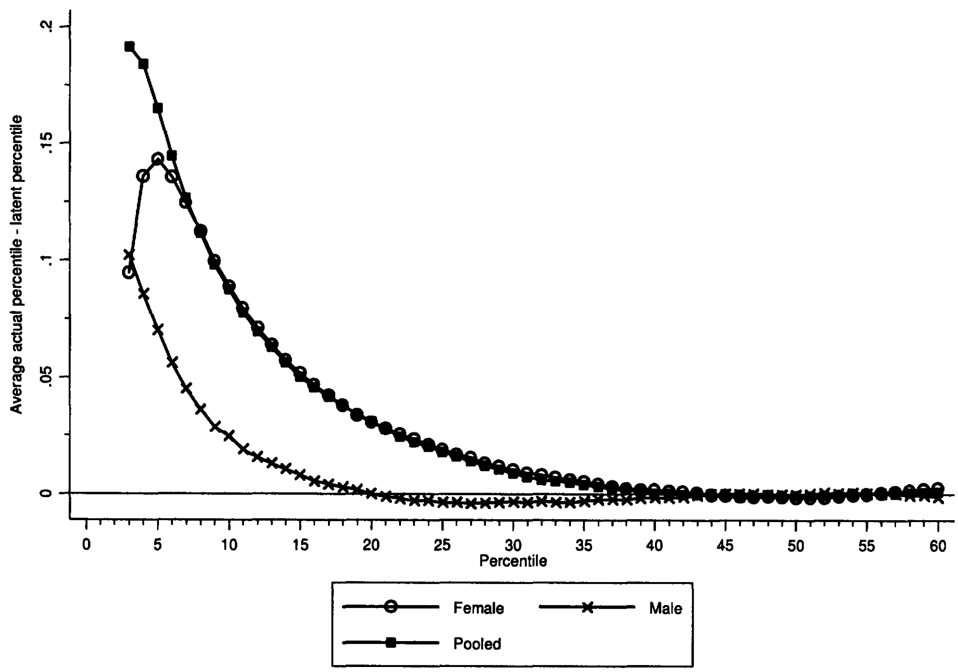


B. Female and male pooled wage distribution, 1979 to 2007



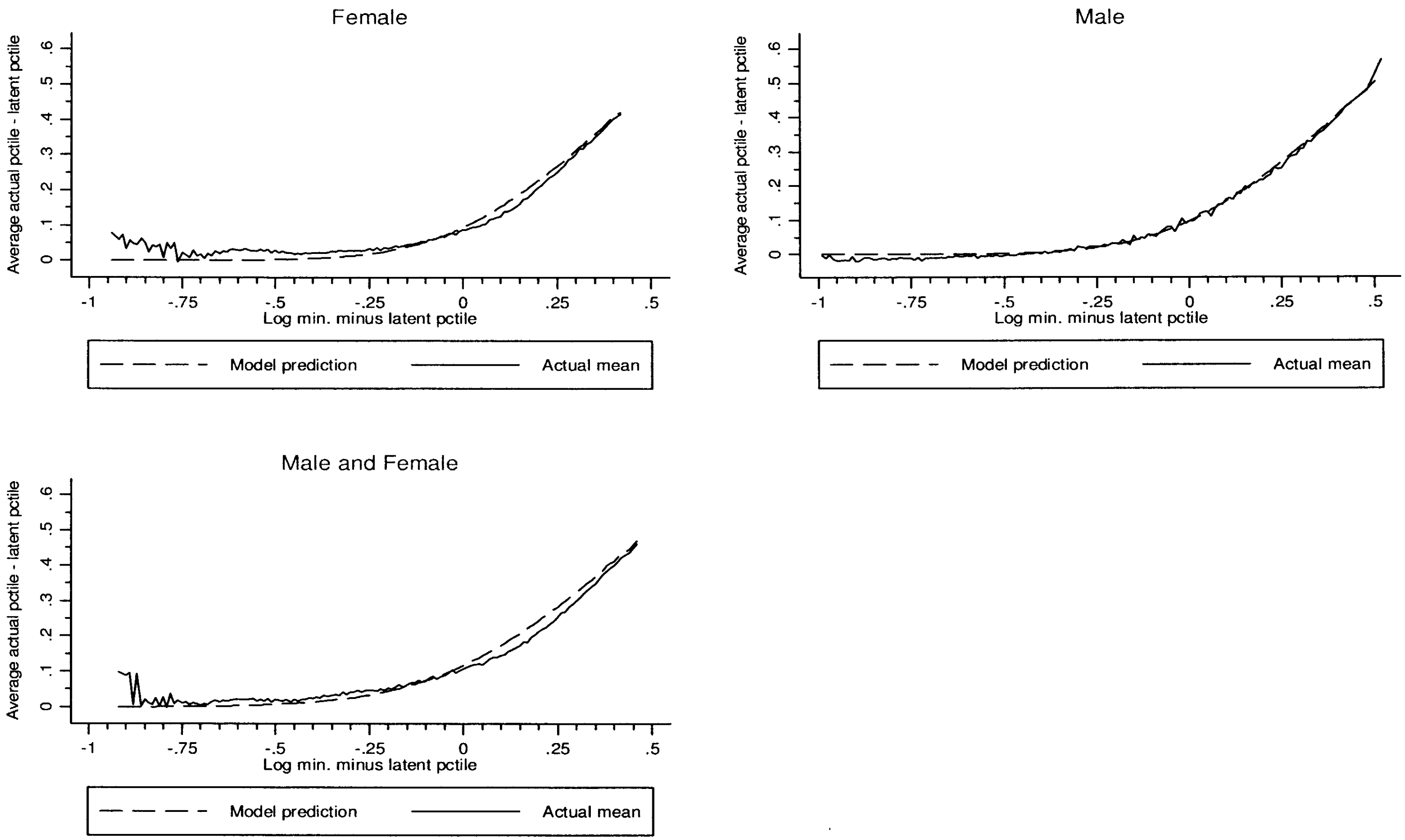
Note: Plots represent the actual and counterfactual changes in the 5th through 95th percentiles of the pooled male and female wage distribution. Counterfactual changes are calculated by adjusting the 1979 and 2007 wage distributions by states' effective minimum wage in 1988 and coefficients from OLS regressions of log(p)-log(p50) on log(min)-log(p50) and its square, and from 2SLS regressions of the annual change in log(p)-log(p50) on changes in log(min)-log(p50) and its square.

Figure 2.10 - Average actual percentile - latent percentile



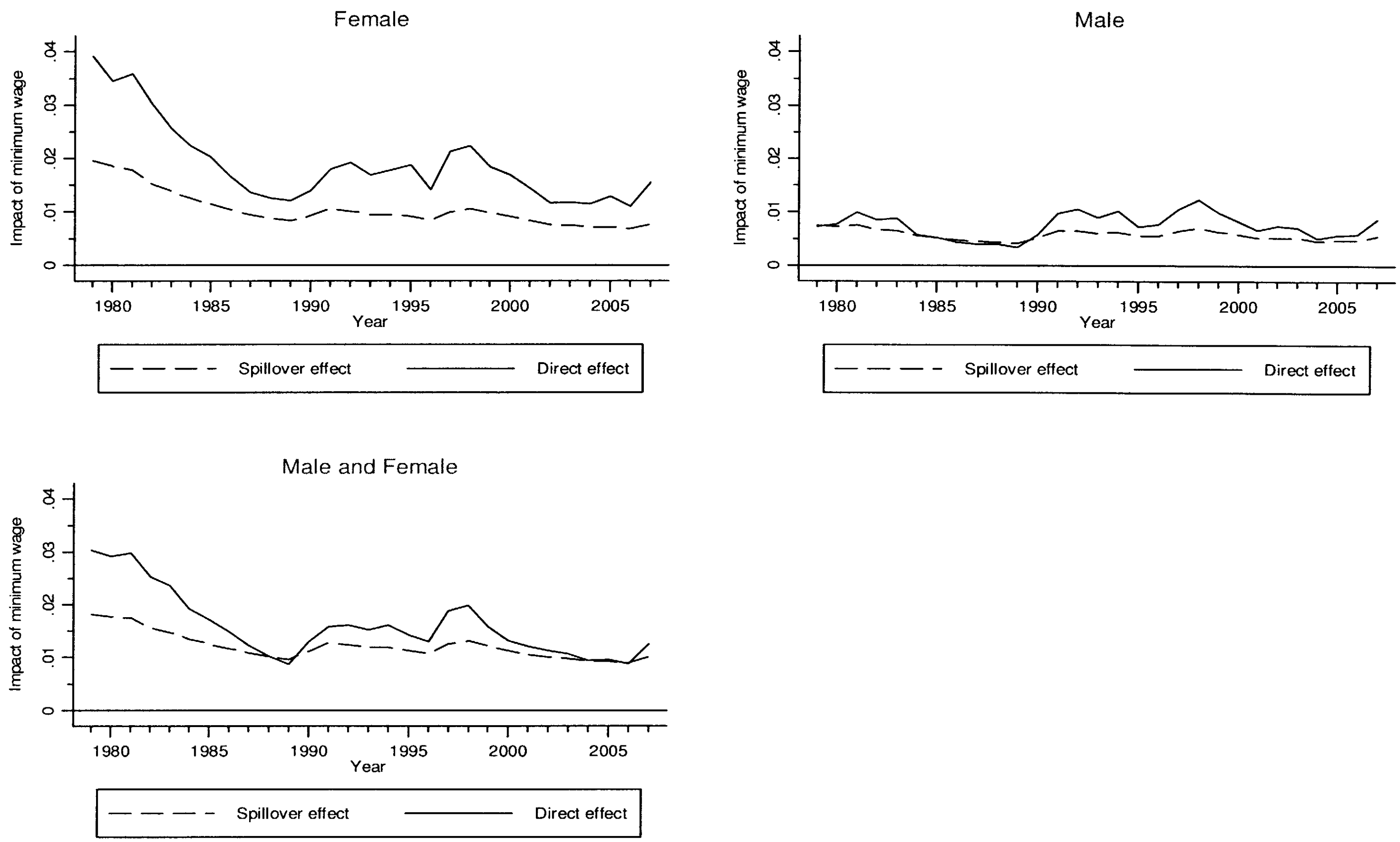
Note: Deviations are averaged across all states and years. See text for description of how devs. are computed.

Figure 2.11 - Empirical relationship between average deviations in actual percentile and estimated latent percentile and the difference between the log of the minimum wage and the actual percentile



Note: y-axis is the average of the difference between the actual pctile and the estimated latent pctile (estimation decscribed in text)
x-axis is the average of the log of the minimum wage minus the estimated latent pctile. Differences are averaged across all states and years.

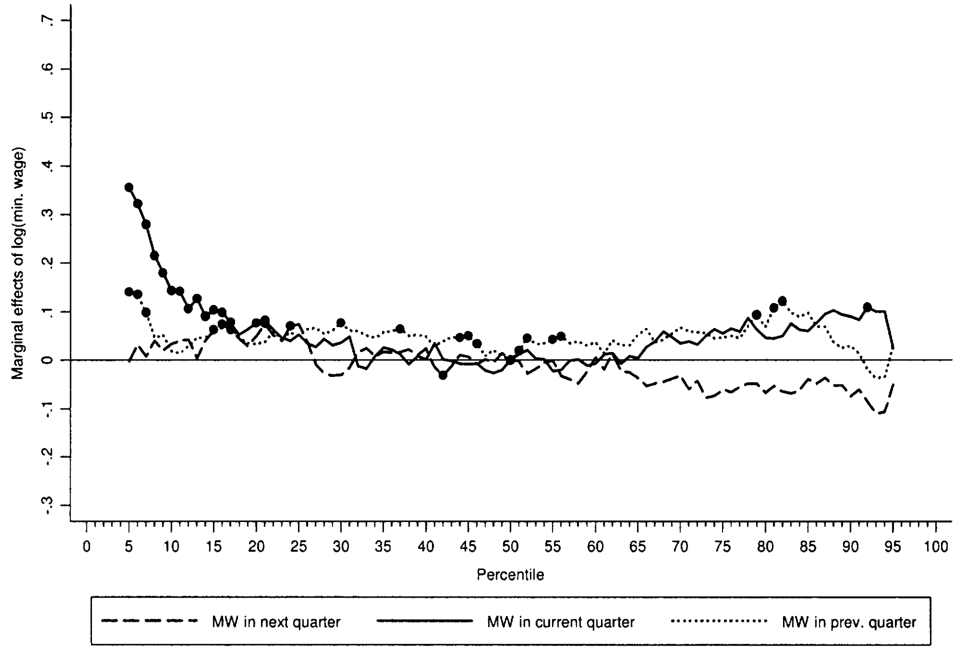
Figure 2.12 - Estimates of the direct and spillover effects of the minimum wage, averaged over lower percentiles



Note: y-axis is the direct and spillover effects of the minimum wage for each year, averaged across lower-tail pctiles (from where the min. binds to the 30th pctile). See text for a description of how latent and spillover effects are estimated.

