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CITIES AND SKILLS

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I. Introduction

Why are wages 32% higher in cities than outside metropolitan areas? Higher costs of living and the inconveniences of cities may explain why labor does not immediately flock to those higher wages, but why do firms stay where the price of labor is so high? If labor markets are perfectly competitive, this wage difference implies that the marginal product of labor is 30% greater in cities than in the hinterland.

This essay examines three possible interpretations of this fact: (1) the urban wage premium is illusory and represents omitted ability variables, (2) the urban wage premium comes from a level effect where cities (either because of reduced transportation costs or because of urban externalities) enhance worker productivity and (3) the urban wage premium is the result of greater wage growth in cities (a growth not a level effect). We use a combination of panel data from the Panel Study of Income Dynamics (hereafter PSID) and the National Longitudinal Survey of Youth (hereafter NLSY) to test between these alternative hypotheses. We use a series of ordinary wage regressions, fixed effects estimation, instrumental variables techniques and data on migrants to distinguish between these explanations of the urban wage premium.

Wages are 32% higher in large cities (of over .5 million inhabitants) than in the hinterland. Wages are 21% higher in Standard Metropolitan Statistical Areas outside large cities (hereafter non-city SMSAs) than in the hinterland. This wage gap falls by less than 4% when we control for education, experience and race. This wage gap falls only 2% more when we control for tenure and occupation. The urban wage premium is significantly higher for older workers, but the gains from living in a city are not higher for the more educated or those with more tenure.

The urban premium, however, falls to 3% when we control for individual fixed effects. We use the longitudinal nature of the PSID to control for an idiosyncratic, time invariant, individual productivity effect, and the urban wage premium disappears on average. There is, however, still an urban wage

premium for older workers even when fixed effects are included in the regression.

The fixed effects methodology gets identification from movers. We examined these migrants who give us the fixed effects estimates in more detail to better understand those estimates. After they move migrants (both rural-urban and urban-rural) experience wage growth of around 10%. Since wages rise moving in either direction (which is necessary to compensate for the costs of mobility), the fixed effects do not show a wage premium. Even interpreting these results as an urban premium of 10% that works in a direct level effect received immediately by new migrants, this effect explains at best one-third of the urban wage premium. We believe that the faster wage growth that some migrants seem to receive over time points to the correct explanation that the bulk of the urban wage premium accrues over time to workers.

To further investigate, we use the NLSY to construct instrumental variables estimators of the SMSA wage premium. Using the place of residence at age 14 as an instrument for current urban residence, we find that the urban wage premium rises. When we include other instruments (meant to capture other, non-ability related, reasons for living in the city) we find that the instrumental variables estimates of the urban wage premium rise even more.

The instrumental variables results, the fixed effects results for older workers, and the extra wage growth received by migrants in cities all suggest that the urban wage premium is not all omitted ability bias. However, the results showing a low immediate migration effect and no fixed effects urban wage premium seem to go against the view of the urban wage premium as a fixed level effect. The one hypothesis readily compatible with all of these facts is the view of cities as generators of human capital growth. This view also explains why the interaction between experience and urban residence is found to be positive in the straight wage regressions -- older workers have lived longer (on average) in the city and have experienced longer periods of high wage growth.

To further understand the wage growth effect we distinguished between two versions: (1) the learning hypothesis where cities enhanced general skill acquisition and (2) the coordination hypothesis where urban labor markets

allowed better matching between workers and jobs. We tested between these hypotheses by including a series of characteristics meant to take account of match quality (occupational information and tenure). After including these variables the interaction between experience and urban resident did not disappear. So we believe that the urban wage growth effect is not simply a result of better labor market coordination in cities. Workers are actually acquiring more skills in dense environments.

The next section discusses the theories of the paper. Section III presents the data. Section IV presents the results. Section V concludes.

II. Discussion

This section presents a setting for the empirical work. We wish to put forward a series of explanations for the differences between urban wages and non-urban wages and some testable implications of these ideas.

Labor Supply and Costs of Living

The traditional approach to wage differences across space builds on the worker's indifference curve (e.g. Rees and Schultz (1970)), Roback (1982)). To clarify the issues in this paper we will assume a particular utility function and demonstrate the workings of the traditional spatial utility model. Individuals maximize a utility function which is Cobb-Douglas in traded and non-traded goods. The price of traded goods is normalized to 1 across locations. The price of non-traded goods is a function of location specific characteristics (denoted Z's) and the price will be written P(Z). Individual wages in each community will similarly be written W(Z). With these assumptions, individuals in a location choose their consumption of goods to maximize:

(1) $X_1^{\alpha}X_2^{1-\alpha}$ subject to $W(Z) \ge X_1 + P(Z) X_2$,

where X_1 is the individual's consumption of traded goods and X_2 is the individual's consumption of traded goods. Solving this problem, the individuals' indirect utility in a location with characteristics Z is:

(2) $A_1W(Z)P(Z)^{\alpha-1}$

where $A_1 = \alpha^{\alpha}(1-\alpha)^{1-\alpha}$ is a constant across locations. Therefore, when migration is free and utilities are maximized across locations it must be true for two locations with attributes Z and Z' that:

(3) $Log(W(Z')/W(Z))=(1-\alpha)Log(P(Z')/P(Z)).$

The difference in the wages precisely compensates individuals for the differences in the cost of the non-traded goods. Rauch (1991) presents the most complete work on this equation. In his paper, Z is local human capital, and the non-traded good is land.

Labor Demand Across Space

There is a labor demand side as well as a labor supply side to this problem. Local area suppliers are assumed to maximize:

$$(4) G(Z)F(K, H(Z) L) - W(Z)L - R(Z)K,$$

where K is capital and L is labor. G(Z) represents any location specific affects that change total output and can range from reduced transport costs to human capital spillovers that raise total output. H(Z) is a location specific effect that acts to increase the productivity of labor. R(Z) is the location specific rental price of capital. We assume that F(K, H(Z)L) displays constant returns to scale. Using the notation $K/LH(Z)=\kappa$, and $F(K/H(Z)L, 1)=f(\kappa)$ we can rewrite (4):

(4') $H(Z)L(G(Z)f(\kappa) - W(Z)/H(Z) - R(Z)\kappa)$

We allow for free entry in this industry so total profits (i.e. (4')) must equal zero, so:

(5) W(Z)= G(Z)H(Z)f(κ) - R(Z)H(Z) κ .

When firms choose capital optimally, it must be true that:

(6) $G(Z)f(\kappa) = R(Z)$, or combining (5) and (6):

(7) $W(Z)=G(Z)H(Z)f(f^{-1}(R(Z)/G(Z))) - R(Z)H(Z)f^{-1}(R(Z)/G(Z)).$

This equation is the analogy for the firm of equation (3). In the case where F(K, L) is Cobb-Douglas, i.e. $F(K, H(Z)L) = K^{\sigma}(H(Z)L)^{1-\sigma}$, (7) can be reduced to:

(7') $W(Z) = A_2 H(Z) R(Z)^{\sigma/(\sigma-1)} G(Z)^{1/(1-\sigma)}$

where $A_2=(1-\sigma)\sigma^{\sigma/(1-\sigma)}$, a constant across locations. With two locations with attributes Z' and Z this equation tells us that:

(8) $Log(W(Z')/W(Z))=Log(H(Z')/H(Z)) + 1/(1-\sigma)Log(G(Z')/G(Z))$ - $\sigma/(1-\sigma)Log(R(Z')/R(Z)).$

This equation means that a difference in wages across locations must reflect differences in (1) the productivity of human capital (H(Z')/H(Z)) which translates one-to-one into higher wages, (2) overall productivity ((G(Z')/G(Z) which could mean lower transport costs or better access to suppliers or other location specific productivity effects) or (3) lower costs of capital (due to better monitoring or easier production of capital in some locations).

This paper will focus on wages as indicators of location specific productivity or human capital effects. We will not look at the labor supply side of the equation, but we accept on faith that there must be cost of living differences to equalize workers' utility across locations. The following sections look specifically at potential factors which might make G(Z) or H(Z) higher in urban areas (and thus explain the labor demand side of the urban wage premium).

Cities and Productivity: Neoclassical Explanations

The most standard explanations for differences between urban and non-urban productivity focus on the transport gains to being in the city. Cities are themselves large markets so transport costs to those markets are saved by firms in those cities (see Krugman (1991)). Cities may also have better access to national transportation networks. One version of the Krugman framework (Krugman and Livas (1993)) has a clear tradeoff between high urban wages (created by savings in transport) offset by high urban rents (created by the density in the urban areas).

One simple way to incorporate this effect into the above model requires interpreting G(Z) as a transport cost parameter, which represents a percent of product lost in transport when production occurs outside the city (i.e. iceberg transport costs). In that case, G(Z)=G<1 outside the city and G(Z)=1 in the city. When land is limited, then the cost of land can rise in the city so that the higher wages are offset by higher prices. This transport cost driven effect makes the above framework a fully specified model where cities have lower transport costs, higher wages and higher costs of land.

Other neoclassical explanations also exist for urban wage premia. Inputs might also be more accessible and cheaper (again primarily because of lower transport costs). The cost of capital might be lower in cities since capital is easier to build in cities or because borrowers in cities are easier to monitor. Cities might include access to public goods in cities or private goods that have increasing returns to scale. In general neoclassical explanations for higher urban wages ultimately tend to rely on the lower cost of moving inputs or outputs in big cities and imply that higher wages should be realized by all workers immediately on arrival in cities.

Cities and Productivity: Human Capital Externality Explanations

Externality arguments have been the centerpiece of some of the most important works in the new urban economics. Lucas (1988) and Rauch (1991) both argue that the mass of human capital within cities acts to increase average productivity. Ciccone and Hall (1993) is another important paper in this area. Following much of the modern growth literature, these papers suggest that knowledge spillovers allow us to take advantage of our neighbors' wisdom. Since cities' density make neighbors closer, urban areas facilitate taking advantage of local human capital. Rauch offers evidence showing that the wages of a single worker (controlling for that worker's human capital) are increasing in the average education of that worker's location. These externalities may affect different individuals in different ways. The more educated workers may benefit more from urban areas because the more educated are better able to learn from others or the less educated may learn more because they have a lower stock of their own human capital. Overall these explanations simply suggest that wages should be higher in cities and in particular in well educated cities (as Rauch shows). In particular, externality arguments that are based on access to better technology in cities imply that cities will move wages as a level effect. If higher human capital levels in cities act to make production more efficient, that too should act as a straightforward level effect. We will distinguish these two forms of urban externalities with other forms that suggest that cities will not affect productivity of new workers immediately. In the alternative urban externalities ideas, only over time will workers experience wage growth.

