Down from the Mountain: Skill Upgrading and Wages in Appalachia

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The Appalachian region has experienced persistently higher poverty and lower earnings than the rest of the United States. We examine whether skill differentials or differences in the returns to those skills lie at the root of the Appalachian wage gap. Using census data, we decompose the Appalachian wage gap using both mean and full distribution methods. Our findings suggest that significant upgrading of skills within the region has prevented the gap from widening over the last 20 years. Additionally we find that urban areas within Appalachia have not experienced the rise in returns to skills as in non-Appalachian urban areas.

I. Introduction

We examine the movement of wages within the Appalachian region of the United States and the rest of the country in an effort to understand whether changes in the wage gap between Appalachia and the rest of the

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country are due to different changes in skill, in the returns to skill, or both. Our focus on Appalachia is motivated by several factors related to inequality trends. The Appalachian region has historically had lower levels of skilled labor and income relative to the rest of the country, which some researchers claim has resulted in a "poverty trap" (Caudill 1962; Harrington 1962; Duncan 1999; Easterly 2001; Eller 2008). This has led policy makers to focus extensive resources on the region in an effort to raise the levels of education and income in the area. Appalachia was the focal point for much of the legislation underlying the War on Poverty and, since the mid-1960s, has been a well-defined zone of economic activity. Despite all of these efforts, Appalachia still lags behind the rest of the country in educational achievement and income.

While the Appalachian region has long been the focus of policy makers, it has received relatively little attention from economists (Black, Daniel, and Sanders 2002; Black and Sanders 2004). This is unfortunate since knowledge of how regional differences in skill levels and returns to skill translate into regional differentials in wages is essential to a better understanding of widening inequality in general, as well as for more targeted policy prescriptions for regional economic development (Glaeser and Gottlieb 2008). This seems particularly salient for regions with persistently low levels of income. Parente and Prescott (2005) argue that a country starts to experience sustained increases in incomes when the country's capacity to effectively use modern technological resources reaches a critical threshold. To the extent that their framework is applicable to regions within the United States, the implication of recent technological change, which favors college-educated workers, is that persistent income differentials will continue in regions such as Appalachia until these residents close the college-completion gap. At the same time, the relative supply and demand story found in the inequality literature, for example, Katz and Murphy (1992) and Autor, Katz, and Kearney (2008), is that if there was a nationwide increase in the demand for skilled workers, but a shortage in the supply of such workers in Appalachia, then we would predict the returns to skill to increase over time in Appalachia relative to the rest of the country. This would lead to a convergence in regional wages, which contrasts with the predictions of Parente and Prescott (2005). In spite of these competing explanations, and the long-standing policy issues surrounding the Appalachian wage gap, the literature has been surprisingly silent on wage differentials among workers between regions (Moretti 2008).

To identify the reasons for wage differences we estimate human-capital wage equations for men and women that admit region-specific hetero-

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geneity in the returns to observable and unobservable factors that proxy for skill. Beyond the standard demographics found in scores of studies on wage levels and gaps (Altonji and Blank 1999; Card 1999), we control explicitly for self-selection into the labor force and migration into the region of residence (Juhn, Murphy, and Pierce 1993; Dahl 2002; Blundell et al. 2006). With the secular rise of employment among women and concurrent decline among men, it is important to control for unobserved factors related to these trends and the possibility that these processes differ between Appalachia and the rest of the nation. Even conditional on observables, selection into and out of the Appalachian region may not be exogenous to wages, so our model controls for endogenous migration.

In addition to the conditional mean, we also estimate the determinants of wages across the distribution. Black and Sanders (2004) suggests that earnings inequality in Appalachia in the 1980s and 1990s was lower and rose more slowly than the rest of the United States. This may be due to slower wage growth at the higher ends of the earnings distribution, or it may be due to faster wage growth at the lower ends of the earnings distribution. By specifically examining the determinants of wages throughout the distribution we more clearly understand the implications of the observed changes. We estimate quantile wage equations across the region-gender wage distributions, again controlling for nonrandom selection into the labor force and into the region of residence using the methods of Buchinsky (1998, 2001). Given the estimated coefficients at the conditional mean and conditional quantiles, we decompose the regional wage gaps into the shares attributable to differences in demographics and in coefficients (Oaxaca 1973; Machado and Mata 2005). Applications of mean wage decompositions controlling for sample selection bias are scarce (Chandra 2003; Neal 2004; Neuman and Oaxaca 2004), and the quantile approach with selection is even more rare (Blundell et al. 2006; Albrecht, van Vuuren, and Vroman 2009).

The data for our analysis are the 1980–2000 Integrated Public Use Microdata Samples (IPUMS) of the decennial census. Because counties are not identified in the IPUMS we employ a weighting method that identifies the share of a public use micro area (a PUMA for every 100,000 persons) that is in Appalachia, and weight all regressions by the appropriate share. For historical purposes, our base case compares Appalachia to the rest of the nation. Because there is evidence that more skilled workers tend to live in cities, that the difference in skills between cities and rural areas has been growing recently (Glaeser and Mare 2001; Glaeser and Saiz 2004; Moretti 2004), and that the returns to skills have been growing within cities (Chung, Clark, and Kim 2009), we also consider a number of alternative comparisons such as rural Appalachia to rural non-Appalachia, and urban Appalachia to urban non-Appalachia.

Our results indicate that men and women in Appalachia came “down from the mountain" in the 1980s and 1990s and significantly upgraded their human capital in terms of education attainment compared to men and women in the rest of the nation. This relative skill upgrading prevented the wages of Appalachians from falling further behind those outside the region during the period of widening inequality overall. As a consequence, the wage distribution for men in Appalachia compared to non-Appalachia is less due to demographic shortfalls than to differences in returns to important skills such as education and experience, the latter of which appears to be driven in large part by the relative decline in returns to schooling in Appalachia over the past 2 decades. At the same time, however, for men we find that skill shortages remain more pronounced at the high end of the wage distribution. One potential explanation for our findings is that Appalachia suffers from "missing markets," both a paucity of high-skilled workers and low returns for those with high skills, that is most pronounced in the urban areas of the region.

II. Background and Data

Few regions within the United States have engendered as much attention as Appalachia in discussions of poverty (Caudill 1962; Harrington 1962; Duncan 1999; Eller 2008). In 1964 President Johnson traveled to the small town of Inez, Kentucky, to launch the nation's "War on Poverty," and several presidential candidates have included "poverty tours" of Appalachia as part of their campaigns. Appalachia was first designated as a special economic zone in 1965 with passage of the Appalachian Regional Development Act. The act defined the economic zone of activity and created a federal and state partnership known as the Appalachian Regional Commission (ARC) whose mission is to expand the economic opportunities of the residents by increasing job opportunities, human capital, and transportation. The ARC-designated region traces the Appalachian Mountains from southern New York to northern Mississippi, spanning parts of 12 states and all of West Virginia (see fig. A1 in the appendix, available in the online version of the *Journal of Labor Economics*).[1] As of 2000, 406 counties were included in Appalachia, and over $13 billion had been spent by ARC on the region (Glaeser and Gottlieb 2008).

Although much of Appalachia is rural, it does encompass about 10% of the nation's population and includes several urban centers such as Pittsburgh, Pennsylvania; Knoxville, Tennessee; and Birmingham, Alabama. Historically the region was heavily dependent on resource extraction (coal and timber in the central area), manufacturing (especially steel in the north), and agriculture (cotton and tobacco in the south; Eller

[1] Inclusion in ARC was based in part on proximity to the Appalachian Mountains, in part on economic distress, and in part on political economy (Eller 2008).

2008). Appalachian poverty has exceeded national poverty rates by 10% to 20%, but in the central Appalachian region poverty is nearly double the national rate. Median income in Appalachia is at least $10,000 below the national median, and differences in median income have widened in recent decades.[2] While still lagging behind the United States as a whole, the Appalachian region has shown some social and economic convergence toward the rest of the country during the last decade (Pollard 2003; Black and Sanders 2004; Haaga 2004). Still, perhaps because of the searing portraits of grinding poverty by Caudill (1962) and Harrington (1962), to this day Appalachia is often viewed as "the other America."

As recently as 1980 only 67% of adult residents (25 years old and older) in Appalachia had completed high school or its equivalent, compared to 76% outside the region.[3] By 2000 the fraction of adult Appalachians with at least high school rose to 87%, while it rose more slowly to 89% outside the region. Based on the analysis of Lemieux (2006), we would expect this relative education upgrading to narrow regional wage differentials between 1980 and 2000. At the same time, the gap in the percent of adults with a college degree across regions actually expanded from 6 to 8 percentage points between 1980 and 2000. The results of Autor et al. (2008) suggest that this gap in highly skilled workers would point to widening of regional wage differentials. In fact, the average wage gap between workers in Appalachia and the rest of the nation rose from 9 log points in 1980 to 13 log points in 2000, which seems more consistent with Autor et al. (2008). Both scenarios, however, assume that the standard result of factor-price equalization holds across regions. Recent evidence by Dahl (2002) and Black, Kolesnikova, and Taylor (2009) calls this assumption into question as they find persistent differences in schooling returns across states and cities. How skill returns in Appalachia evolved over time relative to the rest of the nation is not known and yet is critical to the regional evolution of inequality.

Appalachia is of interest not only because of its historical significance in the nation's fight against poverty, but because its large geographic coverage that spans remote rural areas as well as some midsize and large cities offers the opportunity to study the role that urban areas play in regional economic development. It has long been true that urban areas have more skilled workers than rural areas. Moretti (2004) shows that the gap in skill between the most and least skilled urban areas has risen since 1980, and this increase in skill dispersion is correlated not only with the level of workers' skills but also with the size of the area, wealth, and

[2] See "Economic Overview" at http://www.arc.gov/index.do?nodeId=26.