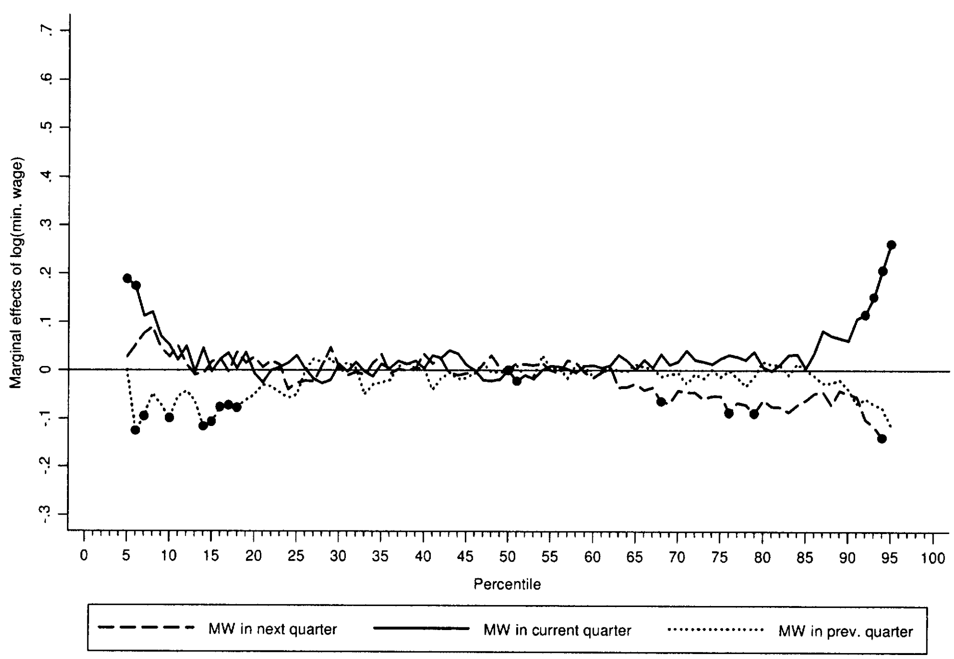
Appendix Figure 2.1: OLS quadratic model of relationship bw. log(p)-log(p50) and log(min. wage), and one lead/lag.

A. Female wage distribution, 1979-2007



Estimates are from OLS regressions of changes in log(p)-log(50) on changes in log(min. wage) and its square, one lead and lag, and year dummy vars. Obs. are state-year observations. Circle indicates sig. at the 5% level.

B. Male wage distribution, 1979-2007



Estimates are from OLS regressions of changes in log(p)-log(50) on changes in log(min. wage) and its square, one lead and lag, and year dummy vars. Obs. are state-year observations. Circle indicates sig. at the 5% level.

Chapter 3

Implications of Adult Labor Market Polarization for Youth Employment Opportunities

3.1 Introduction

One of the most striking recent trends in U.S. labor force participation has been the continued decline in the employment rate of younger individuals (16-21), particularly of high school aged students younger than 18. Between 1999 and 2007, for instance, the July employment rate of 16 and 17 year olds fell from 46 percent to 32 percent, though youth employment rates relative to adult employment rates actually began falling by the mid-1990s (Figure 3.1). This represents a significant decline in the amount of early work experience—and hence, human capital—accumulated while in high school. Even though the majority of jobs worked by high school students are in the retail and food service sector, early work experience may nonetheless provide labor market returns later in life through early exposure to the culture and norms of the workplace, and the early development of a strong work ethic[1].

[1] There is some academic evidence on the impact of working while young, though what exists is often contradictory. For example, see (Tyler 2003) and (DeSimone 2006) for estimates of employment effects on grades and test scores; see (Ruhm 1997) and (Hotz et al. 2002) for conflicting estimates of employment effects on later life labor market outcomes.

The welfare implications of lower teen employment rates depend partially on *why* teens are not working. A shift in youth labor supply—due, for instance, to educational decisions unrelated to conditions in the youth labor market—has significantly different welfare implications, and suggests a different policy response, than if changes in youth employment are due mainly to a reduction in the demand for youth labor: the decline in early-life work experience might not be as worrisome if youth are replacing the human capital lost from less work experience with more formal types of academic human capital. This would be the case if youth are voluntarily choosing to devote more time to education in order to graduate high school or participate in resume enhancing activities to appear more attractive to colleges[2]. One commonly cited piece of supporting evidence is that the summer school enrollment rate, as measured by the percentage of youth who report in the CPS being enrolled in July, has steadily increased since the mid-1990s. This suggests that there has been some substitution from work to schooling, though there is little evidence at the present that explains exactly what additional academic activities youth are pursuing.

A reduction in youth labor supply is unlikely to be the entire explanation: changes in the low-skilled labor market over the past two decades have plausibly reduced the demand for youth labor as well. For instance, (Smith 2008a) provides evidence that increases in low-skilled immigration have affected youth employment to a much greater extent than have affected adult employment, and argues that up to 30% of the recent decline in youth employment may be attributable to growth in low-skilled immigration. (Neumark and Wascher 2007) provides evidence that states with more generous EITC supplements have greater labor force participation rates for the eligible adult population and have lower teen employment rates.

Recent research on the "polarization" of the adult native labor market raises the possibility that labor market competition between lower-skilled native adults and native teenagers has also increased over the 1990s and 2000s. A series of recent papers have documented that the labor market of many industrialized countries has exhibited polarization ((Autor, Katz and Kearney 2006a) and (2008), for the United States; (Goos and Manning 2007), for the U.K.; (Spitz-Oener 2006), for Germany), which is defined as a decrease in the share of the work

[2]For expressions of this view in media reports, see Sudeep Reddy, "Teen Behavior Offers Clue To Why Jobless Rate Stays Low Despite Slowing Growth", *The Wall Street Journal*, June 18, 2007, and Barbara Hagenbaugh, "Most Teenagers Forgo Summer Jobs," *USA Today*, July 9, 2007.

force employed in occupations traditionally in the middle of the wage or skill distribution, and an increase in the share employed in higher and lower paying jobs. Autor, Katz and Kearney (2006a) and (2008) provide evidence that polarization in the U.S. may be due to increased use of computers in production, which reduces demand for jobs that specialize in routine tasks (i.e. manufacturing blue-collar jobs, generally in the middle of the occupational wage distribution), increases demand for jobs that specialize in abstract or cognitive tasks (i.e. managerial or professional jobs), and has little direct effect on demand for jobs which specialize in manual tasks[3]. Given the documented decrease in the share of native adults in middle-wage occupations throughout the 1990s and 2000s, and corresponding increase in the share employed in lower-wage or lower-skill occupations—occupations in which the vast majority of teens are employed—polarization in the adult native labor market may have placed additional pressure on the youth labor market as well. In this way, technological change may have reduced demand for more routine-task intensive occupations, increasing the supply of adult low-skilled labor to jobs that were traditionally common among youth.

The purpose of this paper is to document the strong relationship between the polarization of the adult labor market (as measured by the change in the share of adults in lower-paying occupations) and declines in youth employment, and by doing so, demonstrate that increased labor market competition from native adults is an additional and important factor in explaining recent developments in youth employment. I show that there is a strong and robust relationship between the extent of polarization in the adult labor market by state or commuting zone—as measured by the share of working adults employed in traditionally low-paying occupations—and declines in teen employment rates, teen wages, and adult wages. There is a much more modest relationship between polarization and declines in low-skilled native adult employment. The combination of these facts suggests that youth employment is strongly affected by polarization in the adult labor market, and that youth labor supply is highly elastic relative to adult labor supply (as has been suggested by (Smith 2008a) in the context of immigration induced reductions in youth employment). One contribution of this paper, therefore, is to provide evidence of an additional explanation for declining youth employment and for variation in teen

[3]The general equilibrium effects of polarization may increase demand for service jobs, however—see (Autor and Dorn 2007) and (Mazzolari and Ragusa 2007).

employment across areas. A second contribution of this research is to extend the literature on the labor market impact of polarization, which has so far focused mainly on describing and explaining the phenomenon of polarization rather than exploring the effects of polarization on groups of workers who have traditionally been employed in lower wage occupations.

Section 3.2 of this paper documents the types of jobs that teens, low-skilled prime age native adults, and other categories of workers tend to be employed in, and demonstrates how this has changed over the past two and a half decades. Section 3.3 provides empirical descriptive evidence of the robust relationship between increases in polarization and decreases in youth employment across states and commuting zones, without consideration for why geographic variation in polarization exists. Section 3.4 interprets these empirical findings through the lens of a model of local labor markets in which the introduction of computers reduces the demand for routine labor, thus increasing the supply of labor devoted to manual tasks, and reducing the wages and employment of teens. Section 3.5 documents that, consistent with this model, areas that utilized a greater share of the workforce in routine tasks—or were more manufacturing intensive in 1980—experienced greater amounts of polarization, and saw greater decreases in youth employment over the subsequent two and a half decades. Section 3.6 concludes by discussing the extent to which polarization can explain cross-state variation in youth employment and decreases in youth employment since the 1990s.

3.2 Changes in the Occupational Distribution of Teens and Adults, 1980-2005

3.2.1 Polarization of the U.S. Labor Market

Figure 3.2, similar to Figure 3 from (Autor, Katz and Kearney 2006b), provides striking visual evidence of polarization. The figure uses Census and ACS data to plot the smoothed relationship between changes in the share of the adult population employed in an occupation between 1980 and 1990, 1990 and 2000, and 2000 and 2005, and the occupation's percentile in the wage distribution of all occupations in 1980[4]. Between 1980 and 1990, there was relative growth in the

[4] See the data appendix for details on the construction of the data samples used here, as well as for a description of how I construct measures of polarization.

share of the population employed in traditionally higher-wage occupations. The occupational distribution "polarized" during the 1990s, as the share of adults employed in middle-wage declined and the share employed in either tail increased, and the share employed in the lower tail continued to increased between 2000 and 2005 as well. For the remainder of this paper, I will use the term polarization to describe the growth of employment in lower-paying occupations when ranked by median occupation wage in 1980. The growth of employment in the lower tail is generally viewed as due in part to a technology-driven reduction in demand for occupations in the middle of the occupational distribution, which displaces some workers into lower-paying jobs[5].

Although overall changes in the occupational distribution are indicative of polarization, the actual magnitude of employment changes is modest. For instance, as described in Table 3.1, the share of all adults employed in occupations in the bottom quartile of the 1990 occupational wage distribution increased by slightly over 1 percent between 1990 and 2005. Within education groups, the share of employed adults in lower paying occupations increased somewhat more dramatically (there was a three percentage point increase in the share of adults with some college education, for instance); the overall share of all adults in low paying occupations has increased by a much smaller amount because the share of all adults with some college education has increased substantially over the period.

These aggregate trends mask significant variation in polarization across geographic areas, however, and I will use this geographic variation to identify the relationship between polarization and youth employment. For instance, across all commuting zones in 2005, the share of all native employed adults in the lower quantile of the occupational wage distribution ranged from .25 to .39, and between 1990 and 2005, the change in this share ranged from a decline of .11 to growth of .075.

[5](Autor and Dorn 2007) provide evidence that increasing employment and wages in low-paying *service* jobs is associated with indicators of polarization. Hence, part of the increase in lower-tail employment may be driven by increasing demand for services due to rising real wages. I document, however, that average wages for all lower-paying occupations (not limited to service jobs) fall in areas where employment growth in lower-paying occupations is greater, suggesting that employment growth in lower-paying occupations is not entirely a response to growth in labor demand for such occupations.

3.2.2 The Occupational Distribution of Teens and Adults

The vast majority of employed teens work in traditionally lower-paying occupations. This can be seen in Figure 3.3A and 3.3B, which plot the cumulative density function of employment in occupations ranked by the occupation's median wage in 1980. About 75 percent of employed teens work in occupations that are in the bottom quartile of the occupational distribution, in both 1980 and 2005. There is no evidence from Census data to support the common perception that teens today are more likely to be employed in well-paying internships rather than retail or food-service jobs—less than ten percent of employed teens work in occupations that are in the upper half of the occupational distribution, and there does not appear to be movement into these occupations over the 25 year period. In fact, the percent of employed teens in the bottom quarter of the occupational distribution increased by 15 percentage points over 15 years, and the fraction of teens working as cashiers or in food service—the two most common categories of employment—increased from about 40 to 42 percent. Given that around three-quarters of all employed youth work in occupations in the bottom quarter of the distribution, an increase in the supply of adults to lower-paying occupations may be expected to have negative consequences on youth employment, provided that this increase in adult labor supply is not in response to, or accompanied by, a significant increase in labor demand for these jobs.