Cities and Productivity: Omitted Ability Bias

A third possible explanation for the urban wage premium is that workers in cities are simply better in some unobserved way. In a pure omitted ability bias story these better workers are attracted to the city by non-work related advantages to being in the city or simply by luck. Non-work related advantages might include (1) ability of social relations (especially marriage) with a wider range of other high ability people or (2) the presence of commodities which are particularly desired by high ability workers. Johnson (1953) particularly argued that the differences between urban and non-urban wages is related to intrinsic ability differences. The implication of this theory is that individuals who move to the city will not experience wage gains and individuals who live in the city for non-ability related reasons (i.e. because of exogenous factors determining urban location but unrelated to ability) will not have an urban wage premium. This theory predicts also that instrumental variables estimates of the urban wage premium will show no urban wage premium when the instruments used are uncorrelated with omitted individual ability. The ability bias explanations also suggest that there should be sorting into cities based on observable characteristics.

A related explanation of the urban wage premium is a mixture between ability bias and urban externalities. If cities are particularly attractive places for the

more able to work then more able people will be attracted to cities. Then the urban wage premium will reflect both (1) that cities make more able people more productive and (2) cities attract more able people. This mixture requires that (1) some urban wage premium remains when correcting for ability bias and (2) that the urban wage premium is higher for more able workers.

Cities and Productivity: The Learning Hypothesis

Another possible explanation of the urban wage premium is the idea that urban workers have higher levels of unmeasured human capital not because cities attract the more able, but rather because cities enhance the accumulation of human capital. This type of effect is not well explored in the literature although both Marshall (1890) and Chinitz (1961) suggested that inside cities skills were "in the air." Urban density can increase skill accumulation by speeding the rate of new experiences or the range of experiences that individuals acquire. This faster rate of experience should speed the accumulation of human capital. Workers learning by observing successes and particularly failures more frequently. Cities also might raise skill accumulation by their connection to pools of national (or international) human capital. Cities might also allow formal institutions of learning to cover fixed costs of production and this high number of formal schools could also help human capital grow.

Recent papers suggesting that cities might increase the speed at which skills were accumulated include particularly Becker and Murphy (1993). This paper points out that cities facilitate coordination, therefore individuals can specialize in a narrower range of activities and become proficient in those activities more quickly. Their paper does not say that cities speed human capital accumulation, but rather since the amount of human capital for a fixed level of efficiency is lower in more specialized professions, within cities it will seem as if individuals have more human capital.

A similar hypothesis is that cities act as coordinators. Because of the size and speed of urban labor pools it is simpler for workers to connect with the right firm. Workers will be able to match more precisely to other workers since the available pool is larger. The coordination hypothesis predicts that the urban wage premium will mainly work through better labor market outcomes and than much of the urban wage premium will disappear once variables that measure the quality of the worker's match (like tenure) are included in the regression.

The implications of both the learning and the coordination theories are that (1) the urban wage premium is higher for older workers who have lived in cities longer and (2) new migrants to cities will not see wage gains immediately, but rather over time. These theory predicts that simple fixed effects models (i.e. where identification of the urban wage premium looks at the wage gains experienced by individuals who move from city to hinterland) may not pick up any urban wage premium since the movers from hinterland to city will not experience immediate wage growth. Instead only empirical work that tracks rural-urban migrants over time will pick up the urban wage premium. Instrumental variables approaches will not eliminate the urban wage premium since it is a real effect, not simply omitted variables bias.

A Formalization of the Learning Hypothesis

We, here, formalize some of the ideas described above in an extremely simple extension to the above framework. Migration decisions are permanent and assumed to be made at the beginning of life. We also assume that individual's human capital can be either high or low and everyone's human capital begins as low. Moving from low skilled to high skilled involves meeting someone who is high skilled and then with probability C copying the high skills from that person. I assume that each person has N meetings per period and that only a fraction δ of the population (chosen randomly among the high and low skilled) survives until next period.

We will denote π_t as the proportion of the population with high skills in equilibrium an at time t. The evolution of π_t is determined by 1- δ which is the fraction of skilled workers which die each period and 1-(1- $C\pi_t$)^N which is the fraction of unskilled workers which become skilled. Multiplying 1- π_t (the original number over unskilled) times 1-(1- $C\pi_t$)^N (the share of those that become skilled) times δ (the share of those who survive) gives us the flow into the population of skilled workers, or algebraically:

(9) $\pi_{t+1} = \pi_t - (1-\delta)\pi_t + \delta (1-\pi_t)(1-(1-C\pi_t)^N) = f(\pi_t).$

Equilibria of this system occur when $\pi_{t+1} = \pi_t$. One equality occurs when $\pi_{t+1} = \pi_t = 0$. Other equilibria will be fixed points of f(.).

While we do not have closed form solutions for many values of N, it is possible (1) to give conditions under which another equilibrium exists (other than $\pi_t = 0$), (2) to show that the other equilibrium will be stable and (3) to give the comparative statics of π with respect to N, the frequency of meetings. For this analysis we know that:

$$(10) \partial \pi_{t+1} / \partial \pi_t = f'(\pi_t) = \delta (1 - C \pi_t)^N + \delta C N (1 - \pi_t) (1 - C \pi_t)^{N-1} = f'(\pi_t).$$

Equilibria will be fixed points of f(.). When $\delta + \delta CN > 1$, f'(0)>1 and there exists an $\varepsilon > 0$ such that $\delta - \delta(1-\varepsilon)(1-C\varepsilon)^N > \varepsilon$, so the function f(π) is a continuous mapping from [ε , 1] into itself, and by Brouwer's theorem this function must have a fixed point. Furthermore since f(π) is strictly concave this fixed point must be unique and we will denote this fixed point, π^* . As long as $\partial \pi_{t+1}/\partial \pi_t$ is greater than one at $\pi=0$ (which is necessary for a second equilibrium π^* to exist), then the $\pi=0$ equilibrium is unstable by standard arguments. On the other hand at $\pi=\pi^*$, $\partial \pi_{t+1}/\partial \pi_t = f'(\pi^*) = \delta (1-C\pi^*)^N + \delta CN(1-\pi^*)(1-C\pi^*)^{N-1} < 1$, so that equilibrium is stable (since f(π) strikes the 45% degree line at π^* from above).

For our purposes the interesting comparative static is the relationship between π^* and N. We interpret N, the frequency of meeting, as a parameter capturing density. The distinguishing feature of cities in this model is that individuals meet other individuals at a rapid rate. Differentiating we find that:

(11)
$$\pi^{*'}(N) = -\log(\delta(1-\pi^{*})(1-C\pi^{*}))\delta(1-\pi^{*})(1-C\pi^{*})^{N} / (1-\delta(1-C\pi^{*})^{N} + \delta CN(1-\pi^{*})(1-C\pi^{*})^{N-1}) > 0,$$

so the average number of skilled individuals rise in more dense areas. This greater number of skilled individuals tells us that the overall earnings in cities will be higher and the relationship between experience and earnings will be higher in urban areas.

Figure 1 shows the model in operation. The graph maps π into itself. Line C shows $(1-\delta)\pi$. Curve B gives $\delta(1-\pi)(1-(1-C\pi)^N)$ for N=1, C=.5 and δ =.9. Curve A use the same parameters except N=2. The higher N represents the faster rate of meetings in the city. In Curve A the stable equilibrium shows a higher π , which means a higher proportion of skilled workers. Figure 2 shows the wage growth predicted by the equilibria in Figure 1. The city wages rise more quickly initially, but eventually all workers become skilled and the wages for the oldest workers are the same. The next model formalized a coordination based explanation of the urban wage premium.

A Formalization of the Coordination Hypothesis

This section formalizes the idea that urban labor markets act to better match workers and jobs. This paper represents a fairly straightforward simplification of standard search models (see Mortenson (1986). We will simply look at the matching of workers here, but the model is unchanged if the interpretation because the matching of firms and workers. We will index workers with a variable i which ranges from negative one to one. This index does not effect productivity directly, but workers are more productive when they are matched to other workers who are closer to them in the index. To be precise workers make a once and for all match to another worker and from then on, total discounted lifetime income per worker for workers with indices i and j is:

(12) W+ $A_1 - A_2 | i - j|$.

The discount rate is assumed to be β , and the interest rate is r which is determined so $1/(1+r) = \beta$. The wage is the flow value of the stock of earnings or $rW + A_1 - rA_2 | i - j|$.

Without loss of generality, we will look at the decision problem of the agent with index zero and for all the agents we will relabel k=1j1. This decision problem is the same for all agents and k can just be thought of as the distance between two agents in a prospective match. We assume that there are agents dying and new agents being born so that the distribution of workers met in the labor market does not change over time (the actual size of the labor market is irrelevant, only its distribution matters). The distribution of k's is assumed to be uniform across

the unit interval (which is equivalent to an assumption that j's are distributed uniformly across the interval [-1, 1]). Each worker meets another new worker after an interval 1/N (where again N will indicate the density of the location with more dense locations having more frequent meetings).

Workers who do not match receive the reservation wage, rW (W is the stock value of remaining unmatched forever). This reservation wage can be thought of as the wage in some secondary sector or as unemployment benefits. Since we will be observing wage growth only among employed workers, we will assume that unmatched workers are in fact employed. Workers when deciding to make a match or wait until the next period will decide to match when:

(13) $A_1 - A_2 k \ge \beta^{1/N} V^*$.

where V^{*} represents the expected value of beginning the next period without a match (on top of the wage in the unmatched sector which we simply subtract from each side). The equilibrium involves solving for k^{*}, the furthest distance accepted in equilibrium. At k^{*} (13) holds with equality. Solving for k^{*}, means solving for the expectation of V^{*}:

(14)
$$V^* = \int_{k^*} \frac{\beta^{1/N} V^* f(k) dk}{k} + \int_0^{k^*} (A_1 - A_2 k) f(k) dk$$

Solving equations (13) and (14) for k* yields:

(15) $k^* = (A_2 + (A_2^2 - 2A_1A_2(\beta^{1/N}/(1-\beta^{1/N})))^{1/2})/2A_1$

It is true that $\partial k^*/\partial N < 0$ so the minimum accepted match falls with the speed of new meetings, or with our interpretation, urban density. Likewise it is easy to show that the expected wage in the city (as a function of time) is the probability of having a job as of time t times the expected wage conditional upon getting a job (which we will call $r(A_1-A_2k^*/2)$, where **r** is the per period rate of interesting to convert the stock of life earnings into a flow):

(16) Expected Wage at Time t= $rW+(1-(1-k^*)^{t/N})r(A_1-A_2k^*/2)$.

