

LABOR MARKET ADJUSTMENT IN THE US

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Abstract: This paper analyzes how changes in the local skill distribution of the labor force affect the local wage distribution. I measure the elasticity of wages to changes in the supply of the various skill groups, using time series and cross sectional data on Metropolitan Statistical Areas in the US in 1980 and 1990. Unlike previous studies, I estimate own and cross-wage elasticity for each skill group and I allow for the existence of human capital spillovers in the labor market. Moreover, I introduce a new instrument to control for the bias that occurs when local labor supplies are simultaneously determined with local wages. I find that cross-wage elasticities are significantly different from zero and therefore should not be ignored. I also find that the estimated cross-wage elasticities are not symmetrical across skill groups, and therefore should not be constrained to be symmetrical.

JEL codes: C51, J24, J3

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1. Introduction

In this paper, I analyze how changes in the skill distribution of the labor force in a geographical area affect the area's wage distribution. The results will allow us to better understand how an increase in the relative size of the local college population affects local wages of college graduates, as well as the local wages of college dropouts, high school graduates and high school dropouts. This in turn will shed light on how immigration affects the local wage distribution, depending on how the immigrant inflow alters the skill distribution of the local labor force.

I identify the effects of changes in the skill distribution of the labor force on local wages by measuring the elasticity of wages to changes in the supply of the various skill groups, using time series and cross sectional data on Metropolitan Statistical Areas in the United States in 1980 and 1990. For each skill group, I estimate an

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own-wage elasticity, which picks up the effect of an increase in the supply of the same skill group on the group's wages, and a cross-wage elasticity, which measures the effect of an increase in the supplies of all other skill groups on the skill group's wages. In addition, I test for the existence of human capital spillovers in the labor market by allowing the different skill groups to affect each other's wages in a non-symmetrical fashion. Moreover, I introduce a new instrument to control for the bias that occurs when local labor supplies are simultaneously determined with local wages.

A number of studies in the labor economics literature attempt to explain the changes in the US wage distribution that occurred since 1970 by looking at changes in labor supplies. For example, Juhn and Kim (2000) look at whether the entry of women into the labor force could explain the relative and absolute decline in the wages of less educated males in the US from 1970 to 1990. Though the focus of their paper is different than mine, Juhn and Kim do measure the cross-wage elasticities I am interested in (although with a slightly different definition of the labor groups). However, they control for the bias¹ due to the simultaneous determination of labor supplies with local labor demand conditions by introducing into their estimating equation a measure of labor demand shifts between sectors². To the extent that my methods for controlling the bias differ, my results will vary from theirs. Moreover, they ignore the requirement that cross elasticity estimates must be symmetrical. This paper looks more carefully at the symmetry of cross elasticity estimates, and it evaluates whether human capital spillovers could be an explanation for the lack of symmetry.

Another related literature in labor economics looks at the local wage effects of immigrant inflows. The studies in this literature

¹ Since labor demand conditions are difficult to measure, shifts in labor demand are typically absorbed in the error term. If labor supplies (the independent variables) are correlated with local labor demand conditions, the estimated coefficients on labor supplies are biased.

² Their method does not control for factor specific demand shifts. Those are absorbed in the error term. To the extent that changes in labor supplies are due to factor specific demand shifts, the estimated effects of changes in labor supplies on wage changes are still biased.

utilize both time series and cross section data across the US to measure the local wage effects of immigration. However, they focus on the own-wage elasticity of demand and they ignore the cross effects of different labor groups on each other's wages, thereby missing what I believe to be a big part of the story. Moreover, these studies have varying degrees of success in controlling for the bias that occurs because local immigrant supplies are simultaneously determined with local labor conditions and wages. This paper addresses both of these failings of the immigrant literature and comes up with results that can be used to measure the effects of local immigrant inflows on the local wage distributions.

The next section lays out the theory, section 2 explains the empirical estimation, section 3 introduces the data, section 4 discusses the results and section 5 concludes.