[3] Authors' calculations based on IPUMS data from 1980 and 2000 decennial censuses as described in the Data section. These estimates pool men and women, but we conduct our analyses below separately by gender.

industrial structure. Urban areas with large concentrations of high-tech industries experienced the largest gains in skill over this period. In turn, this growth in the skill gap accounts for some of the overall growth in the income gap between 1980 and 2000. Since the urban areas in Appalachia tend to be smaller, poorer, and contain very little high-tech industry, decomposing wage changes between urban and rural areas within Appalachia, as well as between urban and rural areas inside and outside of Appalachia, will help document the role regional differences in skill and skill accumulation have in accounting for the earnings gap in the United States.

To address the potential importance of urban areas in the analysis, we include comparisons of rural Appalachia to the rest of rural America, of urban Appalachia to urban non-Appalachia, and for the central Appalachian region (the coal-producing states) to the residents in non-Appalachia living in rural areas and metro areas with fewer than 1 million persons. Indeed, the legislation establishing ARC mandated that resources be directed to the locales with the greatest potential for economic growth, which not surprisingly were the urban centers of the region (Eller 2008). Thus, the supplemental analyses on the urban areas of Appalachia are of independent interest.

Data.—Our data derive from the Integrated Public Use Micro Samples (IPUMS) of the 1980, 1990, and 2000 decennial census. The IPUMS contain variables commonly used in estimation of wage equations and also include geographic identifiers. We begin our data in 1980 because earlier IPUMS data contain more aggregated geographic identifiers, making it difficult to estimate individual-level wages separately for the Appalachian region. We select working and nonworking individuals between the ages of 25 and 60 who do not have missing or allocated wages. The age cutoffs are chosen to minimize the presence of full-time students and those nearing retirement. Dropping those with allocated earnings avoids attenuation bias in skill returns (Bollinger and Hirsch 2006). The resulting sample has 7 million men and 8 million women across the three censuses.

The key advantage of the IPUMS data is the long time series of cross sections and the exceptionally large sample sizes that permit identification of region-by-gender skill returns across the wage distribution. The data are limited because the geographic identifiers that are made publicly available are not perfectly coincident with the Appalachian region.[4] The smallest geographic unit reported in the IPUMS is the Public Use Micro Area, or PUMA, containing groupings of 100,000 residents. In most cases the

[4] A lesser concern is the fact that the federal government has changed the definition of the Appalachian region slightly over our sample period. In 1980, 397 counties were included in Appalachia, and by 2000 the number of counties was 406. Throughout our analysis we use the 2000 definition of Appalachia.

PUMA is fully contained within either Appalachia or non-Appalachia and thus individuals can be assigned as Appalachian residents (or not) simply from the PUMA information. However, a few PUMAs contain counties in both regions; for these cases we use supplementary information from the Decennial Census Summary Files to determine the proportion of residents in a particular PUMA who live in Appalachia. These proportions are then used to weight individual observations in the summary statistics and regression models to follow. Since the summary files contain detailed population counts by age, sex, and race, the weights are constructed to reflect the probability that the particular individual actually lives in Appalachia. This weighting procedure has its roots in weighting for stratified samples and weighting for item nonresponse (Groves et al. 2004).

Our outcome of interest is the log real hourly wage. We construct the real wage as the ratio of annual earnings to the product of annual weeks worked and hours of work per week and then deflate the average hourly wage by the personal consumption expenditure deflator with 2000 as the base year.[5] Key demographic variables available in the census and pertinent to our analysis include education attainment, potential experience (defined as age minus years of schooling minus 6), race and ethnicity, marital status, living in an urban area (= 1 if the Beale rural-urban continuum code is 3 or less), and one-digit industry (for workers).

Table 1 contains summary statistics on key economic and demographic variables for our sample of working and nonworking men and women in each of the last three decennial censuses broken down by residency in Appalachia. Among men inside Appalachia versus those outside, we see that the log wage gap widened from 0.094 log points in 1980 to 0.125 log points in 1990 and then held steady at 0.124 in 2000. The widening in the 1980s occurred because male wages in Appalachia fell more than those in the rest of the nation, while in the 1990s the wages of men within Appalachia grew slightly more than the wages outside the region. Among women, the wage gap widened from 0.127 log points to 0.169 between 1980 and 1990, and like men, women in both regions experienced wage

[5] Since we estimate the models separately by year, deflating by the expenditure deflator is not necessary, but it is needed to discuss the summary statistics over time. On the other hand, Card and Krueger (1992) deflate wages by the average wage in the state to account for state-specific differences in cost of living, and Moretti (2008) proposes a city-specific version of the CPI to account for cost-of-living differences across metro and nonmetro areas. A priori it is not clear whether one should adjust wages for local cost-of-living differences, as the latter may be outcomes affected by the preferences of the community, which in turn are affected by the demographic composition (DuMond, Hirsch, and Macpherson 1999). As a consequence we chose not to use a local price deflator, although we capture some broad effect of location by controlling for urban residence.

Table 1
Average Values of Selected Variables of Men and Women within and outside Appalachia

	Appalachia 1980	Non-Appalachia 1980	Appalachia 1990	Non-Appalachia 1990	Appalachia 2000	Non-Appalachia 2000
Men:						
Log of real wage	2.689	2.783	2.629	2.754	2.690	2.814
Wage gap (non-Appalachia less Appalachia)	. . .	.094	. . .	.125	. . .	.124
Employment rate	.890	.914	.884	.912	.860	.890
Usual hours worked per week	37.750	39.118	38.316	40.068	38.019	39.575
Less than high school	.334	.241	.211	.154	.154	.131
High school	.380	.336	.414	.326	.419	.320
Some college	.132	.190	.212	.274	.244	.286
Bachelor's degree	.107	.153	.107	.158	.120	.169
Master's or more	.048	.080	.057	.089	.063	.094
Potential experience ≤10 years	.193	.232	.153	.188	.129	.150
Potential experience >10 years and ≤20 years	.285	.293	.345	.360	.288	.307
Potential experience >20 years and ≤30 years	.221	.212	.253	.244	.315	.312
Potential experience >30 years and ≤40 years	.208	.196	.186	.163	.218	.195
Potential experience >40 years	.092	.067	.063	.045	.050	.036
White, non-Hispanic	.931	.809	.933	.773	.903	.703
White, Hispanic	.004	.060	.005	.089	.009	.060
Black, non-Hispanic	.059	.100	.054	.095	.061	.101
Black, Hispanic	.000	.001	.000	.002	.000	.002
Other, non-Hispanic	.005	.026	.007	.040	.018	.066
Other, Hispanic	.000	.004	.000	.001	.009	.067
Fishing, Mining, and Construction	.175	.127	.176	.147	.159	.149
Durable Goods Manufacturing	.247	.203	.204	.162	.197	.143
Nondurable Goods Manufacturing	.118	.092	.113	.084	.098	.072
Transport, Communication, and Other Utilities	.097	.097	.099	.091	.096	.091
Wholesale Trade	.045	.055	.048	.057	.046	.048
Retail Trade	.086	.102	.106	.118	.117	.127
Finance, Insurance, and Real Estate	.027	.045	.028	.047	.030	.048
Business and Repair Services	.044	.066	.064	.093	.079	.118
Professional and Related Services	.096	.113	.105	.114	.120	.127
Public Administration	.064	.100	.057	.087	.058	.078

Live in urban area	.421	.782	.420	.748	.473	.774
Currently married	.813	.765	.746	.694	.688	.651
Women:						
Log of real wage	2.190	2.317	2.230	2.399	2.394	2.553
Wage gap (non-Appalachia less Appalachia)	. . .	.127	. . .	.169	. . .	.159
Employment rate	.563	.629	.690	.743	.724	.760
Usual hours worked per week	20.239	22.402	25.375	27.632	27.352	29.013
Less than high school	.329	.245	.193	.146	.128	.114
High school	.450	.423	.446	.363	.408	.314
Some college	.119	.179	.223	.289	.281	.317
Bachelor's degree	.081	.117	.090	.139	.119	.171
Master's or more	.022	.036	.048	.062	.065	.084
Potential experience $\leq$10 years	.165	.198	.152	.180	.132	.149
Potential experience >10 years and $\leq$20 years	.286	.294	.331	.344	.286	.300
Potential experience >20 years and $\leq$30 years	.224	.218	.255	.249	.307	.306
Potential experience >30 years and $\leq$40 years	.233	.219	.197	.177	.226	.207
Potential experience >40 years	.093	.070	.065	.050	.049	.039
White, non-Hispanic	.924	.800	.927	.763	.899	.696
White, Hispanic	.004	.058	.005	.082	.007	.056
Black, non-Hispanic	.066	.110	.061	.110	.070	.119
Black, Hispanic	.001	.002	.000	.002	.000	.002
Other, non-Hispanic	.005	.027	.008	.042	.019	.068
Other, Hispanic	.000	.003	.000	.001	.006	.059
Fishing, Mining, and Construction	.022	.026	.026	.030	.023	.027
Durable Goods Manufacturing	.101	.094	.085	.072	.084	.064
Nondurable Goods Manufacturing	.162	.086	.128	.072	.080	.055
Transport, Communication, and Other Utilities	.029	.039	.030	.039	.032	.040
Wholesale Trade	.020	.028	.023	.030	.021	.025
Retail Trade	.172	.165	.185	.168	.183	.158
Finance, Insurance, and Real Estate	.054	.079	.062	.088	.066	.083
Business and Repair Services	.076	.095	.084	.110	.086	.117
Professional and Related Services	.317	.327	.336	.333	.379	.370
Public Administration	.046	.061	.042	.058	.047	.061
Live in urban area	.419	.769	.416	.739	.473	.769
Currently married	.775	.732	.731	.681	.689	.646

growth in the 1990s, but wages of those inside Appalachia grew faster and narrowed the gap to 0.159.