Here it is easy to show that the cross derivative between time and N is positive meaning that while expected earnings at time zero are equal in the city and the suburb expected earnings as of time t are the same.

Figure 3 shows the equilibrium of this model. Line A represents A_1 - A_2k Curves B and C show $\beta^{1/N}V(K)$, the benefit from waiting for a match with the minimum acceptable cutoff being K. Curve B shows the benefit of waiting in the city (when N=2). Curve C shows the benefit of waiting when N=1. The benefit of waiting is uniformly higher in the city than in the hinterland, so the urban residents will always require a higher match to settle. Figure 4 illustrates the path of earnings in the city and the suburbs. The rural resident has higher wages than his urban counterpart early in life, because the rural resident is less picky and accepts a match quicker. The urban resident has higher expected wages later in life and higher expected lifetime earnings. This model presents an alternative explanation for faster wage growth in cities, but in this case faster wage growth should disappear when we control for characteristics of job match.

III. Data Description

The primary data source used in this paper is the version of the Panel Study of Income Dynamics (PSID) used by Topel (1990). It is described more fully in Appendix A of Topel (1990). Roughly, the basic sample includes male heads of households from the first 16 waves of the PSID. Agricultural workers, the selfemployed and workers who are part of the PSID's poverty sample were excluded. Our second sample came from the National Longitudinal Survey of Youth (NLSY), where we again restricted our attention to males. In this case we used only one year of wage evidence (1989).

We have split the PSID sample up into three groups: SMSA and City, SMSA noncity and non-SMSA. SMSA and City refers those workers in the PSID who lived in both a SMSA and a city with more than .5 million inhabitants. SMSA non-city refers to those workers who lived in a SMSA outside of a city of .5 million inhabitants. Non-SMSA refers to those workers who lived outside a SMSA. For all geographical categories we only have information on where the worker lived, not where he worked. For the NLSY we have split workers up only into those we live in an SMSA and those who do not live in an SMSA.

Tables 1 and 2 -- Means and Correlations

Table 1 gives the means and standard deviations for the variables in our regressions. We have 43,657 person-year observations in the PSID. Of these 12,421 observations are SMSA and City observations. 15,581 are Non-city SMSA observation and 15,655 are Non-SMSA observations. The wage variable we chose to use was the log of hourly earnings (described in Topel (1990)). We thought that this variable came closest to capturing the price of labor paid by firms (which is the relevant measure of cross-space productivity effects as per equation (3)). This variable is not deflated by the CPI, but we will use time dummies in all of our regressions which will eliminate both inflation and unrelated business cycle effects. The difference in log wages between the city and non-SMSA is .316. The SMSA non-city average wage lies between those extremes. The next row shows the wages after controlling for year effects and that the wage differences is not simply the result of omitted inflation controls.

The third variable is potential experience (age minus schooling minus five as in Topel (1990)). The average individual in our PSID sample has 20 years of experience but there is little difference in this variable across locations. Schooling does differ across locations. The average city resident has 12.6 years of schooling. The average non-city SMSA resident has 12.5 years of schooling and the average non-SMSA resident has 11.6 years of schooling. There is some evidence of slight selection based on schooling, but this can only be true when comparing non-SMSA with non-city SMSA residents. There is no difference in average schooling between city and non-city SMSA residents. The percent non-white is much higher in urban areas. 39% of the city dwellers are non-white in this sample as opposed to 25.5% for SMSA non-city dwellers. Job tenure is slightly longer inside the city.

We have also created an occupational index based on the average occupation in the individuals one-digit SIC occupation. We find that (as in average education) there is a difference between SMSA dwellers and non-SMSA dwellers in this variable, but there is little difference between city and non-city SMSA dwellers in this occupation variable as well. The NLSY means and standard deviations do not allow us to distinguish between city SMSA and non-City SMSA. We are forced to group all SMSA dwellers together. In this sample, we have many more SMSA dwellers (2492 observations) than non-SMSA dwellers. We find that the SMSA wage is lower than the non-SMSA wage when individual characteristics are not controlled for. We find that city dwellers have slightly more education (which means slightly less experience). All of our workers are of a very similar age group (since this is one year of the NLSY) so having more potential experience is closely correlated with having less education (-70%). There are in fact more non-whites in the SMSA, NLSY sample (due to the NLSY's sampling procedures). The occupational indices are almost the same between these groups.

We have an extra variable in the NLSY which will perhaps help us answer the omitted ability bias question better. We have included the 1981 Armed Forces Qualification Test as a variable for this sample. This variable shows a higher "ability" as measured by this variable for the residents of the city. We cannot tells if this difference is enough to eliminate the urban wage premium until it is placed in a regression format.

Table 2 shows the sample correlations for this group. We have done the correlations for the entire sample for both the NLSY and the PSID samples. We included the table to provide interested readers for more information on the samples.

IV. Results on Wage Regressions

Our estimation procedure basically involves no more than estimating versions of basic wage regressions. Under the conditions sketched above, this equation will yield information on individual productivity and how productivity changes with urban location. Our basic procedure is to estimate:

(17) W_{it} = X_{it}
$$\beta$$
 + C_{it} + S_{it} + X_{it} γ^* C_{it} + α_i + ε_{it}

where W it is the log of the hourly wage. X_{it} is a vector of individual characteristics and β is the price of those characteristics in the non-urban labor market. C takes on a value of one if an individual lives in a city with more than

.5 million inhabitants. S takes on a value of one if an individual lives in a Standard Metropolitan Statistical Area but not in a city with more than .5 million inhabitants. γ represents the premium paid for certain individual characteristics in the urban labor market and α_i captures an individual specific productivity effect (individual ability).

Our estimation procedure will focus on estimates of C and estimates of γ . Our procedure will be to begin with ordinary least squares without individual fixed effects. We will then try estimating the equation with individual fixed effects and with instrumental variables. The goal of those estimations is to eliminate any urban wage premium that might be reflecting the important of omitted ability bias (i.e. the correlation between C and α).

Table Three -- Basic Wage Regressions (PSID)

Table Three presents our basic regression results. Regression (1) shows the urban wage premium controlling for nothing other than time dummies. This regression suggests that the raw wage difference (C) between non-city dwellers and urban residents is 32.34%. Residents of SMSAs who do not live in large cities also receive a large wage premium of 20.99 %.

Regression (2) includes some predetermined individual characteristics (potential labor market experience, education and race) We have tried to distinguish these features (which should not be related to urban labor markets) from characteristics which are clearly a function of agents' local labor market conditions. We find that the urban wage premium (and the SMSA non-city premium) both drop approximately 3% when these variables are included in the regression. In fact there are two countervailing effects of controlling for background characteristics. City residents are better educated, but they are also more non-white. Controlling for education alone would lesson the urban wage premium more. Controlling for race, raises the urban wage premium. The net effect is this 3% move in the premium.

This small change in the urban wage premium that comes about from included observable productivity characteristics makes it questionable whether the remainder of the urban wage premium can be explained by omitted ability factors. These omitted ability factors would have to be (1) much more important and (2) much more correlated with living in the city than the observable ability variables that we have included in our sample. We believe that the small change in the urban wage premium created by controlling for individual characteristics makes it difficult to believe that the entire urban wage premium is omitted ability bias.

Regression (3) includes controls for tenure and average occupational education (job characteristics). It is useful to distinguish between controlling for background characteristics (that should not be a result of urban residence) and controlling for job characteristics (that may themselves be a function of geographical residence). Controlling for these job characteristics drops the urban wage premium by another 2% to 26.88%.

Regression (4) is our first fixed effects estimation. We are now controlling for an individual fixed effect (in essence we are including 4646 individual dummies (which is why the adjusted r-squared is so low). Identification of variables involves looking at whether individuals who change their status in some way have an accompanying change in wages. We see that this methodology essentially eliminates the urban wage premium causing it to fall to 3.24%. One interpretation of these results is that the urban wage premium is all omitted ability factors. Another interpretation is that the urban wage premium is not closely tied (temporally) to moving to a city. If wages accrue to rural-urban migrants only over time, these fixed effects regressions would not pick up an urban wage premium since most movers are followed for only a few years.

Table Four -- Interactions and City and Individual Effects

Table Four allows the urban wage premium to differ according to individual characteristics. Regression (5) allows there to be interactions between the city variable and experience and education. We find that the returns to experience are essentially untouched by place of residence. Contrary to some views of cities which might predict that being in a city is most valuable for the most educated (who are able to take advantage of urban productivity enhancers) we find that cities do not raise the returns to schooling. This evidence goes against the

version of the omitted ability bias story that claimed that better workers were attracted to cities because the return to skill is higher in cities.

However, the returns to experience are higher in cities as shown in regression (5) and Chart 1. The wage gap between inexperienced workers and workers with between 20 and 25 years of experience is 12.4% higher in cities than in the SMSA non-city or non-SMSA areas. Chart 1 shows the progression of the urban wage premium with experience.

Regression (6) includes controls for job level characteristics. These controls are meant to see if the urban-experience cross effect is simply a result of job quality, as it would be under the coordination hypothesis. We believe that tenure and average occupational education may in some sense proxy for job quality. Controlling for these variables does not eliminate the higher returns to education in cities at all. We also find that the returns to being in a "better" occupation are less in cities than in the non-city areas. This means that being outside a city hurts individuals in low schooling occupations more than high schooling occupations.

Regression (7) includes fixed effects into regression (6). One interpretation for the positive connection between urban residence and experience is that less able individuals leave cities over time. So we observe a positive cross -effect between city residence and experience coming from this selection effect. By controlling for individual fixed effects we can eliminate this effect. We still find in equation (7) that the difference between inexperienced workers and workers with between 20 and 25 years of experience is over 10% more in cities than in the non-city areas.

Regression (7) also tells us that the urban wage premium for a white, untenured worker, with less than five years of experience, with 12 years of education and 12 years of education in his occupation is -5%. However, that worker with 20 years of experience has an urban wage premium of 6.5%. The urban wage premium is zero or negative with fixed effects estimates for younger workers. Still it is positive for older workers.