2. Theory

a. Labor supply

The standard labor supply equation assumes that labor force participation is positively related to the wage rate offered on the labor market, and it can be written in log form as:

$$(1) \quad w_{ijt} = g_i(l_{ijt} - n_{ijt})$$

where w_{ijt} denotes the log of the mean wage rate of labor group i in city j at time t , l_{ijt} is the log of the level of employment for that labor group, and n_{ijt} is the log of the population of the same labor group in city j at time t . An implication of writing labor supply this way is that holding employment constant, a rise in the population of a labor group in a city will push wages down for that group.

b. Labor demand

The standard labor demand equation assumes that the wage of a group of workers is negatively correlated with their own level of employment. Moreover, it allows for other factors, both observable and unobservable, to affect the wage level. I extend this labor demand framework by explicitly allowing for non-zero cross effects between the employment levels of the different groups of labor on each other's wages. Thus, I specify the labor demand as:

$$(2) \quad w_{ijt} = a_{jt} - \sum_{k=1, \dots, i} b_i^k l_{kjt} + e_{ijt}$$

This equation states that the log of the mean wage for group i in city j at time t is affected by observable factors (z_{jt}), unobservable factors (e_{ijt}), and by the log of the levels of employment of every labor group in the same labor market. If labor group 1 is complementary with labor group 2 in the labor market, then $\beta_i^k > 0$. Otherwise, $\beta_i^k < 0$. Therefore the β_i^k I estimate not only measure the cross-elasticity of wages within a labor market, but they also tell us whether different labor groups are complements or substitutes with each other.

If there are two labor groups (1 and 2), I run one equation for each group (w_{1jt} and w_{2jt}), and I estimate β_2^1 , β_1^1 , β_2^2 and β_1^2 . The cross-effects are assumed to be symmetrical. Thus, $\beta_i^k = \beta_k^i$. To allow for asymmetric effects of labor groups on each other, I amend the labor demand specification further by introducing spillover effects that are external to individual firms:

$$(3) \quad w_{ijt} = a \quad z_{jt} + \sum_{k=1, \dots, i} d_i^k n_{kjt} - \sum_{k=1, \dots, i} b_i^k l_{kjt} + e_{ijt}$$

This new specification states that wages are affected by the populations of various labor groups in the area (n_{ijt}).

The logic behind these spillovers is that when the population of a certain skill group increases in a geographic area, certain types of industries are then drawn to the area. For example, an increase in the college graduate population in Ohio may bring many high tech industries to Ohio, and that affects the wages of all skill groups in Ohio, aside from the cross-wage effects due to the complementarity of the skill groups within a production process.

c. Equilibrium

Combining labor demand with labor supply, I get a reduced form equation for equilibrium wages:

$$(4) \quad w_{ijt} = a \quad z_{jt} - \sum_{k=1, \dots, i} q_i^k n_{kjt} + e_{ijt}$$

Unlike the labor demand equation, this is a reduced form equation with population, not employment on the right hand side. Assuming that population numbers are exogenously determined the

estimated coefficients are unbiased³. If spillover effects are present then β_k^j is not equal to β_i^k . The above equation allows us to estimate the size and sign of cross-elasticities of wages in a labor market, and it allows us to test for the presence of significant spillover effects within a labor market by checking whether the estimated β_k^j differ significantly from the estimated β_i^k .

3. Empirical estimation

The equation I am interested in estimating is the reduced form equation described above:

$$(5) \quad w_{ijt} = a \quad z_{jt} - \sum_{k=1, \dots, i} q_i^k n_{kjt} + e_{ijt}$$

The right-hand-side of the equation is comprised of the observable labor demand shifters (z_{jt}), which are assumed to be city and time specific, and the log populations of the various labor groups, which are also city and time specific. Any unobservable labor demand or labor supply variables are absorbed in the error term. The effects of the population variables are different for each labor group, but the effects of the observable labor demand shifters are common to all groups. Thus, if there are two labor groups, I would be estimating one set of coefficients for the labor demand shifters and two sets of coefficients for the population variables.

Since I am interested in how the *relative* size of the different labor groups in a local area affects their *relative* local wages, I net out any size effects from the cross-wage elasticity estimates by dividing the local skill populations by the total local population, and adding the latter as a separate regressor on the right hand side. The estimating equation becomes:

$$(6) \quad w_{ijt} = a \quad z_{jt} + l_i p_{jt} - \sum_{k=1, \dots, i} q_i^k \frac{n_{kjt}}{p_{jt}} + e_{ijt}$$

where p_{jt} is the log of the total local population in city j at time t .

³ However, if shifts in population are correlated with unobservable local demand shifts, then estimated coefficients are biased.

I refer to $\frac{n_{kjt}}{p_{jt}}$ as the skill population fraction for skill group k .