3.2.3 Trends in Teen Employment and Differences by Demographic Characteristics

Over the last 15 years, teen employment rates peaked around 1998, began falling prior to the 2001 recession, continued falling throughout and after the recession, and reached their lowest recorded level in 2007 (Figure 3.1). However, relative to adult employment rates, youth employment began actually falling in the mid-1990s. During the tight labor market of the late 1990s, for instance, employment rates for all categories of native workers (by age, sex, and race) increased—with an exception of teens. Hence, the dramatic shift in teen employment really began in the late 1990s, when trends in teen employment separated from trends in adult employment.

There are surprisingly few differences in the occupational distribution of youth across groups defined by race, gender, or parental background. Figures 3.4A, 3.4B, and 3.4C illustrate the first of these facts: the occupational distribution of teens as divided by race or family education are extremely similar, though male teens tend to work in traditionally higher-paying occupations than do females. Again, the idea that more priveledged youth concentrate in better paying jobs appears to be a mispercention—the majority of all youth, regardless of demographic characteristics, work in the lower-paying retail or food service sectors. This would seem to suggest that adult labor market polarization may affect all groups of youth by an equal amount, assuming similar labor supply elasticities across groups. Consistent with this, trends in employment rates are also quite similar across groups, though the overall level of the employment rate varies. Figures 3.5A, 3.5B, and 3.5C demonstrate that employment rates for all groups were mostly stable from the mid-to-late 1990s, after which they fell throughout the remainder of the decade (although the absolute level of employment tends to be higher for white teens and teens from more educated families). Given the similarity of employment trends and occupational distributions across these groups of teens, it is somewhat surprising that I find that the relationship between the polarization of an area and declining teen employment is greater in magnitude for minority teens and teens from poorer families (Section 3.3.3).

There is significant geographic variation in youth employment levels, though employment trends tend to be similar (Figure 3.5D displays employment trends by Census region). Employment rates for youth in the south initially exceed those for youth from other regions, though by the early 1990s employment rates for youth in the northeast are highest. Youth employment rates in the south are always lower than for other regions, though the magnitude of the decline in youth employment over the 2000s is not as severe as in other regions. Teens tend to work in the same sorts of occupations, regardless of geographic location (Figure 3.4D), though youth from western states appear to be more likely to work in higher paying occupations. Since the teen occupational distribution is similar across areas, yet there is significant variation in polarization across areas, regional variation in polarizaton may also provide a potential explanation for regional variation in youth employment rates.

3.3 The Relationship Between Polarization of the Adult Labor Market and Youth Labor Market Outcomes

3.3.1 Baseline estimates

In this section, I provide initial empirical support for the hypothesis that some of the decline in youth labor force participation is due to crowd-out from adults by demonstrating that there is a robust, negative relationship between the share of adults in lower-paying occupations and teen employment. In the subsequent sections, I argue that an increasing share of adults in lower-paying occupations can be understood as coming from a reduction in labor demand for occupations that are traditionally in the middle of the wage distribution. Given this, the empirical relationships described in this section can be understood as the result of a technology-driven reduction in labor demand for middle-paying occupations, which increases the supply of labor to lower-paying occupations, and crowds out youth employment.

Figures 3.6A-3.6D illustrate the relationship between changes in state employment rates and log wages for native teens and native less-educated adults (without a high school degree), and polarization—as measured by growth in the share of all employed adults in jobs from the bottom quartile of the 1980 occupational wage distribution. The plots demonstate the primary empirical finding of this section: there is a striking, negative relationship between changes in teen employment rates and changes in the number of adults employed in traditionally lower-paying jobs, but there is little relationship between changes in adult employment rates and changes in polarization. There appears to be a stronger relationship between this measure of polarization and adult wages than teen wages. Of course, part of the relationship for adults is mechanical, since an increase in the share of adults in lower-paying occupations would reduce average wages through compositional effects even in the absence of a direct effect on wages. Hence, in the more rigorous empirical results that follow, I demonstrate that the wages of adults employed in lower-quartile occupations fall as the share employed in these occupations increases.

To examine the extent of this relationship more thoroughly, I estimate the following equation separately for teens and adults:

$$y_{gt} = \alpha_t + \theta_g + \beta SHARE_{gt} + \gamma X_{gt} + \varepsilon_{gt} \tag{3.1}$$

where g is the geographic level of analysis (either state or commuting zone), t is year, y_{gt} is a labor market outcome, such as average log wages or the fraction employed in the last week, X_{gt} are area-level, time-varying controls such as area-level time trends or other demographic controls, which I include in some specifications. $SHARE$ is the share of all employed adults (18-64) who report working in jobs from the bottom quartile of the occupational wage distribution in 1980. There is no inherent reason why the share in the bottom quartile should be used as the regressor of interest, instead of the bottom decile or bottom multiple deciles, though the relationship between y and $SHARE$ is robust to how I define lower-tail polarization (Section 3.3.2).

I view this equation as a description of the equilibrium relationship between youth and adult labor market outcomes, and employment shifts into the lower tail of the occupational distribution. This regression does not have a causal interpretation, and as such does not recover any fundamental parameter of labor supply or labor demand. Although I view an increase in $SHARE$ as primarily a labor demand driven phenomenon (reduced demand for routine-intensive/manufacturing, middle-paying occupations that drives some adults into lower-paying occupations), β will be determined by a combination of labor demand parameters (elasticity of substitution between teens and adults) and labor supply parameters (elasticity of employment participation for teens and adults). Since I do not have a plausibly excludable instrument for labor demand or labor supply, I cannot separately identify these parameters.

An increase in $SHARE$ can be interpreted as coming from two labor-demand side explanations: either an increase in labor demand for lower-paying occupations, or a decrease in demand for middle-paying occupations, pushing some adults into lower-paying occupations. Given that I document a decrease in wages associated with higher values of $SHARE$, and that changes in $SHARE$ are positively associated with the amount of computer-substitutable labor used in an area in 1980 (see section 5), increasing values of $SHARE$ are most consistent with a reduction in labor demand for middle-paying occupations.

Another concern with the interpretation of equation 3.1 is that a larger share of adults work in lower-paying occupations in some areas because local teen employment rates are lower in these areas—that is, causality may run in the opposite direction. I view this as unlikely, because although most employed teens work in lower-paying occupations, teens actually occupy only a small fraction of these jobs: in the 2000 Census, only 7% of all bottom-quartile occupations are held by teens.

Table 3.3 displays estimates of equation 3.1. Panel A estimates the relationship between employment growth at the bottom of the occupational wage distribution and the fraction of individuals who report being employed in the previous week. Panel B reports the same relationship, using average log wages as the dependent variable. The baseline specification is reported in columns 1 and 2. In this specification, equation 3.1 is estimated at the state-year level using Census and ACS data from 1980, 1990, 2000, and 2005, and includes state and year fixed effects, but no additional controls. The coefficients from this baseline specification imply that a 1 percentage-point increase in the share of adults employed in the bottom quartile of the occupational distribution is associated with a 1.2 percentage point lower teenage employment rate, has no association with adult employment rates, would is associated with 1 percent lower teen wages and 3 percent lower adult wages[6]. Teen and adult estimates are statistically different from each other. To put these magnitudes in perspective, referring back to table 1, the fraction of native adults employed in the bottom quartile increased by around 1 percentage point nationally (and on average, across states), between 1990 and 2005.

One concern is that within-state changes in the polarization measure may be correlated with other time-varying state characteristics. A potential solution is to include state-specific time effects (columns 3 and 4). The estimated relationship between $SHARE$ and teen and adult labor market outcomes is now larger in magnitude, and the coefficient on $SHARE$ in employment regressions for adults and teens are no longer statistically different from each other. However, inference is limited by standard errors that are much larger than before: adding state-specific time trends reduces the remaining variation in the employment share measure by almost

[6] As discussed above, the negative association between low-skilled adult wages and $SHARE$ is partly mechanical, since an increase in $SHARE$ implies that a larger share of adults are employed in traditionally lower-paying occupations. However, the relationship between $SHARE$ and low-skilled adult wages only for those in bottom-quartile occupations is similar in magnitude to that for the entire sample of low-skilled adults.

60%. To exploit additional geographic variation, I estimate equation 3.1 at the commuting zone level. Commuting zones (CZs) are a geographical distinction most recently used by (Autor and Dorn 2007), and divide the entire country into 741 groups based on commuting patterns[7]. Hence, CZs provide significantly more identifying variation than when estimating at the state level, and unlike MSAs, CZs are defined for the entire country[8].

Columns 5 and 6 display estimates of equation 3.1 when estimated at the CZ level rather than the state level. The coefficients are estimated more precisely than when estimated at the state level. Again, employment effects for teens are larger than for adults, and wage effects for adults exceed those for teens. Point estimates are uniformly smaller in magnitude than when estimated at the state level. One possible explanation for this is that using finer levels of geography increases measurement error in the estimates of employment shares, attenuating coefficient estimates towards zero[9]. I attempt to correct for this by randomly splitting the Census sample into two groups, calculating the CZ-year level employment share measure for each group, and using one estimate to instrument for the other. These estimates are presented in columns 7 and 8, and the magnitude of the point estimates are larger than in OLS estimation (the exception is employment effects for high school dropout adults).

Regression results reported in columns 9 and 10 add CZ-specific time trends, and columns 11 and 12 additionally include a host of CZ-level demographic variables[10]. The inclusion of CZ-specific time trends implies much larger employment effects than before: a one percentage point increase in the polarization rate is associated with a 2.3 percentage point reduction in teen employment rates, and a 1 percentage point reduction in adult rates. Teen employment effects are still significantly different from adult effects, although now there is no statistical difference between wage effects. An F-test for the joint significance of the CZ-specific time trends (not reported) rejects the hypothesis that they are all equal to zero, and so they are included for

[7] Commuting zones were first defined by (Tolbert and Killian 1987) and updated by (Tolbert and Sizer 1996).

[8] There are some complications when estimating at the commuting zone level using Census data, as some PUMAs cross commuting zones. Details of how I deal with this and related issues are provided in the data appendix.

[9] For instance, (Aydemir and Borjas 2005) argue that sample size issues are one explanation for why estimates of the labor market effects of immigration may be smaller when estimated at smaller units of geography.

[10] The included variables are the share of the adult population that is: without a high school degree, with some college, male, white, black, hispanic, immigrant, immigrant (conditional on being without a high school degree), and the log of the number of people in the CZ.

the remainder of the analysis. Including additional demographic variables as controls makes little difference above the inclusion of time-trends, and regardless, some of the controls may themselves be endogenously affected by polarization (for instance, the educational distribution or the immigrant share of the population).

These regressions demonstrate a strong and negative relationship between $SHARE$ and teen employment rates and wages. However, it is also useful to understand the amount by which teens are displaced due to polarization—that is, for every 100 additional adults observed employed in lower-paying occupations, how many fewer teens are employed? To answer, this, I estimate an analog to equation 3.1, using the log of the number of employed teens as the dependent variable, and the log of the number of adults employed in lower-quantile occupations as the regressor of interest (controlling for the log of the number of teens and adults in the CZ and including CZ and year dummies, and CZ-specific time trends as additional controls). A one percent increase in the number of adults in lower-paying occupations is estimated to reduce the number of employed teens by 1.25%, and the estimate is highly significant. On average (across CZs and years), 50,800 adults and 2,900 teens are employed in a CZ at the time of the Census. Hence, for every 100 additional adults in lower-paying occupations, 7 fewer teens are observed to be employed: polarization displaces teens, but displacement is far from one-to-one[11]. This displacement estimate is in fact quite similar to that estimated in (Smith 2008a) in the context of immigration, which found that 4 fewer teens are employed for every 100 additional low-skilled immigrants who live in a city.

3.3.2 Robustness of findings

Table 3.4 explores the robustness of these findings to the definition of lower paying occupations and the time periods used in the analysis. Columns 1 and 2 repeat the CZ-level estimates from the previous table, including CZ-level covariates and CZ-specific time trends. In columns 3 and 4, I report estimates of equation 3.1 where the share of adults employed in lower-paying occupations is defined as the share in occupations in the lower decile of the distribution rather than the lower quantile. The relationship between the share of adults employed in the lower

[11] A one percent increase in the number of adults in lower-paying occupations is, on average, an increase of 508 adults. A 1.25% decrease in the number of employed teens is, on average, 36, so every 100 additional adults is associated with about 7 fewer employed teens.

decline of occupations and employment rates is larger in magnitude than the estimates from columns 1 and 2, though the estimates are statistically indistinguishable.

The relationship between adult employment polarization and employment rates is stronger in the 1990-2005 period (columns 7 and 8) than in the 1980-2000 period (columns 5 and 6). Since the hollowing out of the middle of the occupational distribution did not strongly develop until the 1990-2000 period, estimates from this later period may be more accurate for predicting the impact of continuing polarization on youth employment.

3.3.3 Effects by race, gender, and family background

Table 3.5 presents estimates of equation 3.1, estimated separately by gender, race, and family income (whether the teen's family is in the upper or lower quartile of the family income distribution). I consider three labor market outcomes: employment rates, the log of the employment rate, and the log of average wages. I include the log of the employment rate as an additional outcome of interest, since (given differences in overall employment rates) an equivalent percentage-point effect represents a larger percentage effect for blacks or hispanics than whites, for females than males, and for lower-income families than higher-income families.