There are several other trends of note in table 1. First, there is a slight decline in employment among men, and a more discernible rise among women. The regional gap in employment rates for men range from 2 to 3 percentage points, and employment fell more rapidly among men in Appalachia between 1980 and 2000. Women in Appalachia, however, had employment rates 7 percentage points lower in 1980 compared to women outside the region, but cut the gap roughly in half in the ensuing 2 decades. Second, there is evidence of relative education upgrading in Appalachia between 1980 and 2000. Appalachian men are now significantly more likely to graduate from high school and to complete some college, while Appalachian women showed large gains in some college and advanced degrees. Ceteris paribus, this convergence in education attainment should narrow the gap in wages. Third, the Appalachian region has become slightly more ethnically diverse with a decline in the percentage of white, non-Hispanic men and women over this period. Borjas (2004) shows that the South experienced marked increases in immigrants during the 1990s from increases in the number of newly arrived persons as well as from internal migration to the South. These new immigrants were much more likely to settle in the Appalachian South than in earlier decades. These immigrants tend to be low skilled, and this could possibly exacerbate regional wage differences. Fourth, for men there is a large secular decline in the percentage currently married across the board of about 16%. Last, in terms of industrial composition of the male workforce, both regions experienced employment declines in manufacturing and transportation, and both experienced growth in retail trade, FIRE (finance, insurance, and real estate), and business and repair services. In most cases, though, the regional difference in industrial composition either held steady or converged.

III. Wage Determination and Wage Decompositions

We begin by specifying the typical human capital wage equation:

$$\ln W_{ijrt} = X_{ijrt}\beta_{jrt} + \varepsilon_{ijrt}, \tag{1}$$

where $\ln W$ is the natural log of the real average hourly wage rate for individual i of gender j residing in region r (Appalachia and non-Appalachia) during decennial census year t. The demographics X that serve as observable proxies of skill include indicators for education attainment (high school dropout [omitted], high school, some college, college, post-graduate), indicators of potential experience (0–10 [omitted], 10–20, 20–30, 30–40, >40), interactions of education and experience (Heckman, Lochner, and Todd 2003), race and ethnicity, marital status, and urbanicity. We also present results of models that include industry controls so that we can examine the role that changes in industry composition had on the wages of workers.[6] Least squares estimation of equation (1) will fail to provide consistent estimates of β_{jrt} if $E[\varepsilon_{ijrt}|X_{ijrt}] \neq 0$, which we hypothesize can occur for two reasons—nonrandom selection into the labor force and nonrandom selection into the geographic region of residence.

A. Endogenous Selection into Employment and Region

Wages are observed only for those who are employed. Although concerns about selection on unobservables into work have been more prominent in research on women's wages than men's, the differential decline across regions in labor force participation of men in table 1, and the differential rise in employment among women, implies that endogenous selection into and out of work is a potential concern not just for women but for men as well (Blundell and MaCurdy 1999; Bound and Burkhauser 1999).

To address labor-market selection we specify a latent variable model of the form

$$E^*_{ijrt} = Z_{ijrt}\gamma_{jrt} + \eta_{ijrt}, \tag{2}$$

where E^*_{ijrt} is the latent propensity to work, Z_{ijrt} are observed characteristics, and η_{ijrt} are unobserved components. Since we only observe whether the person is employed or not, that is, $E_{ijrt} = 1$ or 0, then being employed implicitly occurs when $E^*_{ijrt} > 0$. A key issue in selection models is how the selection effects are identified separately from the observed factors affecting wages. We rely on exclusion restrictions such that Z includes the variables in X along with additional person- and state-specific covariates. The person-specific exclusion restrictions available in the census to identify selection into work but not wages follows from the canonical model of labor supply (Blundell and MaCurdy 1999), including nonlabor income, the total number of children, and the number of children under age 5. The state-specific variables used to identify the employment decision include those that affect the generosity of welfare and disability, such as the combined maximum monthly benefit guarantee for the Supplemental Security Income plus food stamps and the combined maximum monthly benefit for Aid to Families with Dependent Children (AFDC) and food stamps; institutional constraints, including the state minimum wage; business cycle conditions such as the state unemployment rate; and state political preferences as represented by the party affiliation of the state's governor. We also include the family-size-specific subsidy rate for

[6] There are a few other possible covariates available in the census that might bear on a worker's productivity, including veteran's status and health status. Both variables have been shown to be important determinants of workers' wages (Berger and Hirsch 1983; Angrist 1990; Haveman, Stone, and Wolfe 1994), but in general they are endogenous to wages and thus we exclude them from our analyses.

the federal Earned Income Tax Credit (EITC; Hotz and Scholz 2003). The state-specific variables are obtained from the University of Kentucky Center for Poverty Research (http://www.ukcpr.org/AvailableData.aspx).

In addition to employment selection, the structure of wages can also be influenced by potential endogenous migration decisions (Dahl 2002). The standard model of migration predicts that workers will sort into the location offering the highest wages given the level of skills, and if these migration decisions are influenced by factors unobserved to the researcher, then ignoring nonrandom migration will lead to biased estimates of equation (1).

The decennial census contains information on the place of residence as of 5 years prior to the census.[7] We define a "stayer" in Appalachia if one resided in the region in both periods, a "mover-in" to Appalachia as someone who currently resides in Appalachia but did not 5 years prior, and a "mover-out" of Appalachia as someone who lived in Appalachia 5 years ago but no longer lives in the region. Stayers and movers in non-Appalachia are defined similarly. Online appendix table A1 demonstrates that the fraction of persons moving into Appalachia exceeds that of movers out, the result of which is that the 5-year stayer rate in Appalachia is declining over time because in-migration is altering the composition of the region. Online appendix table A2 shows that among both men and women, those who move out of Appalachia are two to three times more likely to have completed college or to have received postgraduate training than those who stay in the region. As for those who move into Appalachia, they too are more educated than stayers, but they have less schooling than those who move out. On net, there is some evidence of a brain drain in Appalachia due to migration.

To address possible endogenous migration we again specify a latent variable model

$$S^*_{ijrt} = D_{ijrt}\pi_{jrt} + \xi_{ijrt}, \tag{3}$$

where S^*_{ijrt} is the unobserved propensity to stay in your current location, D_{ijrt} are observable characteristics, and ξ_{ijrt} are unobservable characteristics. Since we only observe whether the person has stayed or moved, that is, $S_{ijrt} = 1$ or 0, then staying implicitly occurs when $S^*_{ijrt} > 0$. In this case D includes the variables in Z, that is, those variables in the labor force selection equation, along with the identifying variable of whether or not the person was born in a state within Appalachia. Dahl (2002) used the birth state as his identifying restriction under the assumption that state of birth affects latent geographic preferences of where to live, but not wages conditional on making the migration decision. Card and Krueger

[7] In 1980 the census only asked the migration questions for one-half of the sample. Because they were randomly assigned, the data are representative of each region as a whole.

(1992) include state of birth as a direct determinant of weekly earnings, but the argument in Dahl (2002) is that in a two-stage optimization problem state of birth affects the first stage of whether to move or not, but conditional on controlling for the migration choice, state of birth does not affect wages except indirectly through the migration decision. We follow a similar identification scheme as Dahl, but instead of selection into one of 50 states we only estimate selection into one of two regions and rely on the cross-section heterogeneity in state of birth to identify the model. Online appendix table A1 shows that 90% of men and women in 1980 and 1990 currently residing in Appalachia were born in the region, and while it fell to about 86% by 2000, the high concentration of native-born in the region suggests that the variable is a strong predictor of staying.

Based on equations (2) and (3) we specify the conditional mean of the error term in equation (1) as

$$E[\varepsilon_{ijrt}|X_{ijrt}] = \sum_{k=1}^{K} \delta_{kjrt}\lambda^{(k)}_{ijrt}(\gamma_{jrt}) + \sum_{k=1}^{K} \phi_{kjrt}\lambda^{(k)}_{ijrt}(\pi_{jrt}), \quad (4)$$

which is a series estimator that admits possible nonlinearity in labor force selection (the first term) and migration decisions (the second term) via higher-order terms of λ, the inverse Mills ratio (Lee 1984). To operationalize the model, in the first step we estimate the decisions to work and to migrate, which yields the estimated parameters, $\hat{\gamma}_{jrt}$, $\hat{\pi}_{jrt}$. The second step of estimation then involves constructing the terms in equation (4) with the estimated first-stage parameters and appending them to equation (1):

$$\ln W_{ijrt} = X_{ijrt}\beta_{jrt} + \sum_{k=1}^{K} \delta_{kjrt}\lambda^{(k)}_{ijrt}(\hat{\gamma}_{jrt}) + \sum_{k=1}^{K} \phi_{kjrt}\lambda^{(k)}_{ijrt}(\hat{\pi}_{jrt}) + u_{ijrt}. \quad (5)$$

We estimate equation (5) via ordinary least squares (OLS) separately for each region, gender, and year only for those individuals who are working stayers in each region. As a practical matter, we set $K = 1$ in our base case and estimate the work and migration equations (2) and (3) via probit maximum likelihood, which yields the usual two-step Heckman correction (Heckman 1979); however, we also present results when we set $K = 2$ and for the case with a linear probability selection model (Olsen 1980).[8]

B. Mean Wage Decompositions

To compare differences in average wages between two populations (e.g., Appalachia and non-Appalachia in 2000), we employ a modified version

[8] We explored estimating the selection terms with the semiparametric model of Ichimura (1993), but the very large sample sizes coupled with the large number of covariates made the problem prohibitive, and it failed to converge. In addition, we assume independence between the selection terms, the violation of which is typically thought to be second order (Wooldridge 2001).

of the Oaxaca (1973) and Blinder (1973) method that decomposes wage gaps into differences in the coefficients and differences in the observable characteristics that is robust to nonrandom selection. Typically decomposition of the mean actual wages of workers includes the average differences in the selection correction terms (Neuman and Oaxaca 2004).[9] However, in our case we are interested in the wage distribution facing the entire population, including nonworkers as well as workers regardless of realized migration decision. Thus we decompose the offer wage distribution rather than the realized wage distribution.