As a first pass, I run this equation using Ordinary Least Squares. In order for the OLS coefficients to be unbiased, the right hand side variables in the equation must be uncorrelated with the error term. A good argument can be made that the skill population fractions of different labor groups in a geographical area are uncorrelated with local economic conditions (in fact, labor populations have been used in other studies as an instrument for employment, to correct for the bias introduced because employment is correlated with local labor demand conditions). However, in this study, I go even further to ensure unbiased-ness by running a two stage least squares model, which uses instruments for the skill population fractions of the different labor groups, just in case populations are co-determined with local labor conditions.

a. The instrument

In the search of an instrument for local skill populations, I studied the migration rates of various groups in the US. I tabulate the results in table 1.

Looking at migration across metropolitan areas within the US, I find that people older than 44 years have a lower rate of migration than people aged 16-44. This makes sense, since younger people have a longer time horizon to benefit from the gains of a move, and they have fewer attachments to their current geographical locations than do older people. Moreover, females have lower migration rates than males across skill groups⁴, and migration rates increase with education⁵. These results hold in both 1980 and in 1990. Moreover,

⁴ Married couples evaluate whether to move based on what's best for both the husband and the wife. When the reward from moving for one spouse is tied with the loss to the other spouse, theory cannot tell us which decision is made. However, in reality, women often give in under such circumstances more often than men do. This would explain why married women have lower migration rates than men.

⁵ More educated people have more career opportunities outside a local area, and they are better able to learn about those opportunities. Thus, they are more likely to migrate.

the results also held up when I looked at migration rates across states. In fact, Bound and Holtzer (1993) also find that older people's migration decisions are not very sensitive to changes in labor market conditions⁶.

Table 1. **Migration Rates Across Metropolitan Areas**

Sex	Education	1980		1990	
		Age 16-44	Age >44	Age 16-44	Age >44
Male	<= 12th grade	0.19	0.07	0.21	0.08
Male	1-3 yrs college	0.31	0.08	0.21	0.12
Male	4+ yrs college	0.34	0.17	0.38	0.12
Female	<= 12th grade	0.15	0.06	0.16	0.07
Female	1-3 yrs college	0.26	0.13	0.22	0.11
Female	4+ yrs college	0.30	0.14	0.33	0.16

Table 1. continued **Migration Rates Across States**

Sex	Education	1980		1990	
		Age 16-44	Age >44	Age 16-44	Age >44
Male	<= 12th grade	0.13	0.05	0.20	0.06
Male	1-3 yrs college	0.16	0.04	0.20	0.09
Male	4+ yrs college	0.26	0.14	0.34	0.11
Female	<= 12th grade	0.10	0.04	0.16	0.06
Female	1-3 yrs college	0.18	0.10	0.19	0.09
Female	4+ yrs college	0.25	0.11	0.30	0.10

⁶ The authors estimate reduced form equations for the effects of overall demand shifts across local areas on labor market outcomes and labor supply adjustments for various groups. They find that older and less educated workers have the most limited short run labor supply adjustments to demand shifts.

Since older people do not migrate much in response to changes in local labor conditions, the skill distribution of older people in a local area is likely uncorrelated with current local labor conditions. Moreover, since skill distributions do not change drastically over time, the skill distribution of older people is highly correlated with the skill distribution for the overall population in a local area (especially since the total population includes the older population). Therefore, I use the skill population fractions of older people as an instrument for the overall skill population fractions and for the log population in an area.

In addition, I use the fraction of older females who live in the local area compared with the rest of the US, for each skill group, as an over-identifying instrument. The logic here is the same as for the previous instrument.

Since I have eight instruments for 5 variables, I meet the requirements of over-identification, and I can test the validity of the instruments by running a Basman over-identification test. The test cannot reject the validity of our instruments.

b. The data

The study uses micro-data from the 5% sample of the US census of population and housing for 1980 and 1990. The labor groups I focus on are defined along the lines of educational attainment. In particular, I look at four groups: high school dropouts (HSD from hereon), high school graduates with possibly some college attainment (HSG), college graduates (CLG) and professionals (PRF). Every person in the sample belongs to at most one category^{7, 8} depending on the number of years of schooling they attended^{7, 8}. I use the 175 largest Metropolitan Statistical Areas in the

⁷ There was a change in format of the years of schooling question in the US census of population and housing from 1980 to 1990. In 1980, the question was made up of two parts, the first asking the number of years that the individual attended school, and the second asking the highest grade the individual completed. In 1990, the question was consolidated into one part, which asked the highest degree achieved by the individual, in recognition of the fact that people sometimes spend years to get a college degree. A study was done using CPS data from 1988, a year when questions of both formats were asked simultaneously, to determine a way to make the results from

US in 1980 and 1990⁹, and I calculate average real wages¹⁰ for each city/skill group using the population of males aged 16-68, with at least 1 year of labor market experience. The sample contains one observation of the log of mean real wages for each city, skill category and year, yielding a total of 1400 observations.