The association between $SHARE$ and employment rates is somewhat larger in magnitude—both in percentage point, and percentage, terms—for females than for males. This is consistent across races, although standard errors are to large to statistically distinguish the estimates from each other. This is consistent with the observation from Figure 3.4c that females tend to work in lower-paying occupations than males do.

The magnitude of the relationship between $SHARE$ and employment rates is similar across races and teens from higher and lower income families. However, since employment rates tend to be lower for minority youth and youth from lower-income families, this represents a larger percentage impact for these groups; for instance, a one percentage point increase in $SHARE$ is associated with a reduction in black male employment rates by 2.4 percentage points and white employment rates by 2.15 percentage points, but a 15 percent reduction in black employment rates versus a 6.6 percent reduction in white male employment rates. These differences are somewhat surprising, given the similarity in occupational distributions across races and family background (Figures 4a and 4b), and present an interesting question for future research.

3.3.4 Interpretation of findings

So far, this analysis has focused on documenting the relationship between employment growth in lower-paying occupations and labor market outcomes. Since I estimate both negative wage and employment effects, it seems plausible that growth in lower tail employment is driven by an increase in labor supply to these jobs, rather than an increase in labor demand for these sorts of occupations. The next section formalizes this hypothesis within a model of local labor markets and considers the impact of a particular form of skill-biased technical change, which reduces demand for routine tasks while leaving demand for manual tasks relatively unchanged. Section 3.5 then tests implications of the model by exploring correlates of the employment share in lower-paying occupations and other CZ-level demographic and industrial structure characteristics.

3.4 Interpretation of Results Within a Theoretical Framework

A stronger theoretical framework is necessary for interpreting the previous findings. A natural baseline is starting from a model of local labor markets similar to that used in (Autor and Dorn 2007). In their model, local economies produce two outputs, goods and services. Services are produced using a single labor input—manual labor—and goods are produced with computer capital, labor used in routine tasks, and labor used in abstract tasks. They assume that computer capital and routine labor are perfectly substitutable, and both are complementary in production with abstract labor. Less-educated individuals can supply labor to either routine or manual tasks, while more educated individuals supply labor to abstract tasks. The authors demonstrate that within this framework, a reduction in computing costs reduces demand for routine labor and increases demand for abstract labor due to the nature of complementarity and substitutability between these types of labor and computer capital. Demand for manual labor actually increases (as does the real wage for manual labor), as some of the extra income accruing to suppliers of abstract labor is spent on services.

I closely follow the basic framework of their model, but modify it in a few key ways to provide a tractable framework for understanding the relationship between changes in employment and wages for teens and adults and changes in the share of adults employed in lower wage occupations: I include teens in the production of services, I assume that production of services exhibits diminishing marginal returns in labor, and I allow the labor supply of low-skilled adults and teens to be elastically supplied. Further, I consider how the wages of all low-skilled adults (rather than just the wages of those who specialize in manual or routine labor) will respond to a change in the price of computing.

To begin, I assume that services in a local labor market are produced with teen labor (T) and adult manual labor (L_M). Teen and adult manual are perfectly substitutable, and there are decreasing marginal returns to labor within service production:

$$Y_s = \alpha_s(\alpha_{st}T + \alpha_{sm}L_m)^{\delta} \tag{3.2}$$

Goods are produced with computer capital (K), routine labor (L_R), and abstract labor (L_A). I assume that computer capital and routine labor are perfectly substitutable, and assume that the production of goods is Cobb-Douglas, using the routine labor/capital aggregate and abstract labor as inputs:

$$Y_g = \alpha_g(\alpha_r L_r + K)^{\beta} L_A^{1-\beta} \tag{3.3}$$

For simplicity, I drop the efficiency parameters α_g, α_s, though I retain α_{st} and α_{sm} to indicate the potential for differential wages between teens and adults who supply manual labor. I retain α_r because (assuming it varies across states or CZs) it provides a production-driven explanation for geographic variation in the share of labor in routine tasks. The Cobb-Douglas parameter β, and δ, may range from 0 to 1.

All skilled adults (defined as those with some college education) provide abstract labor inelastically. Each low-skilled adult i is endowed with one unit of manual labor and η_i units of routine labor, which, if supplied, they supply to either manual or routine tasks. Individual i^*, for whom $w_m = \eta_i^* w_r$, will be indifferent between providing labor to either routine or manual tasks. All other low-skilled individuals will specialize by providing labor to one task or the other: low-skilled individual i, if choosing to work, will exclusively provide labor to manual tasks as long as $w_m > \eta_i w_r$, and will otherwise provide labor to routine tasks.

Low-skilled individual i supplies labor provided that the wage he receives exceeds his reservation wage R_i. I assume that R_i has a continuous distribution, and may or may not be correlated with an individual's efficiency at routine tasks η_i. For the simple points I am trying to demonstrate with this model, I do not make any further distributional assumptions about R_i or about the joint distribution of R_i and η_i. The nature of the distribution of R_i will define the employment participation elasticity of labor supply for low-skilled individuals $\epsilon_L = \frac{\partial \log L}{\partial \log \bar{w}_L}$, where $L = \sum \mathbf{1}\left(w_i > R_i\right)$, $w_i = \max(\eta_i w_r, w_m)$ and $\bar{w}_L$ is the average wage paid to low-skilled labor (i.e. the labor-weighted average of wages to manual and routine labor). Youth labor supply decisions are made in a similar manner, though they supply labor only to services: $\epsilon_T = \frac{\partial \log L_T}{\partial \log w_T}$, where $L_T = \sum \mathbf{1}\left(w_T > R_i\right)$.

Labor is paid its marginal product:

$$\begin{aligned} w_T &= p_s \alpha_{st} \delta (\alpha_{st} T + \alpha_{sm} L_m)^{\delta - 1} \\ w_m &= p_s \alpha_{sm} \delta (\alpha_{st} T + \alpha_{sm} L_m)^{\delta - 1} \\ w_r &= \frac{\rho}{\alpha_r} = \frac{p_g \beta (\alpha_r L_r + K)^{\beta - 1} L_A^{1-\beta}}{\alpha_r} \\ w_A &= p_g (1 - \beta)(L_r + K)^{\beta} L_A^{-\beta} \end{aligned} \tag{3.4}$$

where ρ is the exogenously determined cost of capital, and p_s and p_g are the endogenously determined prices for services and goods[12].

The average wage paid to low-skilled labor is:

$$\bar{w}_L = \phi \bar{\eta} w_r + (1 - \phi) w_m \tag{3.5}$$

where ϕ is the fraction of employed low-skilled individuals supplying labor to routine tasks, $1 - \phi$ is the fraction supplying labor to manual tasks, and $\bar{\eta}$ is the average η for individuals who supply routine labor.

For interpreting the results from the previous section, it is interesting to consider what this models suggests as potential causes of increasing low-skilled labor in service occupations, and the effects of this on the employment and average wages of low-skilled adults and teens.

[12]Prices for goods and services can be defined in terms of other model parameters and variables by specifying consumers' utility function. For purposes of this model—demonstrating that the wages of low-skilled individuals can fall while the share of adults in lower-paying (service) occupations increases—solving for prices in terms of other model parameters is an unnecessary complication. For an example of how to solve such a mode, see (Autor and Dorn 2007), which assumes a Cobb-Douglas utility function over goods and services.

As in (Autor and Dorn 2007), I consider the implications of an exogenous reduction in the price of computer equipment (capital) ρ. A reduction in the price of computer capital directly reduces wages for routine tasks, since labor for routine tasks and computer capital are perfect substitutes. This reduces the share of low-skilled labor in routine tasks, and increases the share in manual tasks. At the same time, wages for high-skilled individuals increase due to complementarities between high-skilled labor and routine task input. The authors demonstrate that, in their model, real wages for manual task input actually increase due to rising income from higher-skilled workers, despite the increase in labor supply to service occupations from lower-skilled workers. The unambiguity of this result depends, however, on modeling the production of services as a linear function of labor. If the production of service goods has diminishing marginal productivity in manual labor, the impact of falling computer costs (a reduction in ρ) on wages for manual-task input is ambiguous. To see this, note that:

$$\begin{aligned}\frac{\partial \log w_m}{\partial \log \rho} &= \frac{\partial \log w_T}{\partial \log \rho} \\ &= \frac{\partial \log p_s}{\partial \log \rho} + \frac{\delta - 1}{\alpha_{st} T + \alpha_{sm} L_m}\left(\alpha_{st}\frac{\partial \log T}{\partial \log \rho}\right) + \frac{\delta - 1}{\alpha_{st} T + \alpha_{sm} L_m}\left(\alpha_{sm}\frac{\partial \log L_m}{\partial \log \rho}\right)\end{aligned} \tag{3.6}$$

Autor and Dorn (2007) show that this first term can be negative as rising incomes of high-skilled individuals pushes up the price of services. The sign of the second term depends on whether teen wages increase or decrease. This term will be negative if teen wages decrease, since a decrease in ρ will then decrease T. The sign of the last term will be positive, provided that more low-skilled labor switches to manual tasks from routine tasks than exit the labor market. This last term—an increase in the amount of low-skilled labor provided to manual tasks—is what enables a decline in the wage for teens and manual labor in response to a reduction in the price of computer equipment. If the magnitude of this term is greater than the sum of the first two, then teen wages or wages to adults in manual tasks can fall in response to a fall in computing costs.

In the context of the model presented here, a reduction in the price of computing capital (a reduction in ρ):

- reduces the wage for routine tasks, causing some low-skilled labor to shift from routine to manual tasks.

- may increase or decrease teen wages, depending on the magnitude of the increase in service prices, the extent to which service production exhibits diminishing marginal returns, parameters α_{ts} and α_{ms}, and the labor supply elasticity of teen and adult low-skilled labor. If teen wages fall, then the youth employment rate will also fall.

- may increase or decrease wages for adult manual tasks (for the same reasons as why the effect on teen wages is ambiguous).

- may increase or decrease average wages (and hence, labor supply participation) for low-skilled adults. The change in average low-skilled adult wages in response to a change in ρ is:

$$\frac{\partial \bar{w}_L}{\partial \rho} = \frac{\partial \phi}{\partial \rho}(\bar{\eta} w_r - w_m) + \phi \frac{(\bar{\eta} \partial w_r + w_r \partial \bar{\eta})}{\partial \rho} + (1 - \phi)\frac{\partial w_m}{\partial \rho} \tag{3.7}$$

  Provided the average wage to routine jobs exceeds that for manual jobs, the first term is positive, since a reduction in the cost of computing reduces the share of employed low-skilled individuals supplying labor to routine jobs. The wage paid to routine labor falls, so the average η_i of remaining individuals who supply labor to routine jobs will be higher than before—so the second term is ambiguous. The sign of the third term depends on whether wages to those supplying labor for manual tasks increases or decreases. Hence, average wages for low-skilled workers may increase or decrease, and aggregate low-skilled labor supply may then either increase or decrease as well.

This model implies that reductions in the cost of routine-task-replacing capital (such as computers) reduces labor demand for routine tasks. In response, more low-skilled individuals supply labor to manual jobs, leading to an increase in the share of adults in lower-paying occupations. This potentially reduces the wages of teens due to decreasing returns in the production of services, and potentially reduces the wages of low-skilled adults due to the reduction of wages for both manual and routine tasks. According to this model, an increase in the number of adults in lower-paying occupations—and an accompanying reduction in teen employment—stems from a reduction in demand for low-skilled labor in more routine tasks. Again, the fundamental force behind these changes is a reduction in the cost of computing.

One testable implication of this model is that the share of adults in lower-paying occupations is likely to increase more in areas for which a greater share of labor is initially used in routine tasks. To see this, note first that wages to routine labor for individual i are $\frac{\eta_i \rho}{\alpha_r}$, and this is greater in areas with lower α_r (assuming that all other model parameters are uncorrelated with α_r). Provided that service production as a function of low-skilled labor is sufficiently concave (i.e. δ is sufficiently large), then areas with lower α_r will also have have higher routine wages relative to manual wages (relative to areas with higher α_r). Routine wages will fall more in these areas as ρ falls, since $\frac{\partial(\eta_i \rho/\alpha_r)}{\partial \rho} = \frac{\eta_i}{\alpha_r}$. Again, provided δ is sufficiently large, routine wages relative to manual wages will fall by more in these areas, and the share of the low-skilled population in manual (service) occupations will also increase by more. The next section considers this, and explores other factors that may be associated with changes in the share of adults in lower-paying occupations as well.

3.5 CZ-level Characteristics Associated With Growth in Lower-paying Employment

The purpose of this section is to gain a better understanding of the driving forces behind increases in the share of adults in lower paying occupations—and in particular, why this varies across geographic areas. In particular, the goal of this section is to estimate the relationship between changes in $SHARE$ (and teen employment rates) and area-level variables associated with having a larger share of the population that is vulnerable to displacement by computers. Identifying such a relationship will provide suggestive evidence that a technology-driven reduction in demand for middle-paying occupations has driven adults into lower-paying occupations and increased competitive pressures in the lower-skill labor market (thus reducing teen employment rates).