We predict offer wages by using the observed demographics of the whole population of men and women in each region and year along with the selectivity-corrected coefficients, $\hat{\beta}_{jrt}$. Specifically, if we define $\ln \hat{W}^{A}_{ijt} = X^{A}_{ijt}\hat{\beta}^{A}_{jt}$ as the predicted offer wages (of workers and nonworkers, and movers and stayers) of gender j in time period t for the Appalachian region (A), and $\ln \hat{W}^{NA}_{ijt} = X^{NA}_{ijt}\hat{\beta}^{NA}_{jt}$ as the corresponding predicted offer wages outside Appalachia (NA), then we can decompose the offer wages at the means by using either the Appalachian coefficients or the non-Appalachian coefficients as the reference price vector. The average predicted non-Appalachian/Appalachian wage gap based on non-Appalachian coefficients is

$$\ln \overline{\hat{W}}^{NA}_{jt} - \ln \overline{\hat{W}}^{A}_{jt} = (\overline{X}^{NA}_{jt} - \overline{X}^{A}_{jt})\hat{\beta}^{NA}_{jt} + \overline{X}^{A}_{jt}(\hat{\beta}^{NA}_{jt} - \hat{\beta}^{A}_{jt}), \tag{6}$$

where the first term on the right-hand side represents the average offer wage gap accruing to demographic differences across regions, and the second term reflects differences in coefficients. Because the decomposition in equation (6) can be sensitive to the reference set of coefficients we also present estimates of (6) using the Appalachian coefficients as the reference group.[10]

[9] In an earlier version of this paper we presented the decomposition of selectivity-adjusted wages of working stayers in each region, but the current approach is more instructive on the whole structure of wages. That said, it is possible to subtract the difference in actual average wages and the difference in average predicted offer wages to assess the size of selection, as we note below in the Results section. We thank Jim Albrecht for making this suggestion.

[10] As an alternative way of correcting for selection into the labor market, we experimented with the technique used in Chandra (2000, 2003) by giving individuals outside the labor market offer wages equal to the 10th or 25th percentile of the wage distribution within cells defined by our experience, race, education, and region variables. For the most part, our decompositions based on this alternative method of estimating offered wages mirror our results based on the standard selection correction model, the one exception being our results for men in 2000 using the non-Appalachian coefficients as the base. In this case we find that the differential in the mean offered wage is largely due to differences in demographics. However, because the coefficients in our wage regressions are so different from the coefficients in any other wage regression we or others estimate, we simply do not believe these results for men in 2000. In the end we conclude that the

C. Quantile Wage Decompositions

The Oaxaca-Blinder decomposition focuses on differences in average offer wages; however, as noted in the voluminous inequality literature, there have been important changes throughout the earnings distribution. We thus extend our previous analysis to decompose changes in the entire wage distribution using quantile regression techniques and building on the methodology of Machado and Mata (2005). The value of examining the wage distribution is that if by estimating equation (5) we observe that the rate of return to education has increased in Appalachia on average, that increase at the mean may reflect that it shifted up among all persons, or it may be that the lowest rates of return have improved, but the highest rates have not (or vice versa). These distinctions have important implications for the role of increasing skill levels versus rising returns to skill across the distribution.

The Machado-Mata procedure uses estimated quantiles of the conditional wage distribution to conduct a series of counterfactual decompositions of the distribution by simulating the marginal wage distributions under alternative scenarios. This approach differs from that of DiNardo, Fortin, and Lemieux (1996), who estimate wage models with nonparametric kernel densities and are not able to separately identify the contributions of variables compared to coefficients.[11] Autor, Katz, and Kearney (2005) extend the Machado-Mata approach for wage distributions by separately identifying the contribution of "within-group" inequality from "between-group" inequality and observed versus unobserved skill in the spirit of Juhn et al. (1993). Our approach extends the Machado-Mata method in a different fashion from Autor et al. (2005) by explicitly ad-

results using this alternative technique are similar to our main results reported in the text, with this one exception. These results are available upon request.

[11] Recently Firpo, Fortin, and Lemieux (2007) proposed a new method of estimating unconditional quantiles that permits decompositions into differences in coefficients and differences in regressors similar to Machado-Mata. The advantage of their approach over Machado-Mata is that they are also able to identify the contributions of specific regressors to the wage gap, while the Machado-Mata approach only permits a decomposition of the whole vector of regressors. This variable by variable approach has always been possible with the linear Oaxaca-Blinder decomposition method, but as first noted by Jones (1983), the results are sensitive to the choice of reference group if any of the regressors are dummy variables. Although the Firpo et al. method is an elegant extension of the literature, the set of regressors in our model are dummy variables, and our interest is primarily on the full index of skills. More importantly, quantile methods adjusted for sample selection have been developed previously by Buchinsky (1998, 2001) but as of yet similar results have not been established for unconditional quantiles, although Blundell et al. (2006) recently proposed a bounding procedure for quantiles with selection.

mitting nonrandom sample selection bias into the quantile model.[12] As shown in Datta Gupta, Oaxaca, and Smith (1998) there is a close relationship between the Oaxaca approach with selection and the Juhn et al. (1993) method.

To implement the Machado-Mata procedure we first estimate a variant of the selection-corrected conditional quantile proposed by Buchinsky (1998),

$$\ln W_{ijrt} = X_{ijrt}\beta^{\theta}_{jrt} + \sum_{k=1}^{K} \delta^{\theta}_{kjrt}\lambda^{(k)}_{ijrt}(\hat{\gamma}_{jrt}) + \sum_{k=1}^{K} \phi^{\theta}_{kjrt}\lambda^{(k)}_{ijrt}(\hat{\pi}_{jrt}) + u_{ijrt}, \qquad (7)$$

for each quantile θ on the sample of workers and stayers that yields the vector of gender, region, and year-specific coefficients $(\hat{\beta}^{\theta}_{jrt}, \hat{\delta}^{\theta}_{kjrt}, \hat{\phi}^{\theta}_{kjrt})$. In order to capture wide heterogeneity in the distribution of wages we estimate equation (7) for 99 quantiles ranging from 0.01 to 0.99. Using the same identification strategy as in the case of the conditional mean, we estimate the first stages in equations (2) and (3) as probit models and set $K = 1$ under the assumption that the nonlinearity of inverse Mills ratio coupled with the exclusion restrictions should provide sufficient flexibility in the selection process to separately identify $\hat{\beta}^{\theta}_{jrt}$ from $(\hat{\delta}^{\theta}_{kjrt}, \hat{\phi}^{\theta}_{kjrt})$ in the quantile wage equation (7).[13]

With the estimated conditional quantile coefficients we then construct counterfactual distributions by simulating out the marginal "offer" wage distribution using the demographics from the whole population of workers and nonworkers and movers and stayers in each gender, region, and year along with the estimated coefficients on the observed demographics, $\hat{\beta}^{\theta}_{jrt}$. We decompose the predicted offer distributions into differences in skills and differences in coefficients as before, but now for 99 quantile points rather than just the mean. For example, suppose we take the coefficients and demographics from the non-Appalachian region as the reference group. We can construct a counterfactual distribution using demographic characteristics drawn from the Appalachian region by first drawing observations randomly (with replacement) from the Appalachian data and randomly assigning a quantile, θ, $\theta \in [0.01, 0.99]$ to each drawn observation. Then we generate a predicted wage using the non-Appalachian quantile coefficients indicated by that observation's θ and the demographic variables (X) of that observation. This generates a simulated

[12] Independently Albrecht et al. (2009) proposed a similar extension to the Machado-Mata method and applied it to gender wage gaps in the Netherlands.

[13] Buchinsky (1998) used a probit as well as a semi-nonparametric estimator in the first stage, but then a powered-up version of the inverse Mills ratio as we do in the second stage. With two separate selection terms we opted for the parametric first stage in order to enhance transparency and computational feasibility with our very large data sets.

distribution of wages as if individuals in non-Appalachia had the same distribution of X's as the Appalachian region.

The procedure is comparable to the term $X^{A}_{ijt}\hat{\beta}^{NA}_{jt}$ in a standard Oaxaca-Blinder decomposition. We can then compare differences in the non-Appalachian offer wage distribution to this counterfactual distribution: differences are solely due to differences in demographics and are comparable to the term $(X^{NA} - X^{A})\hat{\beta}^{NA}$ in the Oaxaca-Blinder decomposition found in equation (6) with non-Appalachia as the reference price vector. We can also compare differences in the counterfactual distribution and the predicted offer wage distribution in Appalachia: differences are solely due to coefficients on the demographics and are comparable to the term $X^{A}(\hat{\beta}^{NA} - \hat{\beta}^{A})$ in the Oaxaca-Blinder decomposition.

IV. Results

The first-stage estimates for the probability of employment in equation (2) and for the probability of staying in equation (3) are presented in online appendix tables A5 and A6, while the final wage regression estimates are presented in online appendix tables A3 and A4.[14] In general, the exclusion restrictions are highly predictive of work and staying in the region. For example, higher nonlabor income, more children under age 5, and a higher state unemployment rate are each associated with a lower probability of employment, while a more generous EITC increases the odds of employment. Being born in an Appalachian state increases the probability of currently living in Appalachia and not living outside the region. There is strong evidence of nonrandom selection into the region of residence for all years for both men and women, and the same is true for nonrandom selection into work, except for women in 1980, where it appears that controlling for selection on observables was sufficient for wages.

Looking at online appendix tables A3 and A4, we see that both education and potential experience are important determinants of wages for both men and women in each region, but large coefficients on the interactions of education and experience also clearly reject the null hypothesis of separability between education and experience assumed in the canonical Mincer equation (Heckman et al. 2003). Because of the importance of these interactions, this implies that the return to schooling is highly nonlinear. To assist in interpretation, in figures 1 and 2 we plot the percentage wage gain of schooling relative to a high school dropout for a worker with 10–20 years of potential experience for men and women, respectively.