I calculate the populations of the different skill categories using the total population, both male and female, whether they are in the labor force or not.

The observable city characteristics I use are the log of manufacturing value-added, the log of new capital expenditures in manufacturing, and the log of sales, which comprises the total value of retail sales, wholesale sales, service receipts and the value of shipments in manufacturing. I deflate the 1990 values of these variables to yield real values. I also use the log of the relative sizes of retail, wholesale, service receipts and manufacturing shipments out of total sales. These variables capture factor-neutral labor demand conditions in a city at a particular point in time, and their numbers are drawn from the census of manufacturing for 1977 and 1987. In addition, I use the log of the percentage of a city's population that is Black, Hispanic, or married, and the log of the percentage of the population in different age groups (16-24, 25-44, 45-64, 65 and older). Furthermore, I add into the equation skill dummies to control for any city neutral, skill specific boosts to wages, and a 1990-year dummy interacted with skill dummies to remove any city neutral, skill and year specific shocks to wages. Finally, the equation includes

both types of formats equivalent, and I use the transformation they recommend to correct for this potential source of bias.

⁸ HSD: less than 12 years of schooling, 12 = HSG <16 yrs, CLG=16 yrs, PRF>16.

⁹ I only include the largest MSAs to ensure that cell sizes are adequate for the population/education groups.

¹⁰ Individual wages are calculated by dividing salary and self-employment income by the number of hours worked for the year. The latter is defined as the number of hours typically worked per week multiplied by the number of weeks worked in the past year. Those individuals who did not work positive hours and those who had a zero wage were not included in the calculation of average wages.

the log of total population in each city, and the log of the skill population fractions in each city and year.

The equation I estimated was:

$$(6') \quad w_{ijt} = S_i + Y_{it} + a X_{jt} + l_i N_{jt} + \sum_{k=1, \dots, i} q_i^k \frac{n_{kjt}}{p_{jt}} + e_{ijt}$$

where all variables are in logs. S_i is a skill dummy, Y_{it} is a skill/year dummy, X_{jt} comprises the variables that proxy for local demand conditions, and N_{jt} is the log of total population in the city. Finally, n_{kjt}/p_{jt} are the log skill population fractions.

The equation is estimated using Ordinary Least Squares and Two-Stage Least Squares. The following is a list of variables that are potentially endogenous, and the instruments used to correct for the bias they may induce.

Endogenous Variables	Instruments
$\ln(\text{HSD}_{\text{city A}} / \text{Population}_{\text{city A}})$	$\ln(\text{Older HSD}_{\text{city A}} / \text{Older Population}_{\text{city A}})$
$\ln(\text{HSG}_{\text{city A}} / \text{Population}_{\text{city A}})$	$\ln(\text{Older HSG}_{\text{city A}} / \text{Older Population}_{\text{city A}})$
$\ln(\text{CLG}_{\text{city A}} / \text{Population}_{\text{city A}})$	$\ln(\text{Older CLG}_{\text{city A}} / \text{Older Population}_{\text{city A}})$
$\ln(\text{PRF}_{\text{city A}} / \text{Population}_{\text{city A}})$	$\ln(\text{Older PRF}_{\text{city A}} / \text{Older Population}_{\text{city A}})$
$\ln \text{Population}$	$\ln(\text{Older Female HSD}_{\text{city A}} / \text{Older Female HSD}_{\text{US}})$
	$\ln(\text{Older Female HSG}_{\text{city A}} / \text{Older Female HSG}_{\text{US}})$
	$\ln(\text{Older Female CLG}_{\text{city A}} / \text{Older Female CLG}_{\text{US}})$
	$\ln(\text{Older Female PRF}_{\text{city A}} / \text{Older Female PRF}_{\text{US}})$
	Other exogenous variables in the model

HSD: HS Dropouts, HSG: HS Graduates, CLG: College Graduates, PRF: Professionals

Estimation of equation (6') yields coefficients on the effects of skill and year dummies, observable city characteristics variables and the log of total population in the city on the log of mean real wages. Moreover, for each skill group, I get one estimate of the effect of the

own-skill population fraction on the skill group's wages, and three estimates of the effects of the other-skill population fractions on the skill group's wages. We would normally expect that the own effects are negative, since an increase in the number of workers, holding constant the demand for such workers, would drive down their wages. As for the cross effects, their size reflects the interaction of the various labor groups in the production function.