The preceeding model and discussion suggests one such variable—a measure of how intensively a local economy uses routine labor relative to manual labor. As described in the previous section, $SHARE$ may increase more in areas that traditionally used routine labor more heavily. A related argument, which is somewhat more intuitive, though outside the scope of the model, is that a greater share of low-skilled labor may shifts to more manual-intensive (lower-paying) occupations in areas which more heavily utilized routine labor in the past, since there is more low-skilled labor in these areas that can potentially be substituted with cheaper capital (and, the monetary savings are greater for doing so).

I measure a CZ's use of routine task input relative to manual task input (RTI) by using a measure identical to that proposed and used in (Autor and Dorn 2007), which can be thought of as a proxy for the aggregate amount of labor supplied to routine tasks relative to that supplied to manual tasks. The measure is formed by first estimating the "routine-intensiveness" and "manual-intensiveness" of labor within a CZ. Following (Autor and Dorn 2007) (which forms estimates of routine and manual intensiveness by following the methodology described in (Autor, Levy and Murnane 2003)), I estimate the routine-task intensiveness of a given occupation by averaging the occupation's requirement for routine motor tasks (as defined by requirements for "finger dexterity") and routine cognitive tasks (as defined by requirements for setting "limits, tolerances, and standards"). The requirements of each occupation for these and other skills has been graded on a scale of 0 to 10 by the US Department of Labor and is provided in their Dictionary of Occupational Titles (DOT). I take the hours-weighted sum of this variable as a proxy for the "routine-task intensiveness" of employment in a CZ. To proxy "manual-task intensiveness," I take the hours-weighted sum of occupations' demand for "eye-hand-foot coordination" within a CZ. The ratio of this estimated aggregate routine to manual labor input is a proxy for the aggregate intensity that routine tasks are utilized relative to manual tasks in any CZ. Hence, a CZ with a higher RTI more intensively uses routine tasks relative to manual tasks. I normalize this measure to have a mean of 0 and standard deviation of 1 in 1980. In a given year, CZs that more intensively use routine labor have a smaller share of the employed adult population in lower-paying occupations[13].

To test the hypothesis that CZs with more routine-intensive employment may have experienced a greater increase in the share of all adults employed in lower-paying occupations (since a larger share of the workforce could be impacted by labor-replacing computers), column 1 of Table 3.6 displays estimates from a regression of the change in $SHARE$ between 1980 and 2005 on the CZ-level estimate of RTI in 1980, along with other demographic characteristics in 1980.

[13] The coefficient on a CZ-year level regression of $SHARE$ on RTI and year and CZ dummy variables is -.019 with a standard error of .001; a one-standard deviation in RTI is associated with a 1.9 percentage point lower value of $SHARE$.

CZs that more intensively utilized routine labor relative to manual labor in 1980 experienced larger growth in lower-paying occupational employment – a one standard deviation increase in RTI is associated with a 1.3 percentage point increase in the share of adults employed in lower paying occupations.

CZs with a larger share of the population employed in manufacturing industries uses routine labor more intensively (the coefficient on a regression of the share in manufacturing on $SHARE$, along with year and CZ dummies, is .041 with a standard error of .002). Hence, it could be that a secular decline in manufacturing—rather than a reduction in the cost of routine-task substituting technology—is responsible for the increase in $SHARE$. Indeed, column 2 shows that $SHARE$ fell more in CZs for which a larger share of the population was employed in manufacturing in 1980. However, when the 1980 manufacturing share is entered simultaneously with RTI, RTI remains significant and its coefficient remains unchanged in magnitude, while the coefficient on the share in manufacturing falls and is insignificant (column 3). Hence, it appears that the relative intensity of routine-task input, rather than the importance of manufacturing in a CZ, is a stronger predictor of future employment growth in lower-paying occupations.

Since a greater share of adults work in lower-paying occupations in areas where routine tasks were used more intensively or a greater share of the workforce was in manufacturing in 1980, teen employment might also be expected to have fallen by more in these areas. Columns 4-6 display estimates from regressions of changes in teen employment rates between 1980 and 2005 on changes in RTI and the share employed in manufacturing in 1980. A one standard deviation increase in RTI is associated with a 1.5 percentage point reduction in teen employment between 1980 and 2005, and when the share in manufacturing and the value of RTI in 1980 are simultaneously entered, the predictive power falls entirely on RTI. However, there is essentially no relationship between changes in teen real log wages and either RTI or the share in manufacturing. One explanation is that over this 25 year period, there is a significant amount of positive self-selection as youth with higher earnings ability are more likely to remain employed, thus mitigating the observed association between $SHARE$ and teen wages.

3.6 Conclusion

Historically low teen employment rates may be explained by a combination of labor supply and labor demand factors. Greater returns to high school and college education raise the opportunity costs to working both during the school year and summer, and may reduce teen labor supply. Simultaneously, increased availability of substitutable labor (immigrants, EITC or welfare-eligible natives, and low-skilled native adults) may have reduced demand for youth labor. Consistent with this possibility, this paper has shown that a portion of the fall in teen employment may be due to increased labor market competition from native adults. The share of adults employed in lower-paying occupations increased more—and teen employment rates fell more—in areas where routine tasks were used more intensively in 1980. This is consistent with routine-task replacing technology (computers) displacing native adults into lower-paying service occupations, which exerted pressures in the lower-skill labor market and negatively affected youth employment and wages.

This paper is therefore one of the first to provide evidence of negative labor market consequences due to employment polarization on workers whose jobs may not be directly replacable by the technological forces behind overall polarization. Teens tend to work in lower-paying service occupations, and the share of adults in lower-paying occupations has increased somewhat over the past few decades. The actual labor supply reallocation across occupations due to this polarization has not yet been severe—the share of all employed adults in lower-paying occupations has only increased by a percentage point or two since 1990. Hence, the direct impact on youth employment rates is not dramatic. Given the coefficient estimates from Table 3.3, youth employment rates may have been one to four percentage points higher in 2005 if not for adult employment polarization since 1990[14].

Nonetheless, the continued polarization of the adult labor market creates an additional pressure on the youth labor market, and may be expected to continue doing so. For this reason, it should be considered along other labor demand-related explanations for continuing declines in youth employment. The long-term welfare consequences for youth from greater

[14] A 1% increase in $SHARE$ is associated with between a 1 and 4 percentage point decrease in teen employment rates, depending on included covariates and included years. Across CZs, $SHARE$ increased by 1 percentage on average between 1990 and 2005.

labor market competition in the low-skilled labor market depend on the long-term returns to employment while young, and on what youth do if they are not employed. Academic evidence on the first point is mixed, and there is little evidence regarding the second. However, since this paper demonstrates that increasing polarization in the adult labor market may be expected to negatively impact teen employment, this—along with Smith (2008)—provides evidence that greater labor market competition from adults explains at least a portion of the recent decline in teen employment. A downward shift in labor supply, due to an increased emphasis on schooling, may be part of the explanation—but it is not the entire one.

Data Appendix

I use 5% extracts of the 1980, 1990, and 2000 Censuses, and the 2005 American Community Survey, from the Integrated Public Use Microdata Series (IPUMS). Throughout the analysis, I limit the sample to the native-born, who I define as all citizens who do not report being born abroad. Adults are defined as those 19-64. Teens are defined as those 16 and 17. I exclude 18 year olds, as some may be in high school and some may be old enough to have graduated. I collapse employment and wage statistics to the state or commuting zone level, weighting individual data by the Census sampling weight. Regressions are all weighted by the sum of individual sampling weights for the state or commuting zone, for the relevant sample (i.e. either the sum of sampling weights for all native teens or all native adults). Low-skilled adults are defined as those without a high school degree.

I divide individuals into commuting zones based on the procedure used in (Autor and Dorn 2007), and as originally defined in (Tolbert and Killian 1987) and (Tolbert and Sizer 1996). The smallest consistent geographic unit in the Census is the public use microarea (PUMA), but PUMAs sometimes cross commuting zones. To deal with this complication (again, following Autor and Dorn 2007), I reweight individual observations within a PUMA by the fraction of the population that lives in a particular commuting zone. For instance, if an individual reports living in a PUMA that crosses two commuting zones, and exactly half of the PUMA population lives in each commuting zone, then the individual is recorded as living in each commuting zone, but his weight is multiplied by one-half.

To determine an occupation's place in the 1980 wage distribution—in a manner consistent with reporting from later Censuses—I use the IPUMS recode of individual occupations' into a 1990-consistent coding (I further reclassify some occupations that are only observed in one sample by merging them with related occupations). I then rank occupations by their median wage in 1980 (where wage is defined as an individual's annual earnings divided by weeks worked time usual hours worked per week). I then determine each occupation's percentile in the hours-weighted distribution of all jobs in 1980.

Table 3.1 - Share of employment in all occupations in the lower quartile of the 1980 occupational wage distribution

		Employment share, 1990				Employment share, 2005				Change in employment share, 1990-2005			
		Nat.	CZ mean	CZ min.	CZ max.	Nat.	CZ mean	CZ min.	CZ max.	Nat.	CZ mean	CZ min.	CZ max.
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
All adults:													
All	Males and females	0.250	0.255	0.196	0.413	0.267	0.269	0.212	0.418	0.017	0.014	-0.107	0.084
All	Females	0.337	0.345	0.257	0.554	0.350	0.354	0.279	0.516	0.013	0.009	-0.121	0.087
All	Males	0.169	0.172	0.116	0.388	0.190	0.190	0.090	0.352	0.020	0.017	-0.134	0.125
Native adults:													
All	Males and females	0.241	0.244	0.182	0.412	0.252	0.251	0.192	0.388	0.011	0.008	-0.106	0.075
All	Females	0.329	0.333	0.233	0.554	0.332	0.331	0.231	0.496	0.003	-0.001	-0.120	0.095
All	Males	0.158	0.161	0.114	0.388	0.174	0.174	0.090	0.341	0.016	0.013	-0.145	0.118
No high school degree	Males and females	0.400	0.398	0.280	0.613	0.416	0.416	0.045	1.000	0.017	0.016	-0.401	0.525
No high school degree	Females	0.610	0.601	0.460	0.792	0.648	0.639	0.000	1.000	0.038	0.038	-0.646	0.369
No high school degree	Males	0.244	0.250	0.134	0.495	0.243	0.248	0.000	1.000	-0.001	-0.002	-0.451	0.696
At least some college	Males and females	0.167	0.171	0.120	0.332	0.199	0.200	0.132	0.337	0.032	0.029	-0.074	0.106
At least some college	Females	0.217	0.221	0.147	0.383	0.246	0.246	0.147	0.439	0.029	0.025	-0.117	0.192
At least some college	Males	0.119	0.123	0.079	0.325	0.150	0.150	0.068	0.341	0.030	0.028	-0.117	0.139
Native teens:													
All	Males and females	0.752	0.746	0.538	0.893	0.777	0.770	0.387	1.000	0.025	0.025	-0.409	0.277
All	Females	0.757	0.754	0.555	0.963	0.855	0.849	0.339	1.000	0.098	0.096	-0.508	0.340
All	Males	0.747	0.739	0.448	0.880	0.699	0.692	0.134	1.000	-0.048	-0.047	-0.713	0.362

Note: Estimates represent the share of each group (conditional on being employed in the last week) in an occupation whose median wage is less than or equal to the 25th percentile in the hours-weighted distribution of occupations' 1990 median wages. 1990 data is from the 1990 IPUMS Census public use sample, and 2005 data is from the 2005 IPUMS American Community Use survey public use sample. State mean is the population weighted mean of employment shares or changes in shares across states; state minimum and state maximum are the minimum and maximum of employment shares or changes in shares across states.

Table 3.2 - Means and Standard Deviations Across CZs for Select Variables

	1980	1990	2000	2005
	(1)	(2)	(3)	(4)
Employment to population ratio:				
All native adults	0.690	0.740	0.742	0.727
	(0.045)	(0.046)	(0.044)	(0.039)
Native adults without a HS degree	0.556	0.525	0.508	0.491
	0.055	0.063	0.062	0.070
Native adults with some college	0.780	0.813	0.803	0.778
	0.034	0.033	0.033	0.031
Native teens	0.314	0.322	0.316	0.260
	0.075	0.080	0.089	0.090
Average real log wages:				
All native adults	2.055	2.030	2.093	2.123
	(0.104)	(0.142)	(0.133)	(0.181)
Native adults without a HS degree	1.914	1.761	1.726	1.705
	(0.110)	(0.119)	(0.080)	(0.126)
Native adults with some college	2.205	2.167	2.222	2.257
	(0.096)	(0.135)	(0.131)	(0.179)
Native teens	1.327	1.132	1.220	1.159
	(0.048)	(0.090)	(0.061)	(0.125)
Other CZ-level statistics:				
SHARE (P25)	0.261	0.244	0.242	0.251
	(0.039)	(0.040)	(0.034)	(0.033)
SHARE (P10)	0.124	0.111	0.129	0.131
	(0.039)	(0.033)	(0.025)	(0.022)
Share of employed adult population	0.231	0.182	0.152	0.129
in manuf. industries	(0.084)	(0.067)	(0.062)	(0.055)
Share of employed adult population	0.121	0.125	0.135	0.147
	(0.016)	(0.017)	(0.020)	(0.020)
RTI	0.000	-0.020	-0.400	-0.687
	(1.000)	(0.833)	(0.649)	(0.583)
Teen share of population	0.042	0.030	0.030	0.031
	(0.005)	(0.005)	(0.005)	(0.004)
Teen share of employed population	0.020	0.013	0.013	0.011
	(0.004)	(0.003)	(0.004)	(0.004)

Notes: Estimates are means across commuting zones, weighted by the population count for the commuting zone. Standard deviations are in parentheses.