[14] We report the actual coefficients from the probit models in online appendix tables A5 and A6. We report actual coefficients and not the marginal effects because it is the actual coefficients that are used to form the selection correction terms that appear in online appendix tables A3 and A4.

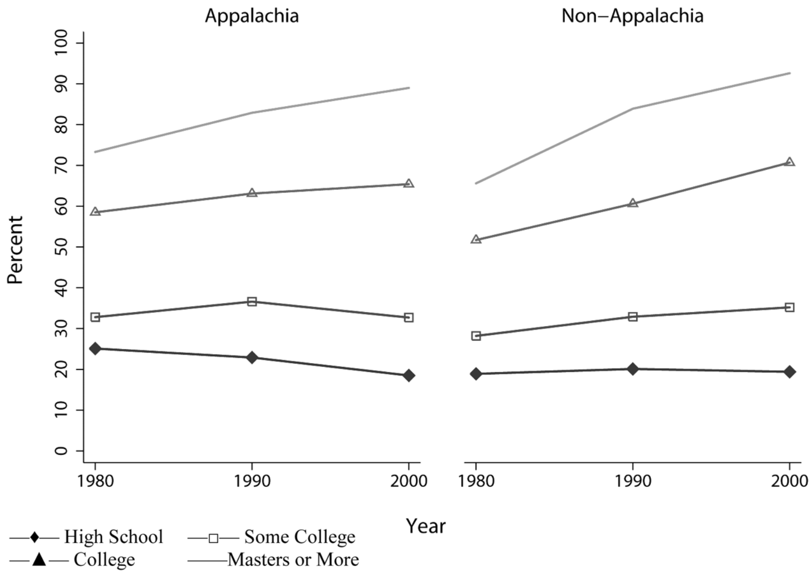

FIG. 1.—Wage gain of men relative to high school dropout with 10–20 years potential experience.

Figure 1 reveals that there was a large increase in the relative return to some college or better in the 1980s for men, both within and outside Appalachia. This result has been well documented in the literature for the nation as a whole, and the estimates here indicate that the trend was also true for the economically depressed region of Appalachia. Indeed, the relative return to college and postgraduate degrees for a man with 10–20 years experience was actually higher in Appalachia in 1980 and 1990 compared to non-Appalachia. This difference is consistent with a higher return offered to workers whose skills are in relatively short supply, which may have characterized the situation in Appalachia since table 1 shows that there are fewer individuals with advanced degrees in Appalachia than in other parts of the country. The 1990s were a different story for men in Appalachia. Although the relative return to college and advanced degrees continued to rise in both regions of the country, they rose more quickly outside Appalachia and actually surpassed the Appalachian returns by 2000. In fact, the proportionate wage gain for high school and some college in Appalachia actually declined after 1990, so that the wage gains at all education levels for this experience cohort of men fell compared to the rest of the nation. This divergence in schooling returns will exacerbate within-Appalachian inequality consistent with the polarization

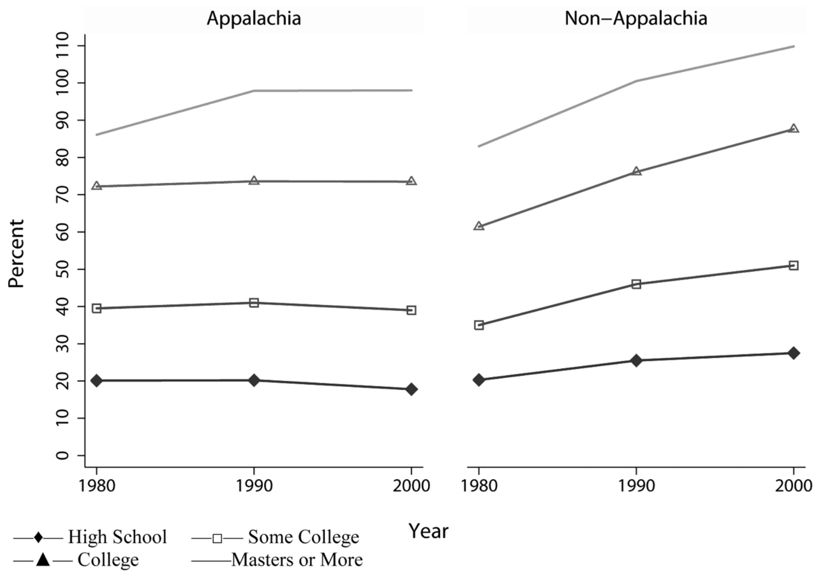

FIG. 2.—Wage gain of women relative to high school dropout with 10–20 years potential experience.

story of Autor et al. (2008) but will also increase between-region inequality. These trends were not specific to the cohort of men with 10–20 years potential experience, as they likewise hold for workers with 30–40 years experience.

Similar to the male experience, in figure 2 there is strong evidence of rising relative returns to skill in the 1980s among women, but this was especially strong outside of Appalachia. Indeed, the wage gain for a college graduate relative to a dropout was a fairly constant 72%–74% from 1980 to 2000, whereas it rose from 61% to 88% in the same period outside of Appalachia. Also like men, there was a reversal between 1980 and 2000 in that the wage gain for women in Appalachia in 1980 exceeded non-Appalachia at nearly every education level but was lower at every level by 2000. Even though there was education upgrading in Appalachia in recent decades, especially at the high school and some college levels, the relative wage gains fell behind the rest of the nation.

The other coefficients in online appendix tables A3 and A4 show that most racial groups earn lower hourly wages than white non-Hispanics, but these gaps appear to be larger outside of Appalachia, at least after 1980. In addition, the premium associated with residing in an urban area is at least double outside of Appalachia for both men and women, suggesting that there are important differences in wage opportunities in urban areas across regions, a point that we return to below. Being married paid off more for men in Appalachia than those outside of the region in both 1980 and 1990; however, the relative difference in the marriage premium fell from 39% in 1980 to a negative 1% in 2000 because of a large secular rise in the returns to marriage in the 1990s among men outside of Appalachia. Both the rates of marriage and the returns to marriage for Appalachian men have fallen over the past decade. Although Wilson's (1987) thesis on the decline of "marriageable men" was initially applied to low-skilled urban African Americans, the results here are suggestive that such a phenomenon may be in evidence in Appalachia as well.

A. Decomposing Changes in Average Wages

In table 2 we report the selection-corrected wage offer decompositions at the means for each year from equation (6).[15] The table shows the mean difference in offered wages (not the actual wage as in the summary statistics in table 1), the portion of the gap due to differences in observed demographics, and the portion due to differences in coefficients. For both men and women, we report the gap first based on non-Appalachian coefficients as the reference group and, second, based on Appalachian coefficients, along with analytic standard errors (Jann 2005).[16]

The mean offered wage gap for men rose about 28% between 1980 and 2000, but that was substantially lower than the 54% increase between 1980 and 1990 (the actual gap in table 1 increased 33% between 1980 and 1990, the difference between the offer wage gap and actual wage gap arising from selection effects). Based on the non-Appalachian coefficients, in 1980 63% of the 0.101 wage gap was due to demographic shortfalls among Appalachian men, and the remainder was due to regional differences in coefficients. By 2000, however, the portion due to demographic differences fell by 20 percentage points, and the portion due to coefficients rose a comparable amount. An even more dramatic shift from demographic gaps to coefficient gaps from 1980 to 2000 emerges when using Appalachian coefficients as the reference prices. The differences are all statistically different from zero. Although there is evidence that skill up-

[15] In online appendix table A7, we present decomposition results where we do not control for selection into the labor market or the region. The results are qualitatively similar to the results in table 2.

[16] The formulas for the analytic standard errors are based on a Taylor series approximation under the assumption of independence across samples. Because of overlap of samples due to our weighting procedure, independence is violated, but the overlap is trivial and is ignored in the standard errors. The variance formulas for each term in eq. (6) are given as $V[(\bar{X}_{jt}^{NA} - \bar{X}_{jt}^{A})'\hat{\beta}_{jt}^{NA}] = (\bar{X}_{jt}^{NA} - \bar{X}_{jt}^{A})'V(\hat{\beta}_{jt}^{NA})(\bar{X}_{jt}^{NA} - \bar{X}_{jt}^{A}) + \hat{\beta}_{jt}^{NA\prime}[V(\bar{X}_{jt}^{NA}) + V(\bar{X}_{jt}^{A})]\hat{\beta}_{jt}^{NA} + tr(\cdot)$ and $V[\bar{X}_{jt}^{A\prime}(\hat{\beta}_{jt}^{NA} - \hat{\beta}_{jt}^{A})] = \bar{X}_{jt}^{A\prime}[V(\hat{\beta}_{jt}^{NA}) + V(\hat{\beta}_{jt}^{A})]\bar{X}_{jt}^{A} + (\hat{\beta}_{jt}^{NA} - \hat{\beta}_{jt}^{A})'V(\bar{X}_{jt}^{A})(\hat{\beta}_{jt}^{NA} - \hat{\beta}_{jt}^{A}) + tr(\cdot)$.