4. Results

a. OLS results

Table 2 displays the effects of the skill dummies, the skill-year dummies, local demand conditions and the log of total population on the log of mean real wages. Table 3 displays the impacts of the log skill population fractions on the log of mean real wages.

The first thing I look at is whether the coefficients on the dummies and on the city characteristic variables are reasonable. Next, I check whether the cross-effects of different labor groups on each other are significantly different from zero. Finally, I analyze the signs and magnitudes of those cross effects, and test whether they are symmetrical.

Looking at table 2, the skill dummies show that additional educational attainment yields a premium on the wages of high school dropouts. On the other hand, the 1990-year dummy indicates that all skill groups suffered a setback in their real wages in 1990 relative to 1980, but the less educated groups got hit the hardest. The effects of total population are negative and significant for all groups as well, meaning that as the number of workers increases, the average wage for each group decreases. These results are consistent with what I expect.

As for the city characteristics, manufacturing value added and spending on new capital expenditures seem to pick up local wages, whereas increases in the share of manufacturing

Table 2.		OLS			2SLS		
		Estimate	Std error		Estimate	Std error	
	Intercept	-0.315	0.331		-0.920	0.451	**
Skill Dummies							
S0	HS Dropout	-----	-----				
S1	HS Grad	0.756	0.354	**	0.991	0.559	*
S2	College Grad	1.467	0.354	**	2.631	0.559	**
S3	Professional	1.308	0.354	**	2.471	0.559	**
Skill*Year Dummies							
	S0*yr90	-0.323	0.059	**	-0.322	0.078	**
	S1*yr90	-0.240	0.059	**	-0.279	0.078	**
	S2*yr90	-0.192	0.059	**	-0.240	0.078	**
	S3*yr90	-0.034	0.059		-0.142	0.078	*
Skill*Log Population							
	S0*lnPop	-0.024	0.011	**	-0.013	0.012	
	S1*lnPop	-0.040	0.011	**	-0.032	0.012	**
	S2*lnPop	-0.040	0.011	**	-0.044	0.012	**
	S3*lnPop	-0.039	0.011	**	-0.041	0.012	**
Total Sales		-0.007	0.018		-0.003	0.019	
% Sales Retail		0.009	0.015		0.017	0.017	
% Sales Wholesale		-0.007	0.008		-0.005	0.008	
% Sales Services		-0.013	0.011		-0.016	0.011	
% Sales Manuf Shipments		-0.048	0.019	**	-0.033	0.022	
Manuf Value Added		0.066	0.017	**	0.058	0.018	**
Manuf New Capital Expenditures		0.014	0.008	**	0.015	0.008	*
% Pop Black		-0.009	0.003	**	-0.008	0.003	**
% Pop Hispanic		0.011	0.002	**	0.013	0.003	**
% Pop Age 16-24		-0.308	0.044	**	-0.305	0.046	**
% Pop Age 25-44		-0.116	0.063	**	-0.107	0.070	
% Pop Age 45-64		0.267	0.046	**	0.263	0.047	**
% Pop Age >64		-0.152	0.027	**	-0.150	0.029	**
% Pop Married		-0.185	0.067	**	-0.250	0.075	**

# Obs		1339			1331		
R-square		0.904			0.900		
Test for Over-Identifying					F-Value:	1.050	
Restrictions:					Prob > F:	0.402	

*: denotes significance at the 10% level **: denotes significance at the 5% level

Table 3.		1% ? CLG/ POP		1% ? PRF/ POP	
Effect on:					
Wage HSD	**	-0.191	**	0.103	**
		0.039		0.032	
Wage HSG		-0.066	*	0.125	**
		0.039		0.032	
Wage CLG		0.049		0.111	**
		0.039		0.032	
Wage PRF		0.027		0.068	**
		0.039		0.032	
		1% ? CLG/ POP		1% ? PRF/ POP	
Effect on:					
Wage HSD		-0.272	**	0.049	
		0.099		0.066	
Wage HSG		-0.078		0.055	
		0.099		0.066	
Wage CLG		0.171	*	0.095	
		0.099		0.066	
Wage PRF		0.225	**	-0.019	
		0.099		0.066	
Test Results	OLS			2SLS	
	Fvalue	Prob > F		Fvalue	P>F

Test:H0				
9.7	0.0001		5.53	0.0001
6.5	0.0108		2.03	0.1545
16	0.0001		10.81	0.001
2.4	0.1216		0.06	0.8059
1.4	0.2393		2.62	0.1058
0.6	0.4234		0.97	0.3243
2.8	0.095		1.19	0.2762
7.2	0.0001		5.16	0.0001

shipments out of total sales sets wages back. The percentage of blacks in a city's population is correlated with lower average wages, and a higher percentage of younger people in the population is also correlated with lower average wages. However, cities with a high percentage of people who are married have lower wages. Though I do not have any strong priors about what these results should look like, none of them stands out as particularly problematic. Thus, the results I have looked at so far do not indicate a problem with our empirical model, and I move on to analyze the results on the estimated elasticities.