Table Five -- Instrumental Variables and the NLSY

Our primary method of dealing with omitted ability bias is to use the experience of migrants. We will return to this methodology in the following section. However, instrumental variables also provide a means of identifying the urban wage premium. If there is a series of variables that are unrelated to individual ability but that do increase the likelihood that an individual will reside in a city then we can use these variables to estimate the urban wage premium. This instrumental variables methodology will also be robust to some of the problems of fixed effects estimation (such as when wage gains are not immediately tied to changes in status).

We have switched from the PSID to the NLSY because the NLSY gives us a more complete individual history and a broader range of taste variables. We will be comparing the wages of 30 years olds. Regressions (8), (9) and (10) in Table Five shows the basic wage regression or this sample. We are here using only the SMSA dummy. Regression (8) shows that the basic SMSA premium was 19.37% for this sample. This premium is not directly comparable to either premium in Table Three because (1) it includes both city SMSA workers and non-city SMSA workers and (2) the NLSY sample is considerably younger and we know that the urban wage premium rises with age. In regression (9) the SMSA wage premium falls to 16.76% once the experience, education and race variables are included in the regression.

Regression (10) includes the AFQT variable from the NLSY. This variable is an ability test given to the members of this sample and is one possible measure of omitted ability that is not captured by the standard individual characteristics. In fact, this variable is higher in SMSAs than in the hinterland so it does make it possible that part of the urban wage premium is omitted ability bias. Controlling for AFQT scores causes only a 1.15 % fall in the urban wage premium. As we argued above, since observable ability factors make only small differences in the urban wage premium we find it difficult to believe that unobservable ability factors are driving the ability bias that remains.

Regressions (11) and (12) present our instrumental variables estimates. Appropriate instruments must be related to the likelihood of living in a city but unrelated to omitted individual ability. In equation (17) these instruments must be correlated with C but not with α . We have focused on (1) individual's place of birth and (2) taste parameters. Our primary instrument is where an individual lived (country or town) at age 14. This instrument is the main contributor to our results and we find that using this instrument we still get a statistically significant 24% urban wage premium as shown in regression (9). We performed a Wu-Hausman test and these instruments passed the exogeneity requirements.

We also included a series of instruments that are less likely to be orthogonal to individual ability: individual taste parameters. The taste parameters we thought might be related to the decision to live in a city (and indeed they are correlated with that decision) are (1) religion dummies that reflect the frequency of religious attendance , (2) attitudes towards traditional role models, (3) age at which first smoked, and (4) a taste for a more active social life (captured in the age the worker first had sex). These variables are meant to capture taste parameters and were all correlated with urban location. They also passed a Wu-Hausman test of the overidentifying restrictions.

The overall effect (after instrumenting with taste variables and the residence at age 14) rises to 25.6%. This result, bigger SMSA premiums with instrumental variables suggest that omitted ability is not driving the urban wage premium. This evidence does not, though, help us distinguish between cities being a wage level or a wage growth effect.

Table Six -- Migrants

Since the Fixed Effects estimates seemed mildly contradictory to our instrumental variables estimates we decided to examine them more closely in Table Six. Regression 13 and 14 include a full set of regressors which are suppressed for easier viewing. Regression 14 also includes a full set of individual fixed effects to help eliminate ability biases or selection effects.

Regression 13 shows the OLS results on migrants. Migrants from non-SMSA to cities earned significantly lower than their expected wages before the migration. Within the first two years after moving the migrants to the city receive the expected wages of city workers with their characteristics. These migrants also

receive the SMSA premium (which is 29% in this regression). By six years after their time of migration, these migrants seem to receive much higher (29% urban wage premium plus 29% when comparing pre-mover dummy with post-mover dummies -- an unbelievably high effect).

Regression (14) controls for fixed effects and gets more realistic estimates. Here we find that the movers receive almost no wage gains during the year that they move. However, by the next year their wages have risen by between 10 and 14%, which is far from the urban wage premium but still a significant difference. Since movers do receive some of their wage gains immediately upon migration, we must ask why the fixed effects methodology failed to show us any premium. The answer is that urban-rural migrants also receive large wage gains from migration and since the wage gains operate in both directions the fixed effects methods do not pick up a city effect. This wage gains working in both directions is not surprising since mobility either way requires paying costs so wage gains must offset those costs.

There is however, one additional fact given to us by the regressions. Wages for urban-rural migrants had fallen precipitously in the years before migration and the actual gain from migration only brought these workers back up to parity with their pre-migration wages. This is not as true for newly urbanized workers. One interpretation might be that urban-rural workers received wage gains because they were fleeing bad job market outcomes while rural-urban workers were receiving the gains from urban productivity effects.

The general results of the migrants evidence is mixed. It does seem that ruralurban migrants (even controlling for fixed effects) receive a wage increase (on the order of 10%) when they come to the city. The OLS estimates suggest that migrants wages rise over time, suggesting the urban wage growth effect. The fixed effects estimates aren't accurate enough to say anything about dynamics of wage paths post migration. This evidence is compatible with a level effect on the order of 10% and is also compatible with an urban wage growth premium.

V. Conclusion

This paper set up three simple, explanations of the urban wage premium : (1) a level productivity effect (as in Rauch or traditional urban economics), (2) omitted ability being correlated with urban status (as in Johnson (1953)) or (3) a learning/coordination effect where urban status effect wage growth not wage levels. The evidence compiled in this paper tells us that the urban wage premium is not robust to individual fixed effects in the PSID, but that the urban wage is robust to instrumental variables estimation in the NLSY.

Looking at migrants suggested that the pure level effects accruing to rural-urban migrants is approximately 10% (which is no more than the level effect accruing to urban-rural migrants). A pure omitted ability bias theory is rejected by both the migrants data and by the instrumental variables estimation. Since (1) the level effect on migrants is at most 10%, (2) migrants experience fast wage growth post-migration in the OLS estimates and (3) there is a cross-effect between urban residence and experience, we believe that the bulk of the urban wage premium comes from an interaction between urban residence and skill accumulation. Cities seem to speed wage growth.

We attempted to distinguish between two potential explanation of higher wage growth in cities: coordination and learning. One explanation is that the rate of skill acquisition was higher in cities. The other explanation suggested that cities acted by facilitating better matching. Our evidence is that the higher urban returns to experience do not disappear once labor market outcomes have been included in the regression. We therefore believe that the city wage growth effect works by enhancing skill accumulation not by improving quality of labor market outcomes.

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FIGURE 1: LEARNING IN CITIES



Curve A represents the newly high skilled workers, i.e. the flow into the stock of skilled workers, as a function of last period's skilled workers in the city.

Curve B represents the newly high skilled workers, i.e. the flow into the stock of skilled workers, as a function of last period's skilled workers outside the city.

Line C represents the old high skilled workers who perished, i.e. the flow out of the stock of skilled workers, as a function of last periods skilled workers.

Equilibria are the intersections of Line C with Curves A and B.

The parameters used to generate this graph are that 10% of the skilled workers perish each period, 50% of all meetings result in skill transfer and there are two meetings per period in the city and one meeting per period in the country.



City Wages shows the path of expected wages for an urban worker; country wages show the path of expected wages for a rural worker. The parameters are the same as in the above figure. In addition, we have set skilled wages equal to two and unskilled wages equal to one.

FIGURE 3: COORDINATION IN CITIES



Line A represents the benefit of accepting a job as a function of match distance.

Curve B represents the benefit of waiting for a job as a function of the maximum job distance which will be accepted in the future for urban workers.

Line C represents the benefit of waiting for a job as a function of the maximum job distance which will be accepted in the future for rural workers.

Equilibria are the intersections of Line A with Curves B and C.

The parameters used to generate these graphs that the stock value of a job is 2 minus .9 times job match, the unmatched wage is .25, the discount factor is .8 (so the interest rate is 25%). There are two meetings per period in the city and one meeting per period in the country.



City Wages shows the path of expected wages for an urban worker; country wages show the path of expected wages for a rural worker. The parameters are the same as in the above figure. Wages in the matched sector are equal to the interest rate times the stock value of the match.

| | | | Ta | ics | | |
|------|--|---------|----------|---------|-----------------|----------|
| | | | Total | City | Non-city SMSA | Non-SMSA |
| | Number of | Mean | 43657 | 12421 | 15581 | 15655 |
| | Observations | Std Dev | | | | |
| | Log of Hourty Earnings | Mean | 2,108 | 2.259 | 2.153 | 1.943 |
| | (LHERNH) | Std Dev | (0.63) | (0.61) | (0.58) | (0.65) |
| | Log of Hourty Earnings | Mean | 1.943 | 2.094 | 1.985 | 1.781 |
| | deflated by year | Std Dev | (0.62) | (0.61) | (0.58) | (0.64) |
| | Experience (EXPEST) | Mean | 20.015 | 20.042 | 19.234 | 20.772 |
| PSID | | Std Dev | (12.69) | (12.53) | (12.39) | (13.05) |
| | Education (SCHOOL) | Mean | 12.203 | 12.598 | 12.468 | 11.625 |
| | (0011002) | Std Dev | (3.09) | (2.98) | (2.96) | (3.21) |
| | Non-White (RACEDM) | Mean | 0.287 | 0.394 | 0.255 | 0.232 |
| | | Std Dev | (0.45) | (0.49) | (0.44) | (0.42) |
| | Job Tenure (TENURF) | Mean | 6.977 | 7.175 | 6.897 | 6.900 |
| | | Std Dev | (7.39) | (7.67) | (7.31) | (7.24) |
| | Average Education in (one-digit) Occupation | Mean | 12.204 | 12.413 | 12.370 | 11.874 |
| | Group (OCCED) | Std Dev | (1.83) | (1.90) | (1.86) | (1.70) |
| | | Mean | | | | |
| | | Std Dev | | · . | | |
| | Number of | Mean | 3136 | | 2492 | 644 |
| | Observations | Std Dev | | | (Includes City) | |
| | Log of hourty Farnings | Mean | 6.835 | ļ | 6.681 | 6.875 |
| | | Std Dev | (0.69) | | (0.60) | (0.71) |
| | Experience | Mean | 10.751 | | 11.368 | 10.591 |
| | | Std Dev | (3.06) | | (2.96) | (3.06) |
| | Education | Mean | 12.679 | | 12.064 | 12.837 |
| NLSY | | Std Dev | (2.42) | | (2.28) | (2.43) |
| | Non-white | Mean | 0.440 | | 0.470 | 0.325 |
| | | Std Dev | (0.50) | ļ | (0.50) | (0.47) |
| | Job Tenure (weeks) | Mean | 171.253 | | 185.983 | 167.446 |
| | | Std Dev | (173.50) | | (186.27) | (169.88) |
| | Average Education in | Mean | 12.693 | | 12.275 | 12.801 |
| | Group | Std Dev | (1.40) | | (1.13) | (1.44) |
| | AFOT Score in 1981 | Mean | 40.690 | | 42.155 | 35.020 |
| | | Std Dev | (29.48) | | (20.82) | (20.40) |