Table 2
Oaxaca-Blinder Decomposition of Offered Wage Gaps between Non-Appalachians and Appalachians

		Non-Appalachia as Reference				Appalachia as Reference			
Year	Difference in Offered Wage (Log Points) (1)	Demographics (2)	Percent Due to Demographics (3)	Coefficients (4)	Percent Due to Coefficients (5)	Demographics (6)	Percent Due to Demographics (7)	Coefficients (8)	Percent Due to Coefficients (9)
Men:									
1980	.101	.064	63	.037	37	.057	56	.045	45
		(.001)		(.008)		(.003)		(.009)	
1990	.155	.071	46	.085	55	.041	26	.115	74
		(.001)		(.006)		(.003)		(.006)	
2000	.129	.056	43	.073	57	.027	21	.102	79
		(.001)		(.006)		(.002)		(.007)	
Women:									
1980	.092	.097	105	−.005	−5	.071	77	.021	23
		(.001)		(.013)		(.004)		(.013)	
1990	.137	.119	87	.018	13	.069	50	.068	50
		(.001)		(.007)		(.003)		(.007)	
2000	.094	.096	102	−.002	−2	.060	64	.034	36
		(.001)		(.008)		(.003)		(.008)	

Note.—Analytic standard errors are provided in parentheses.

grading in Appalachia during the 1980s and 1990s played an important role in equalizing interregional wages, the widening of the average wage gaps is a result of the divergence in skill returns.[17]

The offered wage gap between non-Appalachian women and Appalachian women is both smaller than that of men and widened by less in the 1980s (just the opposite of the actual wage gap in table 1, again highlighting the importance of controlling for nonrandom selection as evidenced in appendix table A7 in the online version with no selection). However, like the gap for men, the gap for women narrowed somewhat in the 1990s. And while qualitatively similar to that for men, the pattern over the past 2 decades toward less of the gap explained by demographics and more of the gap explained by coefficients is much more muted for women. In each year, differences in demographics account for a majority of the wage gap among women.

B. Decomposing the Distribution of Wages

Because of the myriad of estimated coefficients from the quantile models in equation (7)—99 quantiles each with 18 coefficients by year, region, and gender (over 21,000 coefficients in total)—we instead follow Machado and Mata and present our quantile decompositions graphically.

Figure 3 presents the Machado-Mata decomposition for men and women by year using non-Appalachia as the reference group.[18] Within each panel the line labeled "Predicted Differences" shows the difference in the offered log-wage distribution between the non-Appalachian and Appalachian regions from the quantile models—like the first column of table 2 labeled "Difference in Offered Wage." That is, the estimated coefficients from equation (7) are used in conjunction with the demographics (without the selection terms) for workers and nonworkers, movers and stayers, to construct a predicted wage distribution. The second line, labeled "Differences from X's," compares the counterfactual distribution constructed using Appalachian X variables and non-Appalachian coefficients (β's) to the predicted non-Appalachian offered wage distribution—like the second column of table 2 labeled "Demographics." The third line, labeled "Differences from β's," compares the counterfactual distribution and the predicted Appalachian wage distribution—like the fourth column of table 2 labeled "Coefficients." The difference between the results in

[17] One possible explanation for these findings is that the quality of schooling is lower in Appalachia and the gap in schooling quality has risen over time. Unfortunately, we are unaware of any large national data set containing measures of school quality both within and outside Appalachia that would allow us to examine this hypothesis.

[18] Online appendix table A3 presents the decomposition results using Appalachia as the reference group.

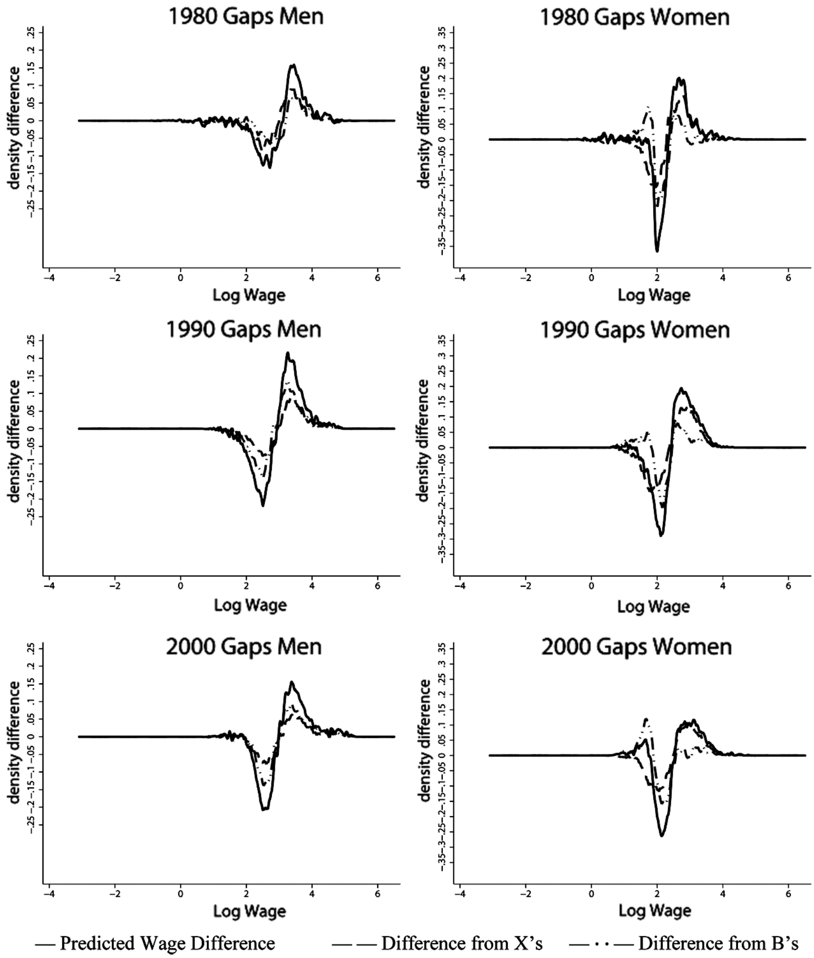

FIG. 3.—Wage distribution comparison: using non-Appalachia as counterfactual.

figure 3 and table 2 are that we can observe which part of the wage distribution is driving the average difference.

The first panel of figure 3 (first row, first column) displays the differences between non-Appalachia and Appalachia men in 1980. The negative values represent places where there is higher density for Appalachia than for non-Appalachia, while the positive values represent areas where there is higher density for non-Appalachia than for Appalachia. Hence, the predicted differences line shows that the distribution of wages for Appalachia is shifted to the left (or lower) of the distribution for non-Appalachia in 1980. The symmetry of the line indicates that the Appalachian distribution is shifted down relatively uniformly along the wage (x) axis. Thus, the average difference in table 2 is not being driven only by a lack of high earners in Appalachia or only by a lack of low earners in non-Appalachia.

The Differences from X's line displays the portion of the distributional difference in the first panel that is due to different demographics of Appalachian workers. We first note that the magnitude of this line is smaller as compared to the Predicted Differences line. Roughly we can say that at least half of the differences in the distribution are attributable to demographic differences. The symmetry suggests that the X's for Appalachia are shifted lower relatively uniformly through the distribution.

The Differences from β's line shows that slightly less than half of the distributional difference is explained by the returns to demographics. This indicates that returns are, in general, higher outside of Appalachia. However, because the distribution is given by the X's times the returns, figure 3 shows that the higher X's in non-Appalachia are associated with higher returns, which may reflect investment in high return characteristics outside of Appalachia (this is confirmed in online appendix figure A2, which shows that the wage gain from completing high school and beyond with 10–20 years of potential experience across the 99 quantiles is higher outside Appalachia at higher wages).

As we move down the three rows for men we see that the magnitudes in the Predicted Differences lines increase between 1980 and 1990 and then fall again between 1990 and 2000. This is consistent with the rise in the average wage gap between 1980 and 1990 in table 2 and with the constant wage gap between 1990 and 2000. Most importantly, these lines remain symmetric: the distribution for Appalachian men is shifted down relatively uniformly such that the Appalachian wage gap is constant throughout the wage distribution.

The differences over time in the other two lines are more striking. By 2000, the magnitude of the differences in the demographics gap is attenuated, and like table 2, we see that demographic differences are less important in explaining the overall wage gap by 2000. With the demographics gap declining, we see the coefficients gap rising consistently. In results not tabulated, when we ignore nonrandom selection even more weight is placed on the coefficients gap, suggesting an increasing role played by selection into work and region in figure 3. A similar story emerges in online appendix figure A3 based on Appalachian coefficients and, if anything, the declining role of demographic differences and rising role of coefficient differences is amplified when Appalachian coefficients are used as the base.

Although there is evidence of convergence in skills between men in

Appalachia and non-Appalachia, this convergence is most evident at low wages, and there still remains a shortage in Appalachia at the right tail of the distribution. The coefficients gap is exacerbated between 1980 and 1990, especially at mean log wages and higher, although it is tempered somewhat by 2000. As highlighted in online appendix figure A2, it appears that the rise in overall differences between 1980 and 1990 was driven by a rise in the schooling returns gap, in particular at the high end. The slight closing of the gap between 1990 and 2000 appears to be driven by a decline in the returns gap. Thus, we see that while much of the average difference story in table 2 is confirmed by the distribution decomposition, we learn that the coefficients gap is more important in explaining the preponderance of low-wage male workers in Appalachia, while both the demographics and coefficients gaps are important for explaining the lack of high-wage workers in Appalachia. In short, Appalachia seems to suffer from a problem of "missing markets" for male workers—the double jeopardy of a lack of high-skilled workers coupled with lower returns on those skills.

The second column of figure 3 presents comparable graphs for women (the second column in online appendix fig. A3 is based on Appalachian coefficients). As with men, the first graph for 1980 demonstrates that the offer wage distribution for women in Appalachia was lower than the distribution for women outside of Appalachia. Moreover, the difference is symmetric and thus represents a relatively uniform shifting down of the overall wage distribution in Appalachia compared to the rest of the country. In contrast to men, the density difference is less disbursed and generally falls between 1990 and 2000. Table 1 shows that the actual mean wage gap narrowed between 1990 and 2000, and the mean offered gap in table 2 falls even more, which reflects differential movements in and out of the labor force and region. Figure 3 suggests that the narrowing in the 1990s occurred throughout most of female wage distribution, with the possible exception of very high wages.

For women the line showing the overall differences due to the demographics gap is roughly symmetric, but the magnitude falls only slightly between 1980 and 2000. Thus, some of the decline in differences between 1980 and 2000 for women is driven by decreasing differences in demographics. The demographics gap appears to be at least half or more of the overall gap in each census year. Thus, unlike for men, differences in demographics are more important across the entire wage distribution: the preponderance of low-wage female workers in Appalachia is explained in part by a lack of skills, and the lack of high-wage workers in Appalachia is also be explained by a lack of skills.