Looking at table 3, the results suggest that high school graduates are complementary with high school dropouts, while college graduates are substitutes for high school dropouts and high school graduates. Interestingly, professionals are complementary with all other skill classes.

Moreover, many of the cross effects are significantly different from zero. Indeed, an F-test rejects the hypothesis that the cross effects are collectively equal to zero. Aside from the signs and magnitudes of the estimated cross-wage elasticities, I test the hypothesis that the cross elasticity estimates are symmetrical. I do this in one combined test, and separately for every skill category pair. The combined test rejects the hypothesis at the 1% level, but of the six tests by skill pair, two reject the hypothesis at the 1% level, one rejects the hypothesis at the 10% level, while the other 3 tests

cannot reject the hypothesis. I interpret this as evidence that spillover effects are significant in the economy. By ignoring the existence of such spillover effects and forcing estimated elasticities to be symmetrical, other empirical studies are biasing their estimates.

b. Two stage least squares results

Next I look at the 2SLS estimation results in tables 2 and 3. If OLS results were biased and if the instruments I use are valid, then these results ought to be unbiased.

The coefficients on the dummy variables, the population variables and the city characteristics are all similar to those estimated under OLS, and so their analysis remains the same.

As for the coefficients on the skill population fractions, many of the estimated cross effects are still significantly different from zero, and an F-test still rejects the hypothesis that the cross effects are jointly insignificant. This strengthens my belief that the cross effects are an important part of the story. The estimated elasticity coefficients maintain the same signs as under OLS, but the magnitudes and statistical significance change. Among the estimates that are significantly different from zero, college graduates are substitutes with high school dropouts, high school dropouts are substitutes with high school graduates and complements with college graduates, and college graduates are complements with professionals. On the other hand, the effect of professionals on all other skill classes and the effect of high school graduates on high school dropouts fade into insignificance.

As for symmetry of the cross elasticity estimates, a joint test of the hypothesis that all cross effects are symmetrical rejects the null at the 1% level. When the test is conducted separately for each pair of skill groups, the test rejects the null in only one out of the six tests. Again, I interpret the result of the combined test as support for the hypothesis that spillover effects are significant, and therefore, leaving them out by constraining the cross effects to be symmetrical would bias the estimates.

Finally, I conduct an over-identification test to check the validity of my instruments. The test I conduct cannot reject the

hypothesis that the instruments are valid, as it yields a statistic that falls within the 0.40 region of the distribution.

c. Comparison with the literature

In order to see how my results fit in with what is already in the literature, I replace the log of population fractions with employment for the various skill groups, and I do not include the log of total population as a separate regressor in the estimating equation. I run this comparison equation with and without including the cross effects, and in OLS and 2SLS forms. The results of this exercise are in table 4.

Interestingly, when I do not include the cross effects of the various skill groups on each others' wages, I get strongly significant and consistently negative own skill effects. This is what the theory predicts. However, as soon as I include the cross effects, the own skill effects are no longer always negative, nor are they always significant. This clearly demonstrates how important the cross effects are for really understanding how the labor market works.

Next, I compare the coefficients estimated from this regression with the results in Juhn & Kim's paper. Even though they use a different definition of skill categories, the results are relatively comparable, and they are very similar. This lends credibility to the estimates I found. Moreover, this means that when I run my equation with population instead of employment, my method for correcting for endogeneity in the estimating equation performs at least as well, since population is not as endogenously related to unobserved local demand conditions as is local employment.

d. Evaluation

I evaluate how well my model performs by using its results to predict how the skill distribution of the labor force changed from 1980 to 1990 given how labor supplies changed over the decade, and comparing the prediction with how things really changed. That tells me how well the model performed in capturing what was happening.