Table 3.3 - Relat. between emp. rates and wages and the share of the adult native population in lower wage occupations, 1980-2005

	Teens	HSD Adults	Teens	HSD Adults	Teens	HSD Adults	Teens	HSD Adults	Teens	HSD Adults	Teens	HSD Adults
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Dependent Variable - Fraction employed last week												
SHARE	-1.235	0.031	-1.903	-1.099	-0.790	-0.062	-0.967	-0.043	-1.949	-0.838	-2.345	-0.970
	(0.473)	(0.268)	(0.567)	(0.637)	(0.170)	(0.087)	(0.213)	(0.101)	(0.400)	(0.293)	(0.438)	(0.247)
F-stat	8.17		2.12		16.28		16.50		13.41		10.83	
p-value	*0.01*		*0.15*		*0.00*		*0.00*		*0.00*		*0.00*	
R^2 adjusted	0.787	0.842	0.918	0.909	0.727	0.781	0.721	0.781	0.840	0.855	0.841	0.875
N	204	204	204	204	2964	2964	2964	2964	2964	2964	2964	2964
Panel B: Dependent Variable - Average log wage												
SHARE	-0.988	-2.930	-2.646	-3.114	-0.469	-1.952	-0.469	-2.197	-1.907	-2.080	-1.817	-1.718
	(0.522)	(0.402)	(0.720)	(0.513)	(0.200)	(0.177)	(0.264)	(0.209)	(0.593)	(0.416)	(0.709)	(0.481)
F-stat	8.14		0.57		38.49		34.24		0.10		0.02	
p-value	*0.01*		*0.45*		*0.00*		*0.00*		*0.75*		*0.89*	
R^2 adjusted	0.849	0.925	0.911	0.968	0.702	0.868	0.703	0.862	0.752	0.914	0.771	0.926
N	204	204	204	204	2964	2964	2964	2964	2964	2964	2964	2964
Level of observations	STATE	STATE	STATE	STATE	CZ	CZ	CZ	CZ	CZ	CZ	CZ	CZ
Split-sample IV							X	X	X	X	X	X
Area-specific time trends			X	X					X	X	X	X
Area-level controls											X	X

Note: Estimates are coefficients on the share of adults in occupations from the bottom quartile of the wage distribution of occupations in 1980, from a state-year or commuting zone-year level regression of employment rates or average wages on the share in lower wage occupations, state and year fixed effects, and additional controls. Regressions use Census data from 1980, 1990, 2000, and ACS data from 2005. Standard errors are reported in parenthesis, and are clustered at the state level. The estimated F-stat and p-value are statistics for testing the equality of coefficients for teens and adults, and were estimated from pooled regressions including both the teen and adult sample.

Table 3.4 - Robustness of results to the definition of the share employed in low wage occupations, 1980-2005

	Teens	HSD Adults	Teens	HSD Adults	Teens	HSD Adults	Teens	HSD Adults
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Dependent Variable - Fraction employed last week								
SHARE (P25)	-2.345	-0.970			-1.951	-0.794	-4.007	-1.808
	(0.438)	(0.247)			(0.413)	(0.261)	(1.748)	(1.258)
SHARE (P10)			-3.403	-1.378				
			(0.666)	(0.454)				
F-stat	10.84		10.41		6.27		2.04	
p-value	*0.00*		*0.00*		*0.01*		*0.15*	
R^2 adjusted	0.841	0.875	0.825	0.868	0.893	0.921	0.738	0.806
N	2964	2964	2964	2964	2223	2223	2223	2223
Panel B: Dependent Variable - Average log wage								
SHARE (P25)	-1.817	-1.718			-2.948	-2.553	-1.861	-0.973
	(0.709)	(0.481)			(0.703)	(0.553)	(2.455)	(1.807)
SHARE (P10)			-3.322	-2.256				
			(1.093)	(0.784)				
F-stat	0.02		0.87		0.59		0.09	
p-value	*0.89*		*0.35*		*0.44*		*0.76*	
R^2 adjusted	0.771	0.926	0.752	0.924	0.845	0.952	0.630	0.830
N	2964	2964	2964	2964	2223	2223	2223	2223
1980, 1990, 2000, 2005	X	X	X	X				
1980-2000					X	X		
1990-2005							X	X

Note: Estimates are coefficients on the share of employed adults in occupations from the bottom quartile of the wage distribution of occupations in 1980, from a CZ-year level regression of employment rates or average wages on the share in lower wage occupations, including CZ and year fixed effecs, CZ-specific time effecs, and other CZ-level controls (see text for full list of controls).

Table 3.5 - Relationship between teen labor market outcomes for various categories of teens and the share of the adult native population in lower wage occupations, 1980-2005

	All teens			White teens		Black teens		Hispanic teens		High inc. families	Low inc. families
	All	Males	Females	Males	Females	Males	Females	Males	Females	All	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Panel A. Dependent Variable - Fraction employed in the last week										
SHARE	-2.34	-2.21	-2.47	-2.15	-2.51	-2.43	-3.23	-4.21	-1.89	-2.58	-2.13
	(0.44)	(0.51)	(0.50)	(0.54)	(0.53)	(1.12)	(1.35)	(1.94)	(1.46)	(0.69)	(0.64)
Mean (1980)	0.31	0.33	0.29	0.36	0.32	0.17	0.14	0.27	0.22	0.37	0.23
Mean (2005)	0.26	0.24	0.28	0.28	0.32	0.13	0.16	0.17	0.18	0.29	0.19
	Panel B. Dependent Variable - Log of fraction employed in the last week										
SHARE	-7.69	-7.34	-8.17	-6.64	-7.03	-15.06	-19.77	-17.44	-8.47	-7.31	-10.15
	(1.50)	(1.86)	(1.71)	(1.80)	(1.63)	(9.94)	(9.57)	(10.96)	(8.33)	(2.25)	(3.29)
Mean (1980)	-1.19	-1.13	-1.27	-1.04	-1.17	-1.86	-2.08	-1.37	-1.60	-1.02	-1.52
Mean (2005)	-1.40	-1.48	-1.35	-1.33	-1.21	-2.16	-1.93	-1.91	-1.83	-1.29	-1.81
	Panel C. Dependent Variable - Log of average hourly wage										
SHARE	-1.82	-1.87	-1.71	-2.94	-1.93	-0.68	-2.32	3.22	-1.61	-4.31	-0.89
	(0.71)	(0.87)	(0.94)	(1.06)	(1.13)	(4.64)	(4.29)	(5.05)	(4.51)	(1.38)	(1.85)
Mean (1980)	1.32	1.35	1.29	1.36	1.29	1.38	1.35	1.38	1.33	1.38	1.28
Mean (2005)	1.16	1.18	1.13	1.18	1.13	1.16	1.06	1.21	1.21	1.23	1.12

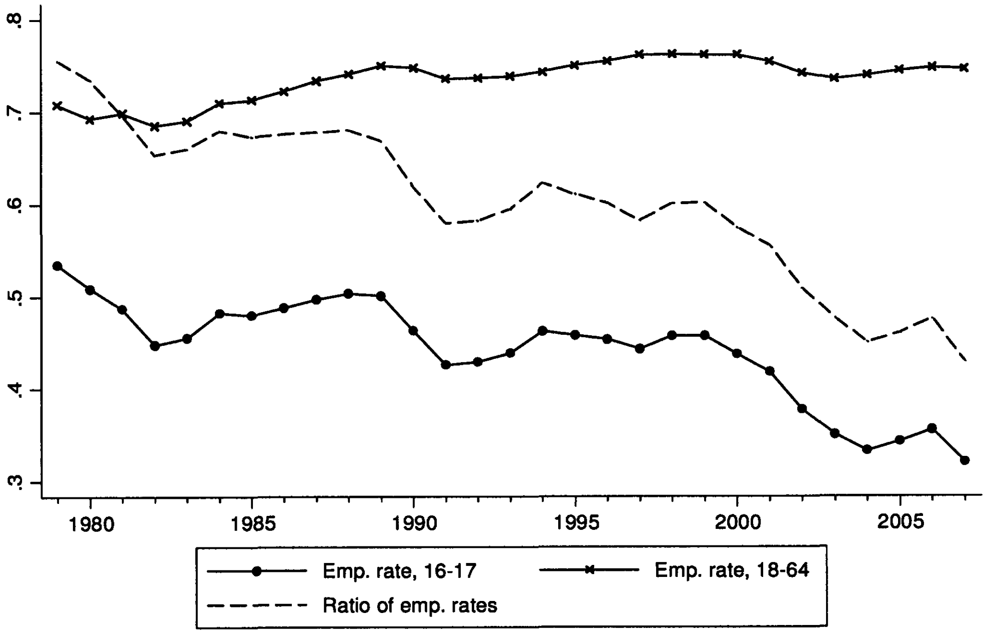
Note: Estimates are coefficients on the share of employed adults in occupations from the bottom quartile of the wage distribution of occupations in 1980, from a CZ-year level regression of the employment rate, the log of the employment rate, or the log of average wages for the given category of youth on the share in lower wage occupations, including CZ and year fixed effecs, CZ-specific time effecs, and other CZ-level controls (see text for full list of controls).

Table 3.6 - Association between the CZ-level share of employed adults in the lower quarter of the occupational distribution and other CZ characteristics

Dependent Variable:	Change in *SHARE*, 1980-2005			Change in teen employment rate, 1980-2005			Change in teen log real wages, 1980-2005		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RTI (1980)	0.013		0.013	-0.015		-0.016	-0.001		-0.005
	(0.001)		(0.002)	(0.004)		(0.005)	(0.006)		(0.008)
Fraction of employed in manuf. occupations (1980)		0.074	-0.011		-0.096	0.005		0.021	0.051
		(0.014)	(0.017)		(0.037)	(0.048)		(0.057)	(0.076)
Fraction male (1980)	0.330	0.122	0.336	-0.932	-0.683	-0.935	0.291	0.338	0.263
	(0.095)	(0.094)	(0.095)	(0.263)	(0.254)	(0.265)	(0.416)	(0.399)	(0.418)
Fraction white (1980)	-0.051	-0.049	-0.049	-0.072	-0.074	-0.073	0.001	-0.010	-0.010
	(0.021)	(0.022)	(0.022)	(0.059)	(0.061)	(0.060)	(0.094)	(0.095)	(0.095)
Fraction black (1980)	-0.039	-0.004	-0.039	-0.113	-0.154	-0.113	-0.124	-0.138	-0.125
	(0.025)	(0.026)	(0.025)	(0.070)	(0.070)	(0.070)	(0.111)	(0.109)	(0.111)
Fraction hispanic (1980)	0.102	0.111	0.098	-0.129	-0.143	-0.127	-0.272	-0.259	-0.255
	(0.016)	(0.018)	(0.017)	(0.045)	(0.048)	(0.048)	(0.072)	(0.076)	(0.076)
Fraction immigrant (1980)	-0.234	-0.116	-0.252	0.730	0.578	0.737	0.044	0.077	0.125
	(0.075)	(0.081)	(0.080)	(0.208)	(0.218)	(0.222)	(0.329)	(0.342)	(0.351)
Fraction of HSD pop. immigrant (1980)	0.080	0.032	0.091	-0.572	-0.508	-0.577	0.449	0.418	0.398
	(0.042)	(0.046)	(0.045)	(0.117)	(0.125)	(0.126)	(0.184)	(0.196)	(0.200)
Fraction HSD (1980)	-0.135	-0.180	-0.132	-0.393	-0.338	-0.395	-0.285	-0.281	-0.298
	(0.026)	(0.027)	(0.027)	(0.074)	(0.073)	(0.075)	(0.116)	(0.114)	(0.118)
Fraction with some college (1980)	-0.190	-0.092	-0.199	-0.548	-0.670	-0.543	0.060	0.065	0.102
	(0.025)	(0.026)	(0.029)	(0.070)	(0.071)	(0.081)	(0.111)	(0.111)	(0.127)
Adjusted R^2	0.174	0.110	0.173	0.446	0.438	0.445	0.225	0.225	0.225
N	741	741	741	741	741	741	741	741	741