The line showing the role of coefficient differences suggests that the coefficient difference is concentrated at the median of the wage distribution. Non-Appalachia appears to have a wider distribution of returns, while for Appalachia the coefficients are concentrated near the median. This indicates a lack of high and low returns in the wage distribution. There may be high characteristic women who are receiving lower returns for those characteristics than their non-Appalachian counterparts receive, while there may be low characteristic women who are receiving higher returns for their characteristics than their non-Appalachian counterparts. We also note that by 2000, the differences between Appalachia and non-Appalachia are muted and there is less of a clear distributional story. It appears that the coefficients are no longer driving the differences, while the *X*'s appear to drive the differences. The muddled coefficient story for women is explained by the fact that labor force selection and migration play a much more important role for women than for men; indeed, in models that ignore selection we find that the role of coefficient gaps explains roughly half the total wage gap in each period. Thus, the wage distribution story for women is similar to that for men in trends, and like men, there is a widening gap in skill returns at high wage, but selection plays a much bigger role for women in the lower part of the wage distribution.

C. Sensitivity Analyses

We considered a number of robustness checks to our results. Because the analysis underlying the trends in average wage gaps largely carries over to the distributional wage gaps, we focus on how the mean decompositions change in response to alternative specifications. In addition, in order to economize on space we report results based only on the non-Appalachian coefficients, and note in passing that as in the base case of table 2, the trends among men toward skill upgrading are more pronounced using the Appalachian coefficients.

1. Industrial Composition

As highlighted in the summary statistics in table 1, the employment trends affecting many one-digit industries were similar across regions, but there were some differences. To account for possible shifting industrial composition we reestimated our wage models including indicators for industry (but excluded industry from both selection equations) and report the results in the top panel of table 3. When industry controls are included, the schooling premium for men increases across the board, while it declines for women. In terms of the Oaxaca-Blinder wage decompositions, the percent attributable to demographics falls in 1980 relative to the base case in table 2, but the trend to more of the gap being explained by differences in coefficients is robust, and indeed strengthened, with the inclusion of industry, especially for women.

Table 3
Robustness of Oaxaca-Blinder Decomposition of Offered Wage Gaps between Non-Appalachian and Appalachian Men and Women (Non-Appalachia as Reference)

	Men					Women				
Year	Difference in Offered Wage (Log Points) (1)	Demographics (2)	Percent Due to Demographics (3)	Coefficients (4)	Percent Due to Coefficients (5)	Difference in Offered Wage (Log Points) (1)	Demographics (2)	Percent Due to Demographics (3)	Coefficients (4)	Percent Due to Coefficients (5)
	Industry Controls									
1980	.103	.056	54	.047	46	.100	.090	90	.010	10
		(.001)		(.008)			(.001)		(.012)	
1990	.159	.064	40	.095	60	.153	.111	73	.042	27
		(.001)		(.006)			(.001)		(.007)	
2000	.136	.049	36	.087	64	.113	.092	81	.021	19
		(.001)		(.006)			(.001)		(.007)	
	Linear Probability Selection									
1980	.113	.060	53	.053	47	.102	.097	95	.005	5
		(.001)		(.008)			(.001)		(.013)	
1990	.160	.067	42	.092	58	.143	.118	83	.025	17
		(.001)		(.006)			(.001)		(.006)	
2000	.105	.055	52	.050	48	.093	.096	103	−.003	−3
		(.001)		(.006)			(.001)		(.007)	
	Lee Quadratic Selection									
1980	.017	.062	365	−.045	−265	.112	.095	85	.016	14
		(.001)		(.015)			(.001)		(.027)	
1990	.180	.066	37	.114	63	.203	.115	57	.088	43
		(.001)		(.010)			(.001)		(.013)	
2000	.125	.054	43	.071	57	.053	.095	179	−.042	−79
		(.001)		(.010)			(.001)		(.014)	

Note.—Analytic standard errors are provided in parentheses.

2. Modeling Selection

A second robustness check was to relax the normal distribution assumption in the first-stage employment and migration models in two ways, one by assuming a uniform distribution and estimating the first stage with a linear probability model and second by relaxing the linearity assumption in the Heckman correction (Olsen 1980; Lee 1984). In the former case, in lieu of the inverse Mills ratio, Olsen (1980) shows that the conditional mean of the error term under least squares is modeled as $(\hat{P} - 1)$, where $\hat{P}$ is the fitted value of the linear probability model. The selection corrections in this case make transparent that identification requires exclusion restrictions that we have in our models. In the latter case, Lee (1984) uses Edgeworth expansions to show that linearity in the control function under normality can be relaxed by taking higher order powers as we show in equation (4). In this case we set $K = 2$. The bottom two panels of table 3 for each of men and women suggest that the baseline story holds up with the linear probability and quadratic selection terms, namely, that among men there was a shift toward skill return differences in accounting for mean wage gaps, but that the gaps were roughly stable among women and explained by mean differences in demographics.

3. Additional Years of Data

Since the Appalachian region has long been a center for poverty in the United States, we wanted to add additional years of data to our analysis in an effort to produce a longer-run view of the influence of changing skill levels and changing returns to skills on the Appalachian/non-Appalachian wage gap. Unfortunately, lack of data severely hampered our efforts.

The 1970 IPUMS data do have county group identifiers that are similar to the PUMA identifiers found in the 1980–2000 census IPUMS data. However, the county groups in the 1970s data are much larger than in the 1980–2000 data. This means that we have a larger number of individuals who cannot be uniquely assigned to Appalachia, which introduces additional error into our analysis. In addition, many of the variables we use to identify the labor force participation model, such as state EITC generosity, state minimum wage, and state food stamp program data, are either not available or have no cross-state variation. And while AFDC data are available, they are less detailed than data available in later years.

Despite these limitations we did estimate our main models using the 1970s data and decomposed the mean Appalachian/non-Appalachian wage gap into the percentage due to demographic differences in the coefficients. The primary result is that a much larger share of the difference in wages is due to differences in the coefficients. We further reestimated the model using the 1980–2000 data but limited ourselves to the variables that are available in 1970. Again, we find that a much larger share of the wage gap is due to differences in coefficients.[19] These results do suggest that lack of additional controls for selection into the labor in the 1970s data results in an upward bias in the coefficients in our wage equation, making us reluctant to draw strong conclusions from the 1970s data.

We also looked into using IPUMS data from the 1960 decennial census. However, in addition to the limitations in the 1970 data, the 1960 data have no substate geographic identifiers, nor is there any information on where a respondent lived 5 years earlier (which we use to identify the migration model). Given the problems with the 1970 data, we decided not to estimate our model using the 1960 data.[20]

4. *School Quality*

A possible reason for the reversal in returns to schooling between Appalachians and non-Appalachians from 1980 to 2000 in figures 1 and 2 is due to differential school quality across regions. A major challenge we face is obtaining county-level data (to map into PUMAs) across the 1980–2000 period. Indeed, this is a major challenge even for a single year like 2000. There is a long literature in economics that eschews the use of inputs such as per pupil expenditures to measure quality, but unfortunately inputs are much more readily available than outputs. In an effort to address school quality at the substate level for 2000 we constructed high school graduation rates, which is possible using data at the county level from the Department of Education's Common Core of Data. Specifically we construct the 4-year graduation rate for each county in the United States for the 1999–2000 school year by taking the ratio of total twelfth-grade graduates in 1999–2000 to the average enrollment of eighth graders in 1995–1996, ninth graders in 1996–1997, and tenth graders in 1997–1998. The idea behind the 3-year average is to reduce the influence of mea-

[19] These results are not reported in the paper but are available from the authors upon request.

[20] At the suggestion of a referee we also tried to control for nonrandom migration by using where someone was born to classify individuals as being part of Appalachia or non-Appalachia. While in principle this is an excellent suggestion, in practice we only know state of birth for individuals, so we run into the same problems with this analysis as we do when we use data on current residence from the 1960 census. Therefore, we concluded that the available data do not support an analysis based on place of birth. As an alternative, since West Virginia is wholly contained in Appalachia we reran the models comparing West Virginia, once with movers and stayers and once with stayers alone, to the rest of the country. In this exercise much more of the wage gap is explained by demographics, but the trend toward a greater share due to coefficients still obtains. As the results do not differ whether we restrict it to stayers in West Virginia, or include movers and stayers, it is suggestive that workers in Appalachia, at least in West Virginia, underinvest in skills.

surement error in the denominator owing to students dropping out and/or moving out of the county.

Our first test with these data was to examine whether 4-year graduation rates were different between Appalachian counties and the rest of the country in 2000. We found that they were significantly lower by about 4 percentage points in Appalachian counties. Given the statistically and potentially economically important difference, we then merged the county graduation rates with our PUMA identifiers, and then into the full 2000 census sample based on PUMA of residence. We then reran our base case models adding graduation rates as a control variable in the selection equations as well as the wage equations. We found graduation rates to be a statistically significant determinant of wages in both non-Appalachia and Appalachia. However, the effect on returns to schooling and the subsequent wage decompositions was minimal. Controlling for 4-year graduation rates does slightly lower the returns to schooling outside Appalachia, but not inside, and the effect on the decomposition is trivial.

Our second test is to include two measures of school inputs to the model with graduation rates. Again the data come from the Common Core for the 1999–2000 academic year and include pupil-teacher ratios and expenditures per pupil. At this point the returns to school for Some College in Appalachia now exceed the return outside Appalachia, but the returns to College and Master's and More in non-Appalachia still exceed those in Appalachia. This continues to point to our missing markets hypothesis at the high end of the skill distribution. Moreover, our finding that the bulk of differences are due to coefficients and not demographics is, if anything, stronger with controls for quality. We thus believe that our results are robust to school quality differences, although we recognize that a complete treatment of this awaits more readily available data on test scores at the local level.