| | | | Table Two - Sample Correlations | | | | | | | |
|--------------|---|--|------------------------------------|------------------------|---------------------------------|-------------------------|-----------------------|---|------------------------|--|
| | | Log of Hourty Earrings (LHERNIT) | Log of Hourly Earnings, in real | City Dummy (CITYSS) | Nan-ally SMSA durrany (SMSA) | Experience (EC/PEST) | Education (SCHOOL) | | Job Tenure (TENURE) | Average Education in (ana-deft) Cosupation Group (OCCED) |
| | Log of Housty Earnings (LHERN+1) | 1.000 | 0.996 | 0.152 | 0.063 | 0.057 | 0.369 | -0.231 | 0.274 | 0.300 |
| | Log of Houty Earnings, in real terms | 0.998 | 1.000 | 0.152 | 0.061 | 0.072 | 0.367 | -0.232 | 0.270 | 0.367 |
| | City Duriny | 0.152 | 0.152 | | -0.470 | 0.001 | 9.061 | Q.150 | 0.017 | 9.972 |
| | Non-City SMSA dummy | 0.063 | 0.061 | -0.470 | 1.000 | -0.046 | 9.004 | -0.061 | -0.008 | <u>0.067</u> |
| P\$10 | Experience (EXPEST) | 0.067 | 0.072 | 0.001 | -0.048 | 1,000 | -0.452 | 0.047 | 0.475 | -0.129 |
| | Education (SCHOOL) | 0.369 | 0.367 | 0.081 | 0.064 | -0.452 | 1.000 | -0.314 | -0.070 | 0.663 |
| | Non-While (RACEDM) | -0.231 | -0.232 | 0.150 | -0.061 | 0.047 | -0.314 | 1.000 | -0.037 | -0.294 |
| | Jab Tenure (TENURE) Average Education in (one | 0.274 | 0.270 | 0.017 | -9.006 | 0.475 | -0.070 | -0.037 | 1,000 | 0.07 4 |
| | digit) Cocupation Group (OCCED) | 0.366 | 0.367 | <u>0.072</u> | 0.087 | -0.128 | 0.585 | -0.200 | 0.074 | 1.000 |
| | ·, | | | | | | | | | |
| | Verlation | Log of Hourly Earnings | Statu dammy | Esperance | Education | Non-white | Tenure | Avertage Education in (one-digit) Compation Group | APQT score in 1981 | |
| | Log of hourly Earnings | 1.000 | 0.113 | -0.132 | 0.263 | -0,130 | 0.206 | 0.220 | 0.291 | |
| | SMSA dummy | 0.113 | 1.000 | -0.103 | 0,129 | 0.118 | -0.043 | 0.152 | 0.096 | |
| NLSY | Experience | -0.132 | -0.103 | 1.000 | -6.702 | 0.057 | 0.144 | -0.305 | -0.337 | |
| | Education | 0.253 | 0.129 | -0.702 | 1.000 | -0.118 | 0.030 | 0.553 | 0.630 | |
| | Man-shite | -0.136 | 0.110 | 0.067 | -0.119 | 1.000 | -0.095 | -0.009 | -0.414 | |
| | Job Tenure (weeks) | 0.206 | -0.043 | 0.148 | 0.030 | -0.095 | 1,000 | 9.000 | 0.124 | |
| | Average Education in (one- digit) Occupation Group | 0.220 | 0.152 | -0.365 | 0.563 | -0.099 | 0.080 | 1.000 | 9.487 | |
| | AFGT accre in 1981 | 0.291 | 0.000 | -0.337 | 0.630 | -0.414 | 0.124 | 0.487 | 1.000 | 1 |

| Indian India Level Back Wage Equation Beact Wage Equation (with Labor Equation 11.15658 India Level Freed Effect Back Wage Equation (with Labor Equation 11.15658 Freed Effect Constant 8 1.7667 1.6568 1.1300 Free Effect Constant 8 0.017.0 0.0161 0.027.0 0.027.0 Geographical 8 0.0224 0.027.0 0.027.0 0.029.0 Wage Premis SMSA non-city 55 0.007.0 0.009.0 0.009.0 0.009.0 SwSA non-city 55 0.007.0 0.009.0 0.009.0 0.009.0 0.009.0 B 0.20469 0.1170.0 0.1516 0.1130.0 0.028.0 Experience (10.15) 55 0.007.0 0.009.0 0.009.0 0.009.0 Experience (10.25) 55 0.022.0 0.026.0 0.009.0 0.009.0 Experience (20.26) 55 0.028.0 0.019.0 0.019.0 0.029.0 Experience (20.26) 55 55 0.028.0 0.028.0 0.029.0 <t< th=""><th></th><th></th><th></th><th>(1)</th><th>0</th><th>6</th><th><u>(</u>()</th></t<> | | | | (1) | 0 | 6 | <u>(</u> () |
|---|----------------------|----------------------|---------------|--------------------------|------------------------|---|--------------------|
| Constant B 1.768/z 1.889/z 1.130 Geographical Wage Premis SE 0.017) 0.016) 0.027 City Premium B 0.2236 0.2000 0.007) 0.0100 B 0.2208 0.2007 0.007) 0.007) 0.007 SKSA non-city B 0.2029 0.11700 0.1541 0.0301 B 0.2029 0.11700 0.1541 0.0301 0.009 B 0.2029 0.11700 0.1541 0.0301 B 0.2029 0.1518 0.1130 0.0090 B 0.0091 0.0091 0.0091 0.0091 Experience (10.15] SE 0.00491 0.00491 B 0.0049 | | | | Simple Level Effect | Basic Wage Equation | Wage Equation with Labor Market Variables | Fixed Effect |
| Bertin - <td>Constant</td> <td></td> <td>B _S€</td> <td><u>1.7687</u> (0.017)</td> <td>1.6689 (0.016)</td> <td>1.1300 (0.027)</td> <td></td> | Constant | | B _S€ | <u>1.7687</u> (0.017) | 1.6689 (0.016) | 1.1300 (0.027) | |
| City Premium SE (0.007) (0.017) (0.007) (0.017) (0.007) (0.017) (0.007) (0.017) (0.007) (0.017) (0.007) (0.017) (0.007) (0.017) (0.007) (0.017) (0.007) (0.017) (0.007) (0.017) <t< td=""><td><u> </u></td><td>T</td><td>SIGNIF. B</td><td>0.3238</td><td>0.2903</td><td>0.2688</td><td>0.0324</td></t<> | <u> </u> | T | SIGNIF. B | 0.3238 | 0.2903 | 0.2688 | 0.0324 |
| Ways Premis B 0.2009 0.1700 0.1541 0.0001 SMSA non-city SE 0.007 0.006 0.005 0.0005 sec | Geographical | City Premium | SE | (0.007) | (0.007) | (0.007) | (0.010) |
| B | Wage Premia | SMSA non-city | B | 0.2099 (0.007) | 0.1700 | 0.1541 (0.006) | 0.0301 |
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| Experience Experience (20,25) 8 (20,10) (0,010) (0,017) <t< td=""><td></td><td>Experience (15,20]</td><td>SICHIF.</td><td></td><td></td><td></td><td>(0.012)</td></t<> | | Experience (15,20] | SICHIF. | | | | (0.012) |
| Dummies Experience (20,29) SE (0,010) (0,010) (0,017) Experience (25,30) SE (0,011) 0,0111) (0,022) Experience (20,35) SE (0,011) (0,011) (0,022) Experience (30,35) SE (0,011) (0,011) (0,029) Experience (30,35) SE (0,010) (0,010) (0,020) B 0.32653 0.1027 -0.0515 Experience >35 SE (0,010) (0,020) B 0.2983 0.1027 -0.0515 Education [0.9] SE (0,000) (0,020) Soer | Experience | | 8 | | 0.3126 | 0.1958 | 0.0687 |
| B 0.3481 0.1965 0.0610 Experience (25,30) SE (0.011) 0.011) (0.022) Experience (30,35) SE (0.011) 0.0111 (0.029) Experience >35 SE (0.011) 0.0177 -0.0515 Experience >35 SE (0.010) (0.020) -0.0515 Seer (0.010) (0.010) (0.020) soer B 0.2983 0.1027 -0.0515 Education [0.9] SE (0.010) (0.020) .0045 Education [0.9] SE (0.000) (0.020) .0045 Education [10,11] SE (0.000) (0.020) .0045 Education [13,15] SE (0.000) (0.020) .0011 Dommies Education = 16 SE (0.000) .00250 .01144 Education > 16 SE 0.0206 .0.0784 .0.0784 .0.0784 Education > 16 SE 0.04129 | Dummies | Experience (20,25) | SE | | <u>(0.010)</u> | <u>(0.010)</u> | (0.017) |
| Experience (25,30) SE (0.011) (0.022) accert accert | | | B | | 0.3481 | 0.1966 | 0.0610 |
| Experience (30,35) SE 0.3663 0.1767 0.0067 Experience (30,35) SE (0.011) (0.011) (0.029) accer | | Experience (25,30) | SE | | (0.011) | (0.011) | (0.022) |
| Experience (30,35) SE 0.0111 (0.011) (0.011) (0.029) Experience >35 B 0.2043 0.1027 -0.0515 Experience >35 SE (0.019) (0.010) (0.032) accer | | Experience (30,35] | <u> </u> | | 0.3563 | 0.1767 | 0.0067 |
| Busine 0.2043 0.1027 -0.0515 Experience >35 SE (0.010) (0.010) (0.032) scorer | | | SE | | <u>(0.011)</u> | (0.011) | (0.026) |
| Experience >35 SE (0.010) (0.010) (0.032) B | | | B | | 0.2983 | 0.1027 | -0.0515 |
| B -0.3700 -0.2991 0.0045 Education [0,9] SE (0.009) (0.009) (0.020) B -0.2111 -0.16965 -0.0066 Education [10,11] SE (0.009) (0.009) (0.020) Education [10,11] SE (0.006) (0.009) (0.019) Education [13,15] SE (0.007) (0.007) (0.011) Education = 16 SE (0.009) (0.011) (0.020) B 0.3229 0.2050 0.1144 Education = 16 SE (0.009) (0.011) (0.020) B 0.4129 0.2549 0.0769 Education >16 SE (0.009) (0.009) (0.023) B 0.4129 0.2549 0.0769 Boser | | Experience >35 | SE | | (0.010) | (0.010) | (0.032) |
| Education [0,9] SE (0.009) (0.009) (0.020) Education [10,11] SE -0.2111 -0.1696 -0.0066 Education [10,11] SE (0.006) (0.008) (0.016) Education [13,15] SE (0.006) (0.007) (0.007) Education [13,15] SE (0.007) (0.007) (0.007) Education = 16 SE (0.009) (0.010) (0.020) Education = 16 SE (0.009) (0.010) (0.020) Education = 16 SE (0.009) (0.010) (0.020) Education >16 SE (0.009) (0.011) (0.020) Education >16 SE (0.010) (0.011) (0.022) B | ├── | | B | | -0.3700 | -0.2961 | 0.0045 |
| Education B | | Education [0,9] | SE | | (0.009) | (0.009) | (0.020) |
| Education Education [10,11] SE (0.006) (0.006) (0.016) Education B 0.1110 0.06633 0.02933 Education [13,15] SE (0.007) (0.007) (0.011) Scoref | | | B | | -0.2111 | -0.1695 | -0.0066 |
| B 0.1110 0.0663 0.0293 Education B 0.1110 0.0663 0.0293 Education [13,15] SE 0.007 0.011 0.011 Education = 16 SE 0.0209 0.007 0.011 Education = 16 SE 0.029 0.000 0.000 Education = 16 SE 0.04129 0.2549 0.076e Education > 16 SE 0.010 0.011 0.0221 B 0.0206 -0.1774 0.0221 B 0.0206 -0.1774 0.0221 Non-White SE (0.000) (0.000) (0.003) B | | Education [10,11] | SE | | (0.006) | (0.008) | (0.016) |
| Education Education [13,15] SE (0.007) (0.007) (0.011) Storesf. | | | B | | 0.1110 | 0.0663 | 0.0293 |
| Score m <td>Education Oummies</td> <td>Education [13,15]</td> <td>SE</td> <td></td> <td>(0.007)</td> <td>(0.007)</td> <td>(0.011)</td> | Education Oummies | Education [13,15] | SE | | (0.007) | (0.007) | (0.011) |
| Education = 16 SE (0.009) (0.010) (0.020) B | | | B | | 0.3239 | 0.2050 | 0.1144 |
| B 0.4129 0.2549 0.0768 Education >16 SE (0.010) (0.011) (0.025) BORHT | | Education = 16 | SE | | (0.009) | (0.010) | (0.020) |
| Education >16 SE (0.010) (0.011) (0.025) Increment in the second of the s | | | B | | 0.4129 | 0.2549 | 0.0768 |
| B -0.2006 -0.1774 0.0221 Non-White SE (0.006) (0.006) (0.003) (0.004) scorer, | | Education >16 | SE signer. | | <u>(0.010)</u> | (0.011) | (0.025) |
| See (0.009) (0.009) (0.009) (0.004) socier | | | B | | -0.2096 | -0.1774 | 0.0221 |
| B 0.0174 0.0009 SE (0.000) (0.001) sourt | LACIU-AA UNAB | | SIGNET. | | | (0.008) | <u>[0.034]</u> |
| Sec (0.000) (0.001) source source | _ | | B | | | 0.0174 | 0.0099 |
| B 0.0475 0.0213 SE | lenure | | SE: | | | (0.000) | (0.001) |
| SE (0.002) (0.002) SIGNAF | Average Educ | ation in (one-diait) | B | | | 0.0475 | 0.0213 |
| B YES | Occupational | Group | SE | | | (0.002) | (0.002) |
| SE YES YES YES YES YES sourt | | | B | | | | |
| B 31.22% Adjusted R-Squared SE 5.09% 26.85% 31.22% -1.13% Scier | Time Dummi | 56 | SE | YES | YES | YES | YES |
| Adjusted R-Squared SE 5.09% 28.85% 31.22% -1.13% sicker. B N SE | | | 8 | | | | |
| N SE 43657 43657 43657 43657 | Adjusted R-S | quared | SE | 5.09% | 26.85% | 31.22% | -1,13% |
| N SE 43657 43657 43657 43657 | <u> </u> | | B | | | | |
| | N | | SE | 43657 | 43657 | 43657 | 43657 |