Table 4. Estimated Factor Price Elasticities

	(1)	(2)	(3)	(4)		Juhn & Kim
Wages of HS dropout men					Wages of men w/ <12yrs	
Labor Quantities: (Men + women)					Labor Quantities: (men)	
HS dropouts	-0.06	-0.151	-0.052	-0.179	<12 yrs	-0.170
	0.009	0.016	0.011	0.021		0.040
HS grads/some college		0.159		0.236	12-15 yrs	0.190
		0.029		0.037		0.070
College grads		-0.098		-0.098		
		0.028		0.050		
Professionals		0.062		0.021	16 yrs +	-0.020
		0.023		0.039		0.050
Wages of HS grads/some college men					Wages of men w/12-15 yrs	
Labor Quantities: (Men + women)					Labor Quantities: (men)	
HS dropouts		-0.055		-0.108	<12 yrs	-0.010
		0.016		0.021		0.020
HS grads/some college	-0.05	-0.038	-0.044	0.043	12-15 yrs	0.000
	0.010	0.029	0.012	0.037		0.030
College grads		-0.028		0.000		
		0.028		0.050		
Professionals		0.080		0.028	16 yrs +	0.050
		0.023		0.039		0.030
Wages of college grad men					Wages of men w/ 12-15yrs	
Labor Quantities: (Men + women)					Labor Quantities: (men)	
HS dropouts		0.000		-0.031	<12 yrs	-0.010
		0.016		0.021		0.020
HS grads/some college		-0.129		-0.118	12-15 yrs	0.000
		0.029		0.037		0.030
College grads	-0.03	0.001	-0.032	0.079		
	0.009	0.028	0.010	0.050		

Professionals		0.088		0.029	16 yrs +	0.050
		0.023		0.039		0.030
Wages of professional men					Wages of men w/ 16yrs +	
Labor Quantities: (Men + women)					Labor Quantities: (men)	
HS dropouts		-0.024		-0.053	<12 yrs	0.060
		0.016		0.021		0.030
HS grads/some college		-0.078		-0.061	12-15 yrs	-0.060
		0.029		0.037		0.060
College grads		0.042		0.098		
		0.028		0.050		
Professionals	-0.04	0.018	-0.035	-0.023	16 yrs +	0.000
	0.008	0.023	0.010	0.039		0.050

Figures 1-4 plot the actual against the predicted changes in the log mean wage for each of the skill categories. The slopes of the plots range from 0.38 for high school dropouts, to 0.71 for professionals. In all four cases, the slopes are positive, which indicates that the predicted changes are in the same direction as the actual changes.

This result increases my confidence in the coefficients I estimated. Moreover, since actual changes in wages occur as a result of many changes, whereas the predicted changes I calculated are solely due to the change in local skill distribution, it is surprising that the slopes of the plots are as high as I find them. This implies that the estimates are close to the true elasticities I am seeking.

figure 1. Actual Vs. Predicted Changes in Log Mean Wages of High School Dropouts: 1980-1990

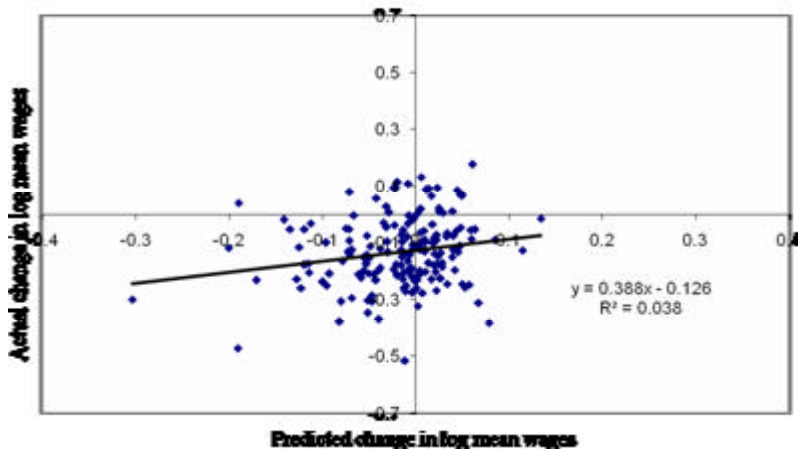


figure 2. Actual Vs. Predicted Changes in Log Mean Wages of High School Graduates: 1980-1990