5. Subregions and the Role of Urban Areas

The wage equation estimates showed that there were significant wage advantages to living in an urban area outside Appalachia as compared to inside Appalachia. In addition, there is a widespread perception that references to "the other America" are directed at the rural areas of Appalachia, not urban centers such as Pittsburgh and Birmingham. As a consequence, in this robustness check we examine the role of urban areas in our wage decompositions for five different subregions: (*a*) comparing rural non-Appalachia to rural Appalachia; (*b*) comparing urban non-Appalachia to urban Appalachia; (*c*) dropping residents living in urban areas with more than 1 million people; (*d*) comparing non-Appalachia to the residents of PUMAs contained in the seven central Appalachian states of Kentucky, Maryland, North Carolina, Ohio, Tennessee, Virginia, and

Table 4
Actual Non-Appalachian/Appalachian Log Wage Gaps for Alternative Subregions

	1980	1990	2000
Men:			
Base case	.094	.125	.124
Rural to rural	−.006	−.005	.027
Urban to urban	.061	.114	.097
Omit urban areas >1,000,000	.049	.040	.059
Non-Appalachia to central Appalachia	.125	.168	.175
Non-Appalachia (omitting urban areas >1,000,000) to central Appalachia	.044	.059	.078
Women:			
Base case	.127	.169	.159
Rural to rural	.013	.009	.030
Urban to urban	.113	.169	.144
Omit urban areas >1,000,000	.059	.061	.072
Non-Appalachia to central Appalachia	.155	.212	.205
Non-Appalachia (omitting urban areas >1,000,000) to central Appalachia	.067	.082	.086

West Virginia; and (*e*) comparing non-Appalachian residents residing in urban areas under 1 million to the residents of PUMAs contained in the central Appalachian states. The rural-to-rural and urban-to-urban comparisons presumably remove some of the unobserved heterogeneity across areas and thus may make a more plausible "treatment group–comparison group" evaluation. Likewise, because Appalachia does not contain any of the very large urban areas such as New York, Los Angeles, or Houston, our base results in table 2 may be unduly influenced by those areas and thus *c* should remove some of that influence. Finally, the central Appalachian states are more similar in terms of geography and demographics compared to the Deep South and northern sections in New York and Pennsylvania, and are often most frequently perceived as being "the" Appalachian region.

In table 4 we report the actual average wage gaps for each of the five subregions as well as the overall gap from table 2 (labeled base case). Most striking is that for men the average wage gap between rural Appalachia and the rest of rural America is zero in both 1980 and 1990, and widens to just under 3 log points in 2000. This suggests that the level of and trend toward a widening wage gap observed over the past 2 decades was driven by differential changes in wages between Appalachian and non-Appalachian urban areas or by differential movements between urban and rural areas in the two regions. The same holds for women in Appalachia as well. When we omit urban areas with population greater than 1 million the wage gaps fall by 5–10 log points depending on year and whether we examine men or women, suggesting that the actual wage gaps are heavily influenced by large urban areas. As expected, the wage gaps widen when we restrict Appalachia to the central states, but when we also drop large urban areas outside Appalachia the wage gaps fall as much as 60%.

Recall, however, that our decompositions focus on offered wages across the population of workers and nonworkers, and thus in table 5 we report the Oaxaca-Blinder mean offer wage decompositions for the five subregions. We estimated the selection equations (2) and (3) and wage equations (5) and (6) separately for each subgroup, but one limitation in the migration selection equation is that we lack identifying information on whether or not the person was born in an urban or rural location, and thus we continue to rely on whether the person was born in an Appalachian state as the exclusion restriction.

In the top panel of table 5 we see that for both men and women the offered wage gaps between rural Appalachia and the rest of rural America are actually negative, meaning that on average offer wages are higher in rural Appalachia. For men, much like the actual gap, the offer wage gap is near zero. Contrary to the base case, the differences in rural areas across all years for both men and women are wholly accounted for by differences in interregional coefficients and not demographics. Comparing urban Appalachia to the rest of urban America in the second panel, we also see that in any given year for both men and women demographic differences explain less of the gap compared to differences in coefficients, but this differential widened over time. This suggests that the base case results in table 2 were driven largely by the increasing importance of urban areas over time offering higher wage returns to skills. Indeed, the remaining three panels in table 5 suggest that it is not that the residents of central Appalachia are somehow different from other Appalachians, nor that urban areas per se were important to widening interregional wage gaps, rather that it is large urban areas with more than a million people driving much of the Appalachia/non-Appalachia wage gaps in recent decades. Appalachia lacks these large urban areas and the corresponding growth in wages that such cities enjoyed in recent decades.[21]

[21] One concern expressed by an anonymous referee was that these results indicate that we are finding a "rust belt" effect as opposed to an Appalachian effect. We tested this hypothesis in two ways. First, we simply dropped the non-Appalachian rust belt states (Michigan, Pennsylvania, Ohio, and Indiana) from the analysis. When we did this our results were similar to what we report in the paper, indicating that the rust belt states were similar to the rest of the country. Second, we included the rust belt states as part of Appalachia. When we did this the actual and predicted wage differential was quite similar between the two regions, particularly when comparing urban areas. Taken together, these results suggest that the Appalachian region is quantitatively worse off than the upper-rust belt region.

V. Conclusion

Our results indicate that men and women in Appalachia came "down from the mountain" in the 1980s and 1990s and significantly upgraded their human capital in terms of education attainment compared to men and women in the rest of the nation. This relative skill upgrading prevented the wages of Appalachians from falling further behind those outside the region during the period of widening inequality overall. As a consequence, the wage distribution for men in Appalachia compared to non-Appalachia is less due to demographic shortfalls than to differences in returns to important skills such as education and experience, the latter of which appears to be driven in large part by the relative decline in returns to schooling in Appalachia over the past 2 decades. At the same time, however, for men we find that skill shortages remain more pronounced at the high end of the wage distribution, which is borne out in the summary statistics in table 1 that show that college completion and advanced degrees in Appalachia are about one-half the rate of attainment in the rest of the country.

Appalachia seems to suffer from "missing markets"—the double jeopardy of a lack of high-skilled workers coupled with lower returns on those skills. Perhaps surprisingly, this is most pronounced in the urban areas of Appalachia and not the rural areas, as commonly perceived. Indeed, the wage gap between rural Appalachia and the rest of rural America is virtually nonexistent—the wage gap is driven by weakness in the urban areas. As lucidly described by Glaeser and Gottlieb (2008) the policy response to such missing markets in urban Appalachia is not clear ex ante. If there are human capital externalities and/or agglomeration economies that have yet to be exploited in Appalachia, or if redistributive concerns take primacy, then the policy response would involve the combination of more heavily subsidizing college-level degree programs—a supply-side issue—along with the demand-side issue of developing high-skill jobs that encourage higher-educated Appalachians to remain in the region rather than migrate to higher returns in other areas of the United States. On the other hand, if agglomeration economies and externalities are most pronounced in other metro areas of the country, and tastes for redistribution weak, then policies that foster migration to those high return areas are likely to be most cost effective. To more effectively inform policy on efficiency grounds, further evidence is needed on the presence or absence of region-specific externalities.

Table 5
Robustness of Oaxaca-Blinder Decomposition of Offered Wage Gaps between Non-Appalachian and Appalachian Men and Women (Non-Appalachia as Reference)

	Men					Women				
Year	Difference in Offered Wage (Log Points) (1)	Demographics (2)	Percent Due to Demographics (3)	Coefficients (4)	Percent Due to Coefficients (5)	Difference in Offered Wage (Log Points) (6)	Demographics (7)	Percent Due to Demographics (8)	Coefficients (9)	Percent Due to Coefficients (10)
	Rural to Rural Comparison									
1980	−.021	.000	0	−.021	100	−.068	.025	−37	−.093	137
		(.001)		(.013)			(.001)		(.019)	
1990	−.012	.000	0	−.012	100	−.032	.021	−66	−.052	163
		(.001)		(.009)			(.001)		(.011)	
2000	−.018	.007	−39	−.026	144	−.020	.022	−110	−.042	210
		(.001)		(.010)			(.001)		(.012)	
	Urban to Urban Comparison									
1980	.101	−.009	−9	.110	109	.095	.026	27	.069	73
		(.001)		(.010)			(.001)		(.019)	
1990	.172	−.018	−10	.190	110	.153	.025	16	.128	84
		(.001)		(.007)			(.001)		(.010)	
2000	.125	−.024	−19	.149	119	.097	.011	11	.086	89
		(.001)		(.008)			(.001)		(.010)	
	Base Case Comparison without Urban Areas >1,000,000									
1980	.074	.030	41	.044	59	.004	.053	1,325	−.049	−1,225
		(.001)		(.010)			(.001)		(.015)	
1990	.059	.019	32	.040	68	.027	.046	170	−.019	−70
		(.001)		(.007)			(.001)		(.008)	
2000	.052	.022	42	.030	58	.034	.044	129	−.010	−29
		(.001)		(.007)			(.001)		(.009)	

	Comparison of Non-Appalachia to Central Appalachian States									
1980	.140	.108 (.001)	77	.032 (.014)	23	.161	.145 (.002)	90	.016 (.021)	10
1990	.210	.116 (.001)	55	.094 (.010)	45	.180	.174 (.001)	97	.006 (.011)	3
2000	.173	.100 (.001)	58	.073 (.011)	42	.104	.150 (.001)	144	−.045 (.014)	−43
	Comparison of Non-Appalachia Excluding Urban Areas >1,000,000 to Central Appalachian States									
1980	.056	.044 (.001)	79	.012 (.014)	21	.055	.071 (.001)	129	−.016 (.021)	−29
1990	.105	.032 (.001)	30	.073 (.010)	70	.061	.065 (.001)	107	−.004 (.012)	−7
2000	.082	.030 (.001)	37	.052 (.011)	63	.039	.056 (.001)	144	−.016 (.015)	−41

NOTE.—Analytic standard errors are provided in parentheses.

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