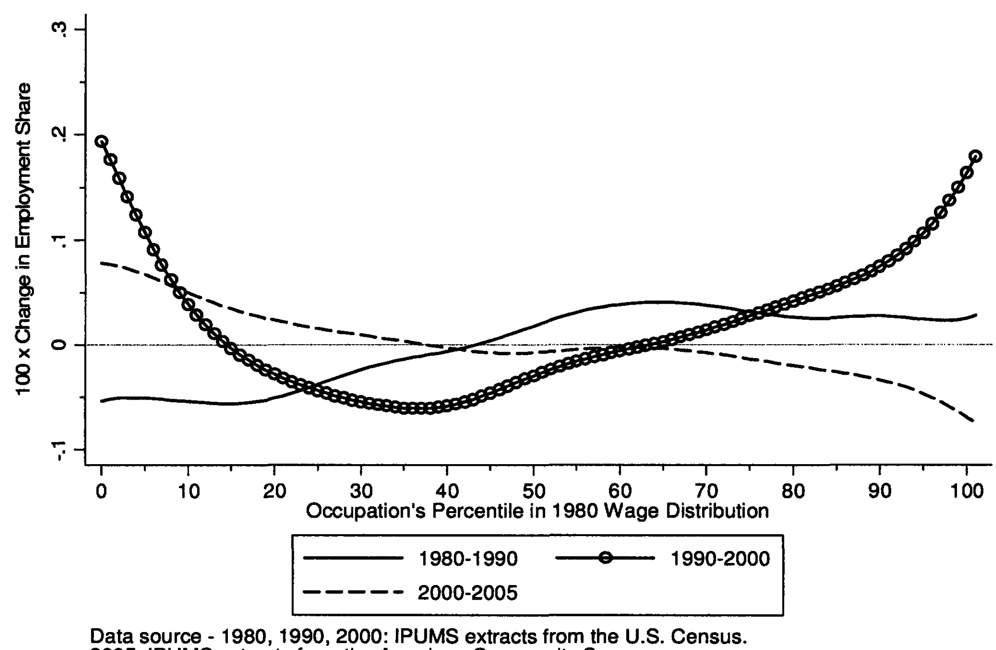
Notes: Regressions are run at the commuting zone level. Standard errors are presented in parenthesis, and are clustered at the commuting zone level. The dependent variable in regressions for columns (1)-(3) is the change in the share of all employed native adults employed in the lower quartile of the occupational distribution between 1980 and 2005. The dependent variable in regressions for columns (4)-(6) is the change in teen employment rates between 1980 and 2005. The dependent variable in regressions for columns (7)-(9) is the change in teen log real wages between 1980 and 2005. All independent variables are measured in 1980. RTI is relative routine-task intensity, as defined in the text.

Figure 3.1: Trends in July Employment-Population Ratio, Adults and Teens



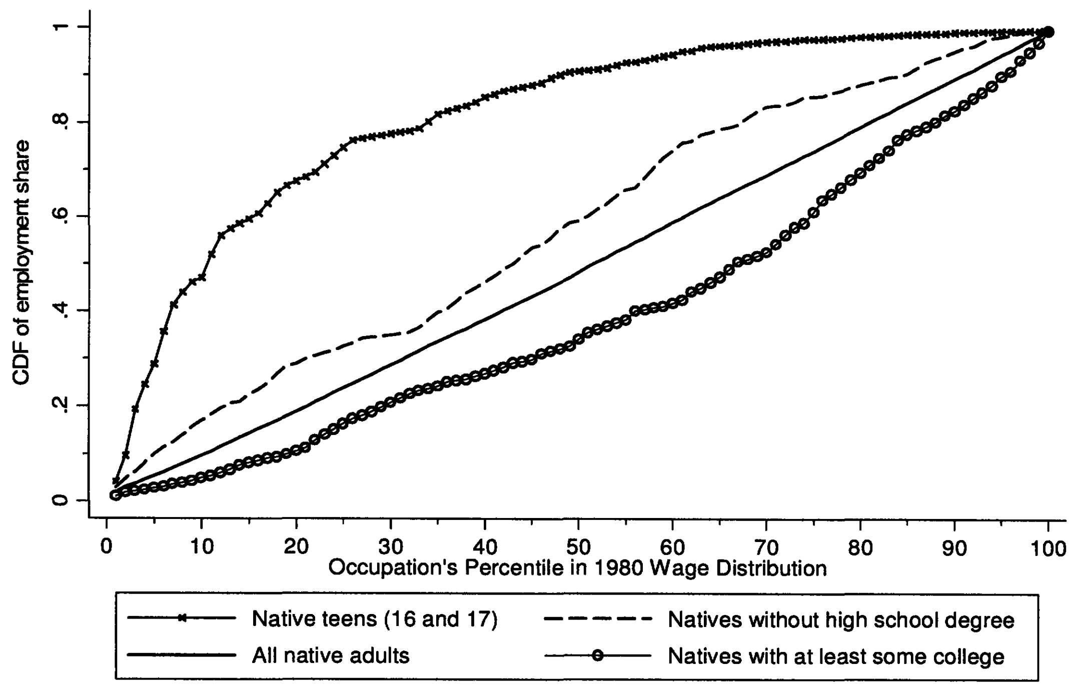
Source: CPS monthly data, NBER extracts.

Figure 3.2 - Changes in Employment Share of an Occupation, by 1980 Wage Levels



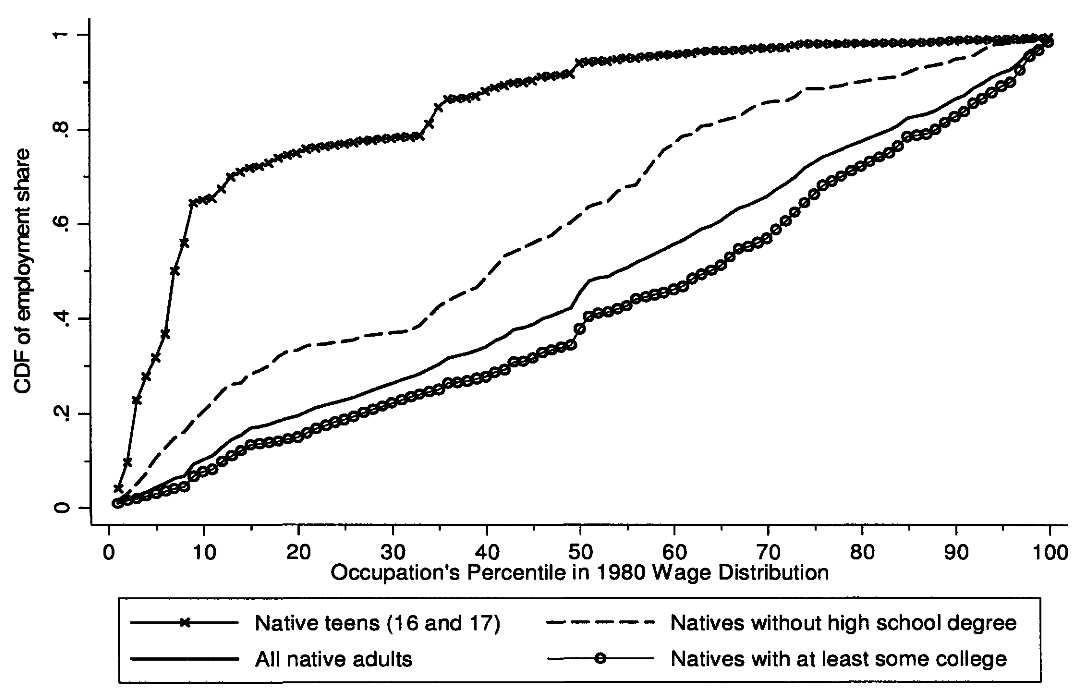
Data source - 1980, 1990, 2000: IPUMS extracts from the U.S. Census.
2005: IPUMS extracts from the American Community Survey.

Figure 3.3a - CDFs of employment share, 1980



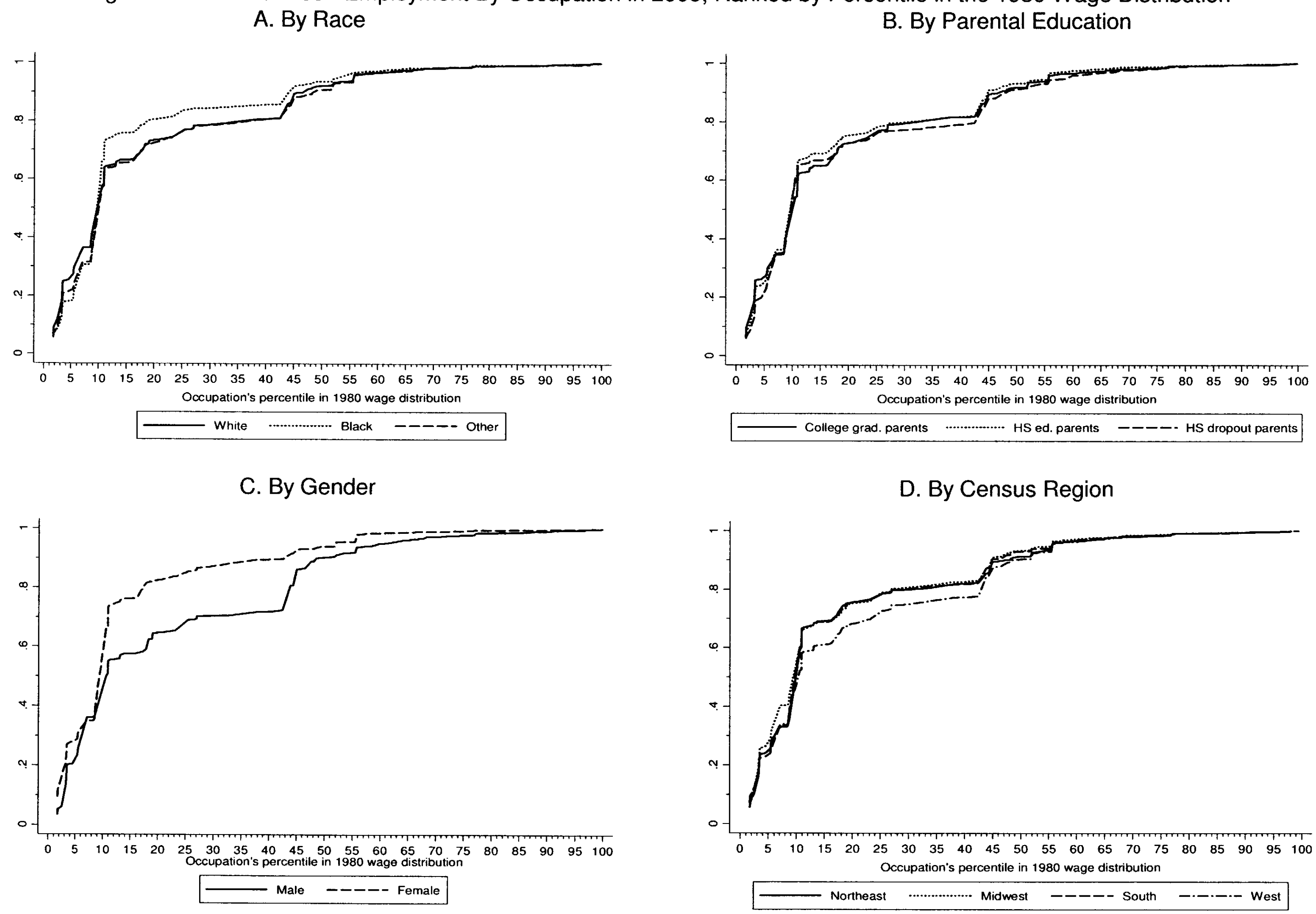
Data source - 1980 IPUMS extracts from the U.S. Census.