| | | | Table Four - Interactions of City and Human Capital Variables - PSID | | | | | | |
|--------------|-----------------------|---------|---|--------------------------|----------------|--------------------------|----------------|--------------------------|--|
| | | | (5) | | (| 5) | | | |
| | | | Basic Wage Equation with Human Capital Interactions | | Full Inte | ractions | Full Interac | tions (Fixed cts) | |
| | | | No interaction | Interaction with City | No Interaction | Interaction with City | No interaction | Interaction with City | |
| | | I B | 1.8762 | - Outsing | 1.0817 | our and | | Quinny | |
| Constant | | 86 | (0.009) | | (0.030) | | | | |
| | | SIGNIF | | | | | | | |
| City dummy | | B | 0.2502 | | 0.4194 | | 0.1161 | | |
| | | SIGNIF. | | | (0.000) ••• | | • | | |
| | | | 0.1693 | | 0.1507 | | 0.0296 | | |
| SMSA (Non- | SMSA (Non-city) dummy | | (0.006) | | (0.006) | | (0.009) | | |
| ┣─── | 1 | B | -0.2472 | -0 0272 | -02112 | -0.0241 | -0.1781 | -0.0475 | |
| | Experience (0,5) | SE | (0.012) | (0.023) | (0.012) | (0.022) | (0.010) | (0.018) | |
| | | SIGNIF. | | | | | | | |
| | Experience (10, 15) | B SF | 0.13/4 | 0.0408 | 0.0992 | 0.0456 | 10,000 | 0.0464 | |
| | | SIGNIF. | | | | | | | |
| [| | В | 0.2426 | 0.0520 | 0.1664 | 0.0690 | 0.1076 | 0.0350 | |
| | Experience (15,20] | SIGNIE | (0.011) | (0.021) | (0.011) | <u>(0.021)</u> | (0.013) | <u>{0.018}</u> | |
| | | B | 0.2646 | 0.0974 | 0.1663 | 0.0978 | 0.0719 | 0.0650 | |
| Oummies | Experience (20,25) | SE | (0.012) | (0.022) | (0.012) | (0.022) | (0.018) | (0.021) | |
| | | SIGNIF. | 0.2151 | | 0 1912 | 0.0464 | 0.0520 | | |
| | Experience (25,30) | SE | (0.013) | (0.023) | (0.013) | (0.023) | (0.023) | (0.023) | |
| | | SIGNIF. | | * | | - | * | • | |
| | European (20.26) | B | 0.3259 | 0.0599 | 0.1622 | 0.0435 | 0.0001 | 0.0363 | |
| l | Experience (30,35) | SIGNIF | (0.013) | <u>(U.U</u> 24) ** | <u>(0.013)</u> | <u>(CLUZD)</u> | [0.027] | (0.025) | |
| | | B | 0.2546 | 0.1171 | 0.0691 | 0,1106 | -0.0566 | 0.0307 | |
| | Experience >35 | SE | <u>(0.011)</u> | (0.021) | (0.012) | (0.023) | (0.033) | (0.029) | |
| <u>├</u> | + | | 0.3966 | | .0 2954 | 0.0051 | • | 0.0096 | |
| | Education (0,9) | SE | (0.010) | (0.021) | (0.010) | (0.021) | (0.022) | (0.029) | |
| | · | SIGNIF. | | | | | | | |
| | Education (10, 11) | B | -0.2191 | -0.0328 | -0.1565 | -0.0448 | 0.0026 | -0.0131 | |
| | | SIGNIF. | | - (0.013) • | | (U.U10) | | (0.024) | |
| Education | | B | 0.0955 | -0.0123 | 0.0672 | -0.0061 | 0.0196 | 0.0298 | |
| Dummies | Education [13, 15] | SE | <u>(0.009)</u> | <u>(0.016)</u> | (0.009) | (0.016) | (0.012) | (0.017) | |
| | F | B | 0.3193 | -0.0066 | 0.1961 | 0.0257 | 0.1136 | 0.0074 | |
| 1 | Education = 16 | SE | (0.011) | (0.019) | (0.012) | (0.021) | (0.021) | (0.024) | |
| ĺ | | SIGNIF. | | 0.0494 | | 0.0121 | | 0.0004 | |
| | Education >16 | SE | (0.013) | (0.023) | (0.014) | (0.025) | (0.026) | (0.027) | |
| | | SIGNIF. | | | | _ | | | |
| Non White | | B | -0.2032 | | -0.1720 | -0.0200 | 0.0065 | 0.0465 | |
| | | SIGNIF. | (0.006) | | (0.007) | (0.013) | (0.030) | <u>(0.021)</u> | |
| | | B | | | 0.0173 | 0.0004 | 0.0099 | -0.0003 | |
| Tenura | | 8E | | | (0.000) | (0.001) | (0.001) | _ (0.001) | |
| | | SIGNIF. | | | 0.0526 | -0.0156 | 0.0240 | -0.0005 | |
| Average Edu | cation in (one-digit) | SE | | | (0.002) | (0.004) | (0.002) | (0.004) | |
| | | SIGNIF. | | | | . | | * | |
| | | | VEO | | VED | | VE0 | | |
| | | SIGNIF | 153 | | 152 | | 162 | | |
| | | В | | | | | | | |
| Adjusted R-S | quared | SE | 26.2% | | 31.3% | | -1.0% | | |
| | | SIGNIF. | | | | | | | |
| N | | | 43657 | | 43657 | | 43657 | _ | |
| | | SIGNIF. | | | | | | | |