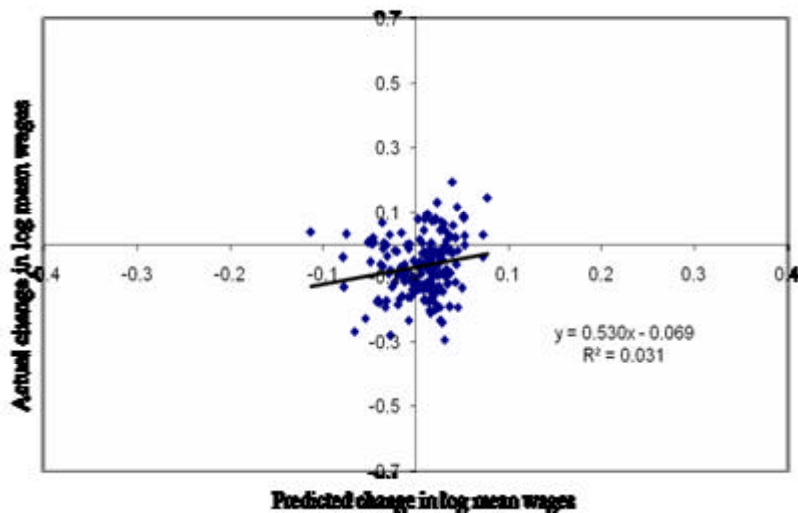


Figure 3. Actual Vs. Predicted Changes in Log Mean Wages of College Graduates: 1980-1990

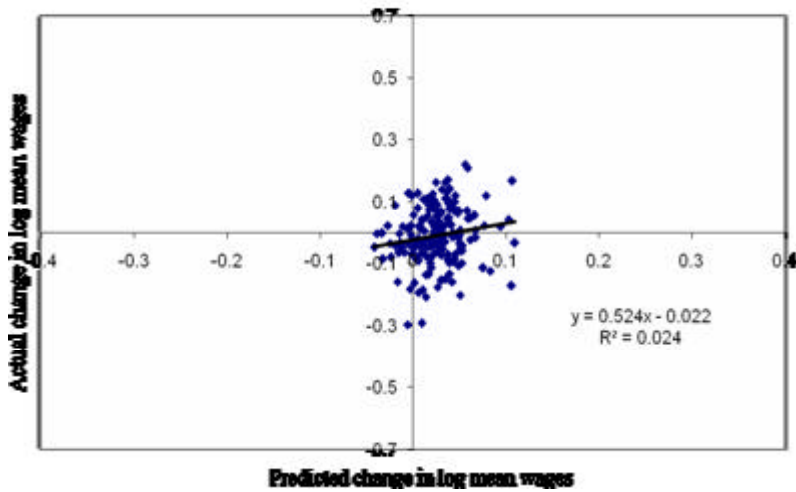
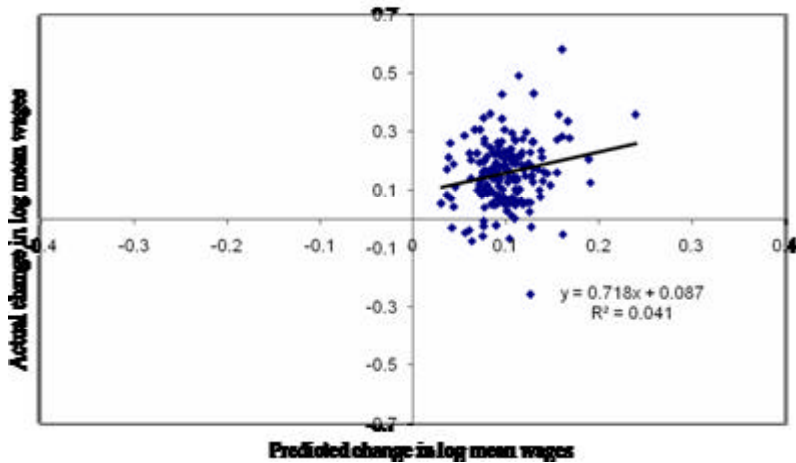


Figure 4. Actual Vs. Predicted Changes in Log Mean Wages of Professionals: 1980-1990



5. Conclusion

This paper analyzed how changes in local skill distributions affect local wage distributions, by estimating the own and cross wage elasticity of changes in the supply of various groups of workers. I found that the cross elasticities are significantly different from zero and therefore should not be ignored.

I also found that the estimated elasticities are not symmetrical across skill groups, and therefore should not be constrained to be symmetrical. Moreover, I introduced a new instrument for controlling the bias due to the potential correlation between local skill populations and unobserved local labor demand conditions, and found that I could not reject its validity using an over-identifying test. Finally, I calculated predicted changes in mean wages using the estimated elasticities and plotted these predictions against the actual changes that occurred between 1980 and 1990, and I found that the slopes of the plots were positive and surprisingly large. This gives me confidence that the estimated elasticities I found are closer to actual elasticities than has previously been found in the literatures. These estimated elasticities can be used to calculate the effects of changes in local skill supplies due to native worker mobility, or to immigrant inflows.

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