Figure 3.3b - CDFs of employment share, 2005



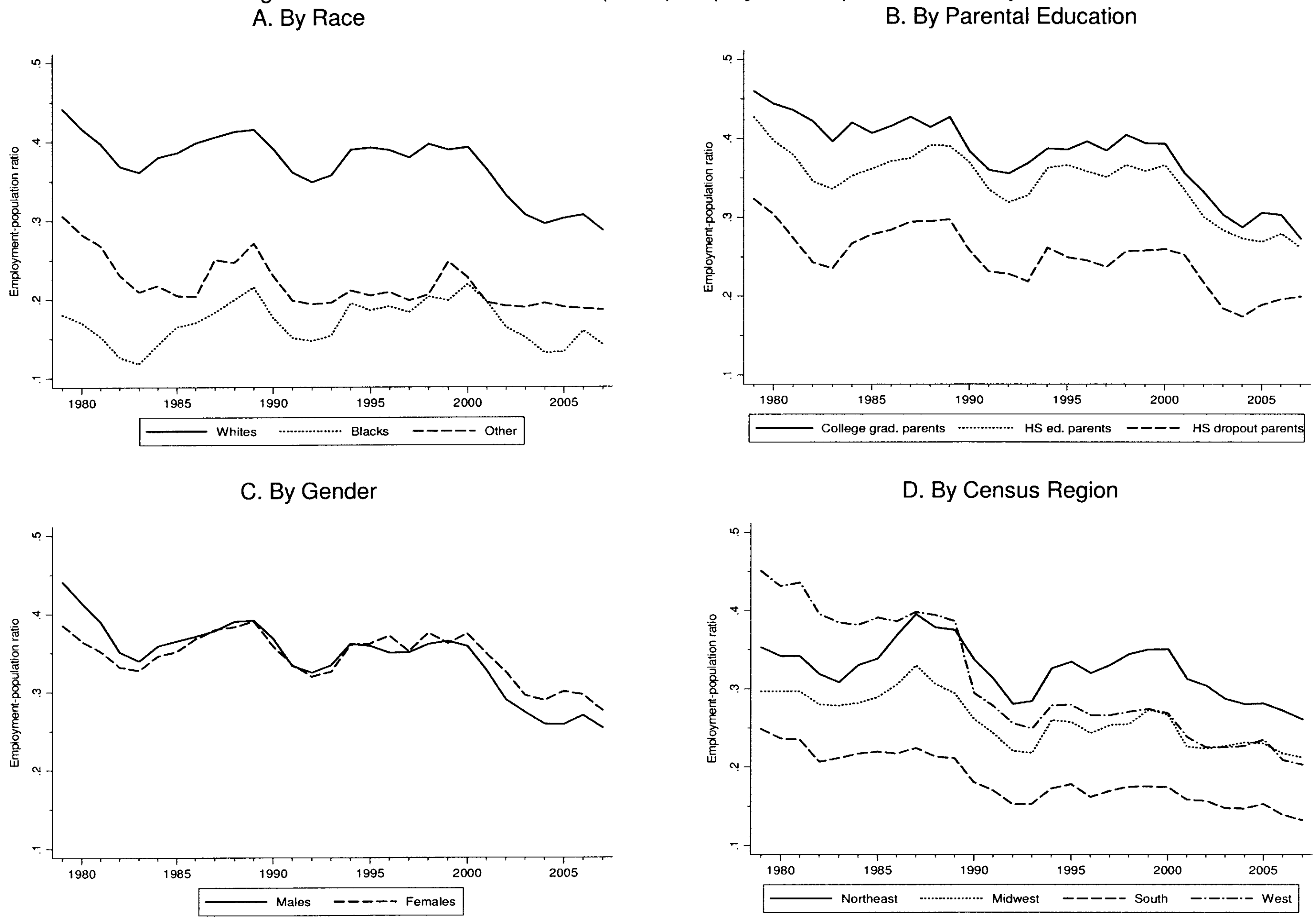
Data source - 2005 IPUMS extracts from the U.S. Census.

Figure 3.4 - CDF of Teen Employment By Occupation in 2005, Ranked by Percentile in the 1980 Wage Distribution



Notes: Graphics are plots of the empirical, non-smoothed CDF of the occupational employment distribution for teens, by race, parental education, gender, and Census region. Occupations are ranked by their percentile in the hours-weighted adult wage distribution of all occupations in 1980. Data is from the 2005 American Community Survey.

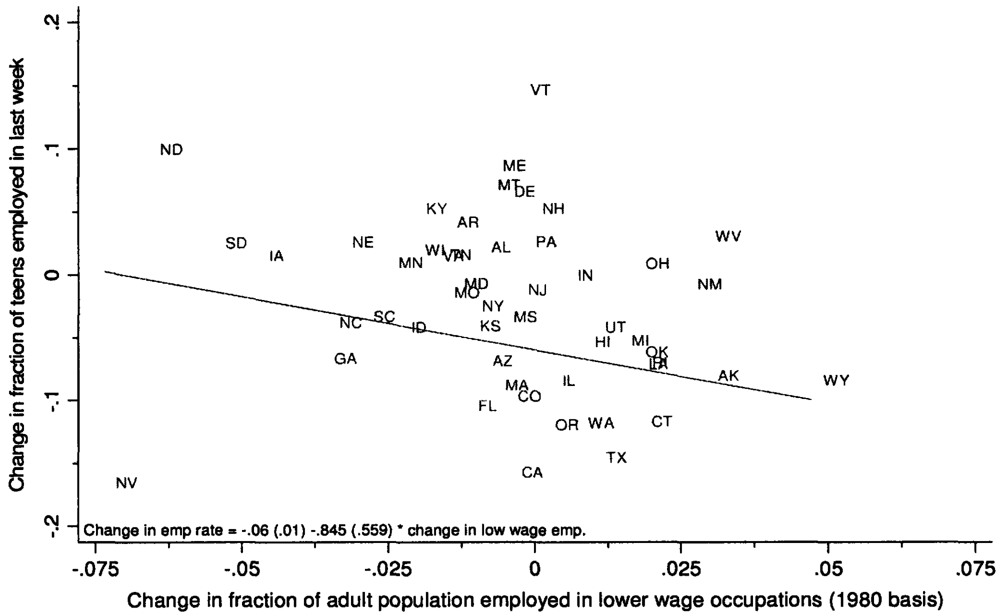
Figure 3.5 - Trends in Annual Teen (16-17) Employment-Population Ratio, By Race



Notes: Graphics are plots of the employment-to-population ratio for teens age 16-17, by race, parental education, gender, and Census region. Data is aggregated from monthly CPS data from the NBER extracts.

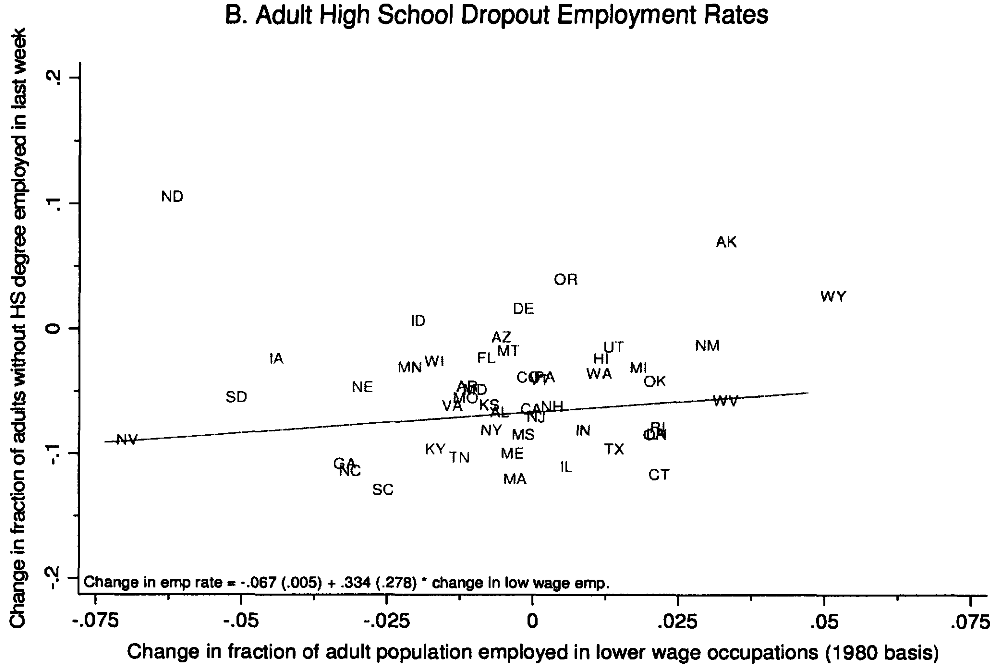
Figure 3.6 - Relationship between change in native teen or adult labor market outcomes and change in share of employed native adults in lower paying occupations (1980-2005)

A. Teen Employment Rates



Notes: Low paying occupations are those in the bottom quartile of the hours-weighted wage distribution of occupations in 1980.
1980 data is from the IPUMS public use sample for the 1980 Census.
2005 data is from the IPUMS public use sample for the American Community Survey.

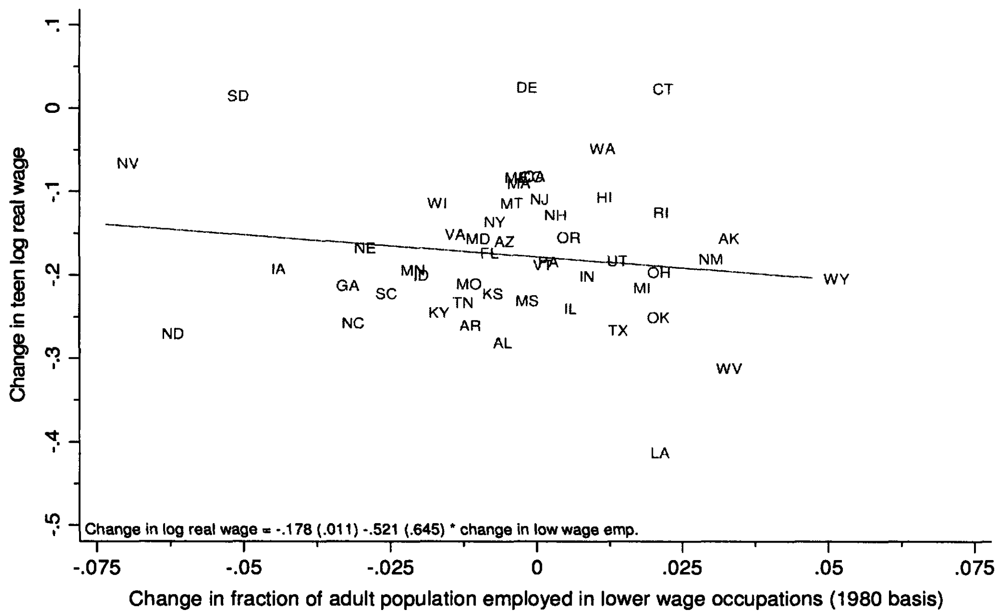
B. Adult High School Dropout Employment Rates



Notes: Low paying occupations are those in the bottom quartile of the hours-weighted wage distribution of occupations in 1980.
1980 data is from the IPUMS public use sample for the 1980 Census.
2005 data is from the IPUMS public use sample for the American Community Survey.

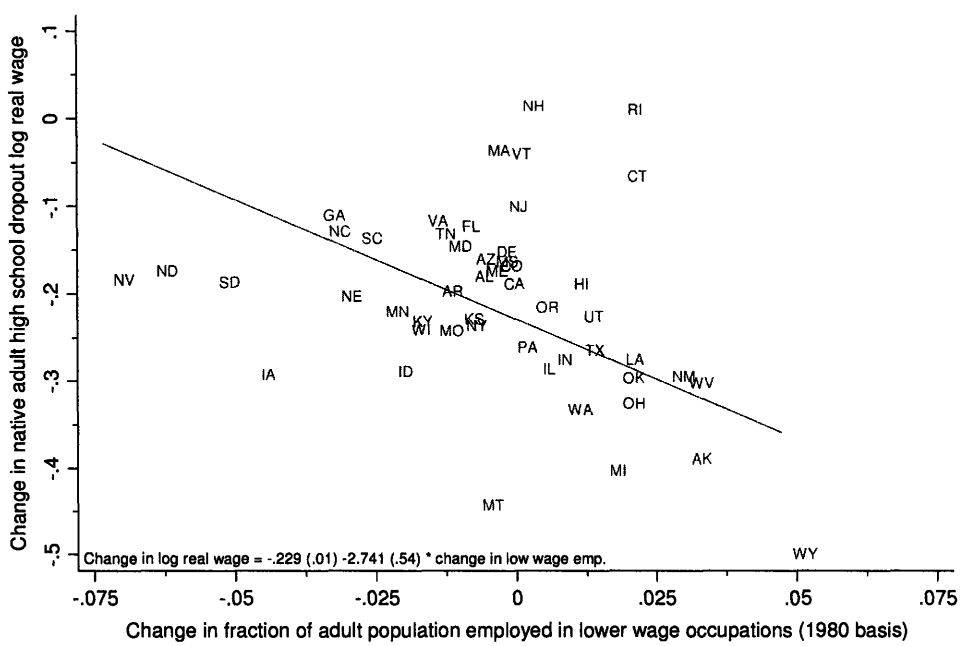
Figure 3.6 - Relationship between change in native teen or adult labor market outcomes and change in share of employed native adults in lower paying occupations (1980-2005)

C. Teen Average Log Wages



Notes: Low paying occupations are those in the bottom quartile of the hours-weighted wage distribution of occupations in 1980.
1980 data is from the IPUMS public use sample for the 1980 Census.
2005 data is from the IPUMS public use sample for the American Community Survey.

D. Adult High School Dropout Log Wages



Notes: Low paying occupations are those in the bottom quartile of the hours-weighted wage distribution of occupations in 1980.
1980 data is from the IPUMS public use sample for the 1980 Census.
2005 data is from the IPUMS public use sample for the American Community Survey.

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