| | | | able Five- I wo Stage Least Squares Estimates (NLSY) | | | | |
|--|--|----------------|--|---|--|------------------------------|---|
| | | | OLS Level Effect | OLS Wage Equation | OLS Wage Equation with AFQT variable | 2SLS (Supply instruments) | 2SLS (Supply and demand instruments)) |
| | | В | 6.6810 | 6.0554 | 6.1001 | 6.0728 | 6.0688 |
| CONS | TANT | SE | (0.027) | (0.143) | (0.144) | _(0.154) | (0.153) |
| | | BONF | | 0.4674 | - | - | - |
| SM | SA A | <u> </u> | 0.1937 | (0.029) | (0.029) | 0.2432 | 0.2560 |
| - Official states of the second states of the secon | | SE BIOME | | | - | - | - |
| | r d | B | | 0.0369 | 0.0149 | 0.0210 | 0.0219 |
| | EXP2 | SE | | (0.062) | (0.062) | (0.063) | (0.063) |
| | | SIGNIF | | | | | |
| | | В | | 0.1563 | 0.1360 | 0.1440 | 0.1452 |
| | EXP3 | SE | | (0.230) | (0.229) | (0.230) | _(0.230) |
| Experience | | SIGNE | ļ | 0.4000 | 0.1105 | | 0.000 |
| GUITHITHES | EVDA | 8 | | 0,1308 | 0.1165 | 0.1348 | 0.1369 |
| | CAP4 | SE | <u>}</u> | [U.235] | (0.234) | [0.230] | (0.230) |
| | | R | t | -0.1133 | -0.1299 | -0,1333 | -0,1338 |
| | EXPS | SE | | (0.240) | (0.239) | (0.240) | (0.240) |
| | | | | | | | |
| | | 8 | | -0.1046 | -0.0494 | -0.0496 | -0.0497 |
| | 0<=ED<=11 | SE | | (0.036) | (0.037) | (0.038) | (0.038) |
| | | SIGNEF | | _ | | | |
| | | 8 | | 0.1391 | 0.0905 | 0.0670 | 0.0865 |
| | 12 <ed<16< td=""><td>SE</td><td></td><td>[0.032]</td><td>(0.034)</td><td>(0.034)</td><td>(0.034)</td></ed<16<> | SE | | [0.032] | (0.034) | (0.034) | (0.034) |
| Dummies | | | | 0.3185 | 0 2278 | 0 2280 | 0.2260 |
| | ED=16 | 9 92 | | (0.046) | (0.049) | (0.049) | (0.049) |
| | 20-10 | 30 | <u> </u> | | | - | |
| | | B | | 0.2624 | 0.1438 | 0.1469 | 0.1474 |
| | 16 <ed< td=""><td>SE</td><td></td><td>(0.064)</td><td>(0.067)</td><td>(0.068)</td><td>(0.068)</td></ed<> | SE | | (0.064) | (0.067) | (0.068) | (0.068) |
| | | SIGNIF | | - | - | - | - |
| | | В | · · · | 0.1393 | <u>-0.0781</u> | -0.0903 | -0.0921 |
| NON-W | VHITE | SE | | (0.024) | (0.026) | (0.031) | (0.031) |
| | | SIGNE | | | | | - |
| TEM | 05 | B | i | 0.0008 | 0.0007 | 0.0007 | 0.0007 |
| ICN | JRE | SE | | 10.000/ | | (0.000) | |
| | | BRUNNF PL | <u> </u> | 0.0380 | 0.0271 | 0.0241 | 0.0236 |
| EDUCATION | IN OCCUP | SF | ╂╾───────── | (0.010) | (0.010) | (0.011) | (0.011) |
| | | SIGNE | l | | | - | |
| | | В | | | 0.0031 | 0.0030 | 0.0029 |
| AFO | at I | SE | | | (0.001) | _(0.001) | (0.001) |
| | | SIGNE | | | | - | |
| | | <u> </u> | <u> </u> | | | | |
| Adjusted R | t-Squared | <u>SE</u> | 1.26% | 12.87% | 13.62% | 12.94% | 12.97% |
| | | 31GN17 | } | ⊢- <u>·</u> | | | |
| N | 1 | SF | 3136 | 3136 | 3136 | 3136 | 3136 |
| | • | SIGNAF | | | | | 1 |
| | | | | | | | |
| /u-Hausman Reject H0 of | Test Statistic. exogeneity if | 8 | | | | 0.73 | 0.01 |
| Þ1. | .96 | <u> </u> | | | 1 | 0.19 | <u>v.</u> #1 |
| | | SKINF | ↓ | | 1 | | <u> </u> |
| | F-STAT for | B | | | | 02.02 | - |
| Results from | variables | SE_ | <u>├</u> ─── | <u> </u> | <u> </u> | <u> </u> | 10.40 |
| First Stage | | 1 51GNIF | ┼──── | | | t | · - |
| Regressions | Adjusted R- | SE | 1 | | 1 . | 10.64% | 11.32% |
| | Squared | - . | + | <u> </u> | 1 | 1 | 1 |

| Constant B 1.6704 Constant SE (0.016) SKM# | -0.1098 |
|---|--------------------|
| B 1.670% Constant SE (0.016) Schuff. | -0.1098 (0.074) |
| Constant B 1.07/05 SE (0.016 SigN# | -0.1098 (0.074) |
| Constant SE (U.010 signer. Observed 6 to 17 years before a move B -0.138 SE Observed 1 to 5 years before a move B -0.130 Signer. Observed 1 to 5 years before a move B -0.130 SE Observed 1 to 5 years before a move B -0.130 Signer. Observed 2 years after moving B -0.130 Signer. Observed 2 years after moving B 0.037(SE Observed 2 years after moving B 0.037(SE Observed 3 to 5 years after moving B 0.0383(Signer. Observed 6 to 17 years after moving SE (0.053) Signer. Observed 6 to 17 years before a move B 0.1693(Signer. Observed 6 to 17 years before a move B -0.159 Signer. Observed 1 to 5 years before a move B -0.159 Signer. Observed 1 to 5 years after moving B 0.0567 Signer. Observed 2 years after moving B 0.0576 Signer. Observed 3 to 5 years after moving SE (0.061) Signer. Observed 6 to 17 years after moving B 0.1177 SE Observed 6 to 17 years after moving SE (0.0557 Signer. < | -0.1098 (0.074) |
| Signifier Image: signifier Observed 6 to 17 years before a move B -0.138 Observed 1 to 5 years before a move B -0.130 Observed 1 to 5 years before a move B -0.130 Observed 1 to 5 years before a move B -0.130 Observed within a year of moving B -0.161: SiGNIF Observed 2 years after moving B 0.037(SE Observed 3 to 5 years after moving SE (0.053) Observed 3 to 5 years after moving SE (0.078) Observed 6 to 17 years after moving B 0.083f Observed 6 to 17 years after moving B 0.069: SiGNIF Observed 6 to 17 years before a move B -0.159 Observed 1 to 5 years before a move SE (0.030) SiGNIF | -0.1098 (0.074) |
| Observed 6 to 17 years before a move B -0.130 SE Move from Non- SMSA to City Observed 1 to 5 years before a move B -0.130 SE Move from Non- SMSA to City Observed 1 to 5 years of moving B -0.161 SE Observed 2 years after moving B 0.037(SE Observed 2 years after moving B 0.037(SE Observed 3 to 5 years after moving SE (0.078) SIGNIF Observed 6 to 17 years after moving B 0.0833(SE Observed 6 to 17 years after moving B 0.0693(SIGNIF Observed 6 to 17 years before a move B -0.057 Observed 1 to 5 years before a move SE (0.030) SIGNIF Observed 1 to 5 years before a move B -0.159 SIGNIF Observed 1 to 5 years before a move SE (0.030) SIGNIF Observed 2 years after moving B 0.0576 SE Observed 3 to 5 years after moving SIGNIF | (0.074) |
| wears before a move SE (0.076 SIGNEF | |
| Move from Non-SMSA to City Observed 1 to 5 years before a move B -0.130 Move from City Observed within a year of moving B -0.161 Observed 2 years after moving B 0.037(Observed 3 to 5 years after moving SIGN#F. | |
| B -0.130 Move from Non-SMSA to City Observed within a year of moving B -0.161 SMSA to City Observed within a year of moving B -0.161 Observed 2 years after moving B 0.037/ Observed 3 to 5 years after moving SE (0.053) Observed 6 to 17 years after moving B 0.037/ Observed 6 to 17 years after moving B 0.038/ Observed 6 to 17 years after moving B 0.169/ Observed 1 to 5 years after moving SE (0.072) SIGNIF | |
| Move from Non-SMSA to City years before a move observed within a year of moving SE signif. (U.046 signif. Observed within a year of moving B -0.161 SE (0.051) Observed 2 years after moving B 0.037/ SE 0.037/ SE Observed 2 years after moving B 0.0337/ SE Observed 3 to 5 years after moving B 0.0337/ SE Observed 6 to 17 years after moving B 0.0337/ SE Observed 6 to 17 years after moving B 0.0693 Observed 6 to 17 years before a move B 0.0693 SIGNIF | -0.1413 |
| Move from Non-SMSA to City Observed within a year of moving B 0.161 Observed 2 years after moving SIGNIF. | (0.044) |
| Move from Non- SMSA to City Observed within a year of moving B 0.161 SE Observed of moving SE (0.051) Observed 2 years after moving B 0.037/ SE Observed 2 years after moving SE (0.053) Observed 3 to 5 years after moving B 0.0833 Observed 6 to 17 years after moving B 0.0833 Observed 6 to 17 years after moving B 0.0833 Observed 6 to 17 years after moving B 0.0693 Observed 6 to 17 years before a move B 0.0693 SKGNIF | |
| Move from Non- SMSA to City year of moving SE (0.051) Observed 2 years after moving B 0.037/ SE 0.037/ SE Observed 2 years after moving SE (0.053) SKM#F. | -0.0939 |
| Move from Non- SMSA to City Stick *** Observed 2 years after moving B 0.037/ SE Observed 3 to 5 years after moving SE (0.053) Observed 3 to 5 years after moving B 0.083: Observed 6 to 17 years after moving B 0.169: Observed 6 to 17 years before a move B 0.057 Observed 1 to 5 years before a move SE (0.041) Observed 1 to 5 years before a move SE (0.030) Observed 2 years after moving SE (0.051) Observed 2 years after moving SIGNIF. *** Observed 3 to 5 years after moving SIGNIF. *** Observed 3 to 5 years after moving SIGNIF. *** Observed 3 to 5 years after moving SE (0.058) SIGNIF. *** *** Observed 6 to 17 years after moving B 0.1177 SE (0.090) SIGNIF. *** Observed 6 to 17 years after moving *** *** Observed 6 to 17 years after moving *** *** Observed 6 to 17 years after moving *** *** | (0.037) |
| SMSA to City Observed 2 years after moving B 0.037/ SE Observed 2 years after moving SE (0.053) Observed 3 to 5 years after moving B 0.083: SE Observed 3 to 5 years after moving SE (0.072) Observed 6 to 17 years after moving B 0.169: SIGNIF. Observed 6 to 17 years before a move B -0.057 Observed 1 to 5 years before a move SE (0.041) Observed 1 to 5 years before a move B -0.159 Observed 1 to 5 years before a move SE (0.030) Observed 2 years after moving SIGNIF. | |
| after moving SE (0.053) Observed 3 to 5 sign# 0 Observed 3 to 5 SE (0.078) years after moving SE (0.078) Observed 6 to 17 B 0.1692 years after moving SE (0.072) Observed 6 to 17 SE (0.072) years after moving SE (0.072) SiGNF | -0.0024 |
| SIGNF. B 0.083: Observed 3 to 5 SE (0.078) years after moving SE (0.078) Observed 6 to 17 B 0.169: years after moving SE (0.072) SIGNF. | (0.040) |
| Observed 3 to 5 years after moving B 0.083: SE Observed 6 to 17 years after moving B 0.169: SIGNIF Observed 6 to 17 years after moving B 0.169: SIGNIF Observed 6 to 17 years before a move B -0.057 Observed 6 to 17 years before a move B -0.057 Observed 1 to 5 years before a move B -0.159 Observed 1 to 5 years before a move B -0.056 Observed within a year of moving SIGNIF | |
| Years after moving SE (0.078) Observed 6 to 17 B 0.169: Years after moving SE (0.072) Observed 6 to 17 SE (0.072) Years after moving SE (0.072) SIGNIF | -0.01/3 |
| Move from City Observed 6 to 17 years after moving B 0.169: SE (0.072 signif. Observed 6 to 17 years after moving SE (0.072 signif. | (0.059) |
| Observed 6 to 17 years after moving B 0.163, SE Observed 6 to 17 years before a move SE (0.072 SIGNIF: ** B -0.057 Observed 6 to 17 years before a move SE (0.041) Observed 1 to 5 years before a move B -0.159 Observed 1 to 5 years before a move B -0.056 Observed within a year of moving SE (0.030) Observed within a year of moving SE (0.051) Observed 2 years after moving B 0.0576 Observed 3 to 5 years after moving SE (0.058) Observed 6 to 17 years after moving B 0.1177 SigNIF: ** ** Observed 6 to 17 years after moving SE (0.105) SigNIF: ** ** Observed 6 to 17 years after moving SE (0.105) SigNIF: ** ** Observed 6 to 17 years after moving SE (0.105) SigNIF: ** ** Observed 6 to 17 years after moving SE (0.105) SigNIF: ** ** Observed 6 to 17 years after moving SE (0.105) SigNIF: ** ** Observed 7 years after moving | |
| years after moving SE (0.072 SIGNIF: ** Observed 6 to 17 B -0.057 years before a move SE (0.041 SIGNIF: ** Observed 1 to 5 B -0.159 years before a move B -0.056 SigNIF: ** B Observed within a year of moving SE (0.051) Non-SMSA Observed 2 years after moving B 0.0576 Observed 3 to 5 SE (0.058) years after moving SE (0.058) SigNIF: ** B 0.1777 Observed 3 to 5 SigNIF: ** Observed 6 to 17 SE (0.090) years after moving SIGNIF: ** Observed 6 to 17 SE (0.1057) years after moving SE (0.1057) SigNIF: ** B 0.1177 years after moving SE <td< td=""><td>-0.0443</td></td<> | -0.0443 |
| SIGNIF: ** Observed 6 to 17 years before a move B -0.057 SigNIF: SE (0.041 SigNIF: SE (0.041 Observed 1 to 5 years before a move B -0.159 Observed 1 to 5 years before a move B -0.056 Observed within a year of moving B 0.0566 Observed 2 years after moving B 0.0577 Observed 2 years after moving B 0.0577 Observed 3 to 5 years after moving SE (0.0587 Observed 3 to 5 years after moving SE (0.0587 Observed 6 to 17 years after moving SE (0.0587 Regressions contains city, SMSA, Education, Experience, Non-white B 0.1177 | (0.059) |
| Observed 6 to 17 years before a move B -0.057 Signif: SE (0.041 Signif: Signif: Observed 1 to 5 years before a move B -0.159 Observed 1 to 5 years before a move SE (0.030) Signif: SE (0.030) Signif: SE (0.030) Observed within a year of moving B 0.0564 Observed 2 years after moving B 0.0570 Observed 2 years after moving B 0.0570 Observed 3 to 5 years after moving SE (0.090) Signif: Signif: Signif: Observed 6 to 17 years after moving SE (0.090) Signif: Signif: Signif: Observed 6 to 17 years after moving SE (0.105) Signif: SE Signif: | 0.4054 |
| vears before a move SE (0.041 Signif. Signif. Observed 1 to 5 B -0.159 years before a move SE (0.030) Signif. SE (0.030) Observed within a year of moving B 0.0564 Non-SMSA Observed within a year of moving B 0.0576 Observed 2 years after moving B 0.0577 Observed 3 to 5 SE (0.090) years after moving SE (0.090) Signif. SE (0.090) Observed 6 to 17 SE (0.090) years after moving SE (0.105) Regressions contains city, SMSA, Education, Experience, Non-white B | 0.1354 |
| Move from City Observed 1 to 5 years before a move B -0.159 Move from City Observed within a year of moving B 0.0564 Move from City Observed within a year of moving B 0.0564 Observed 2 years after moving B 0.0576 Observed 3 to 5 years after moving B 0.0577 Observed 3 to 5 years after moving B 0.1777 Observed 6 to 17 years after moving B 0.1177 SigNiF. | (0.040) |
| Move from City Observed 1 to 5 years before a move B -0.159 Move from City Observed within a year of moving B 0.0564 Observed within a year of moving B 0.0564 Observed 2 years after moving B 0.0576 Observed 2 years after moving B 0.0577 Observed 3 to 5 years after moving SE (0.058 Observed 3 to 5 years after moving SE (0.090) SigNiF. | |
| Move from City years before a move SE (0.030 Move from City Observed within a year of moving B 0.056 Non-SMSA Observed 2 years after moving B 0.057(Observed 2 years after moving SE (0.030 Observed 3 to 5 years after moving SE (0.058 Observed 6 to 17 years after moving SE (0.090) SigNif. | -0.0014 |
| Move from City Non-SMSA Observed within a year of moving B 0.056 SE Observed of moving SE (0.051 Observed 2 years after moving B 0.057(SE Observed 2 years after moving B 0.057(SE Observed 3 to 5 years after moving B 0.177(SE Observed 6 to 17 years after moving B 0.1177(SE Observed 6 to 17 years after moving SE (0.090) SIGNIF. Regressions contains city, SMSA, Education, Experience, Non-white B | (0.029) |
| Move from City Observed within a year of moving B 0.056 Non-SMSA Observed 2 years after moving B 0.057(Observed 2 years after moving B 0.057(Observed 3 to 5 years after moving SE (0.090) Observed 6 to 17 years after moving SE (0.090) SigNif. ** ** Observed 6 to 17 years after moving SE (0.105) Regressions contains city, SMSA, Education, Experience, Non-white B 0.1177 | |
| Move from City Non-SMSA year of moving Userved 2 years after moving SE (0.051 SIGNIF. Observed 2 years after moving B 0.057(SE Observed 3 to 5 years after moving B 0.1777 SE Observed 3 to 5 years after moving B 0.1177 SE Observed 6 to 17 years after moving B 0.1177 SE Regressions contains city, SMSA, Education, Experience, Non-white B | 0.0178 |
| Move from City Non-SMSA Signif. Observed 2 years after moving B 0.057i SE Observed 2 years after moving B 0.177i SE Observed 3 to 5 years after moving B 0.177i SE Observed 6 to 17 years after moving B 0.117i SE Observed 6 to 17 years after moving SE (0.090 SIGNIF. Regressions contains city, SMSA, Education, Experience, Non-white B | (0.037) |
| B 0.0.077 Signif. Signif. Observed 2 years after moving SE (0.058 Observed 3 to 5 years after moving SE (0.090 Observed 6 to 17 years after moving SE (0.090 Signif. ** Observed 6 to 17 years after moving B 0.1177 Signif. ** Observed 6 to 17 years after moving SE (0.105) Signif. ** B 0.1177 Signif. ** Observed 6 to 17 years after moving SE Signif. ** B 0.1177 Signif. ** | 0.0162 |
| after moving SE (0.058 after moving SIGNIF, 0 Observed 3 to 5 B 0.177 Observed 3 to 5 SE (0.090 signif, ** Observed 6 to 17 B 0.1177 Vears after moving SE (0.105) Signif, ** Observed 6 to 17 B 0.1177 Vears after moving SE (0.105) Signif, ** B 0.1177 Second 100 Signif, Closerved 6 to 17 B Vears after moving SE Signif, ** Closerved 6 to 17 SE Vears after moving SE Signif, ** Closerved 6 to 17 SE Vears after moving SE | 0.0163 |
| SIGNIF. SIGNIF. Observed 3 to 5 B 0.177' SE (0.090) SIGNIF. ** Observed 6 to 17 B 0.117' Years after moving SE (0.105) SIGNIF. * SIGNIF. Paragressions contains city, SMSA, B Education, Experience, Non-white SE | (0.044) |
| B 0.1177 years after moving SE (0.090 SIGNIF ** Observed 6 to 17 B 0.1177 years after moving SE (0.105 SIGNIF SE (0.105 SIGNIF SE (0.105 SIGNIF SIGNIF SIGNIF Regressions contains city, SMSA, B SE Education, Experience, Non-white SE SE | 0.1060 |
| years after moving SE (0.090 SIGNIF. Observed 6 to 17 years after moving B 0.117 SE Regressions contains city, SMSA, Education, Experience, Non-white B | |
| Signification ** Observed 6 to 17 B 0.117 Observed 6 to 17 SE (0.105 years after moving SiGNF. SiGNF. Regressions contains city, SMSA, B Education, Experience, Non-white | (0.067) |
| Observed 6 to 17 B U.11/ years after moving SE (0.105 SIGNEF. SIGNEF. SIGNEF. Education, Experience, Non-white SE SE | |
| years after moving SE (0.105 Regressions contains city, SMSA, B | 0.1351 |
| Signer. Regressions contains city, SMSA, B Education, Experience, Non-white SE | (0.079) |
| Regressions contains city, SMSA, B Education, Experience, Non-white SE | i |
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