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Social, Spatial, and Skill Mismatch Among Immigrants and Native-Born Workers in Los Angeles

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Introduction

In February 1998, President Bill Clinton's Initiative on Race came to California to consider the intersection of poverty and ethnicity. The setting could hardly have been more appropriate: while the persistence of lower incomes and less stable employment among communities of color is a nation-wide phenomenon, it is the 1992 civil unrest in the state's largest city, Los Angeles, that drove home the consequences of allowing such difficulties to fester.

Addressing the nation’s continuing inequality will require political will, a difficult challenge in light of the emergence of suburban voters and the nation’s rightward drift (Grant and Johnson, 1994). Yet even if the President's Initiative and other efforts are able to inculcate a new sense that reducing racial differential is an appropriate realm for governmental action, the correct policy approach remains unclear. This is, in part, because racially differential economic outcomes stem from multiple causes, including a variety of different “mismatches” between minority employees and available jobs.

The "mismatch" most commonly examined in both the popular and academic literature is that of skill: when individuals are not qualified for existing jobs, they are likely to settle further down the job queue (if they can find a job at all) and lower (or no) wages will be the result. Another important mismatch, particularly for minority workers, is spatial: when people live far from work, perhaps because the suburbanization of employment has depleted their own neighborhoods of job opportunities, finding and keeping jobs is bound to be difficult.

A final sort of mismatch - one that has received more emphasis in the recent literature and increasingly in the popular press - is “social.”[1] As it turns out, individuals often obtain employment through personal contacts, that is, through their “networks.” However, when personal networks consist of friends and family who are not well-connected to higher income jobs, this may limit success in the job search: searchers will either have both more problems in finding any sort of employment and, when successful, will tend to be placed in less lucrative positions.

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[1]See Abigail Goldman, "A Hidden Advantage for Some Job Seekers," Los Angeles *Times*, Novermber 28, 1997, p. A1, on the how social networks help Latino immigrants secure what she labels "a foot in the employment door" in the Los Angeles area. As we will note below, this "foot in" does not necessarily translate into higher wages.

This paper explores how these various "mismatches" determine labor market outcomes in Los Angeles County. The primary data source, from which we draw individual human capital and social network quality, is the Los Angeles Survey of Urban Inequality (LASUI). We combine this database with both a unique dataset on job location and composition and Census-based data. The combination allows us to create better measures of spatial mismatch than those used in most of the previous literature, including a variable capturing job growth in a localized labor market and an innovative measure of the divergence between the skill base of local residents and the skill requirements of local employment.

The focus throughout is on the *wage* impact of these spatial, skill, and social mismatches. We concentrate on wages rather than employment for several different reasons. First, wage and employment possibilities tend to be correlated by space - where there are more jobs being created, wages will rise - and so wages can be used as a general measure of labor market conditions. Second, wages are a continuous rather than dichotomous variable, allowing us to use a “grouped effects” regression technique that controls for the fact that many individuals are in the same neighborhood and therefore share the same degree of spatial mismatch.[2] Third, the continuity of wages also allows for a finer test of our continuous right-hand variables on spatial opportunity and skill mix.[3]

The results may be summarized as follows. For a sample of employed males, wage differences are indeed impacted by both "pure" spatial mismatch - job growth in the local area - and spatially-based skill differences; equally important, however, is the lack of “high-quality” social networks. However, there are important differences by ethnicity and recency of immigration: network quality matters most for Anglos, spatially-based skill mismatch is important for African-Americans and U.S.-born Latinos, and Asians (and somewhat important for Anglos); job growth *per se* is most important for recent Asian immigrants. On the policy side, these results cast some doubt on strategies which focus purely on business attraction; bringing jobs to a poor community does not insure that the local gaps of skill and networks will be overcome, with the result being employment gains accrue to those who live elsewhere.

The paper develops these points as follows. We begin with a brief review,then explain our data sources and the construction of key variables. We turn next to our regression results, explaining the “grouped” effects methodology and presenting panels for the overall sample and various ethnic groups. Finally, we summarize the results and draw some policy conclusions.

Literature Review

The notion that inner city locations, particularly areas of concentrated poverty can have negative impacts on individual economic performance has a long pedigree in urban political economy. The initial impetus was John Kain’s work suggesting that Blacks fared poorly in the labor market because housing segregation prevented African-Americans from moving in pace with the suburbanization of employment (Kain, 1968). This “spatial mismatch” hypothesis was later stressed by Wilson (1987) and subsequent research has generally demonstrated that inner-city residence has a negative impact on individual economic outcomes (O’Regan, 1993; Ihlanfeldt and Sjoquist, 1990a, 1990b; and Ihlanfeldt, 1992).[4] Yet the basis for this spatial view remains underdeveloped: the regressions testing the effect of location on the

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[2]Control procedures for grouped effects have not yet been developed for the logit-style regressions and logits are necessary for estimating a binary employment probability.

[3]Sexton (1991) also focuses on wages albeit slightly different reasons.

[4]On the other hand, some researchers suggest that it is race, not residence, which is critical to predicting employment; see Acs and Wissoker (1991) and Ellwood (1986). For an excellent overall review of the literature, see Kasarda and Tinj (1996).

labor market have tended to make use of simple city-suburb distinctions, an approach which assumes that there are differentials in job availability between these two broad areas of a metropolitan area rather than making a refined calculation of the exact magnitude and importance of any such differences.[5]

A few recent papers have taken a more nuanced approach. For example, Stoll (1997) has gone beyond city-suburb *per se*, using data from the L.A. Survey of Urban Inequality (LASUI) to look at the impact of job search in several different broad labor markets in Los Angeles. The results suggest that searching in areas distant from black residential areas has a positive effect on blacks' employment and wages, while having a wider spatial job search radius positively affects employment only. Stoll's work builds in part on Raphael (1997a, 1997b) who has suggested that job growth, rather than jobs per resident, is the proper of job availability.[6]

Of course, more complex versions of the spatial mismatch framework focus not just on location but on skill. In particular, analysts stress that the shift in urban areas from blue-collar jobs to white-collar jobs has negatively impacted minority workers. Thus, employment may be spatially available but is functionally inaccessible to geographically proximate but poorly educated residents. A few studies have indeed found a strong imbalance between the number of job seekers and job availability in low-income, inner-city areas. Holzer (1996), for instance, finds that very few jobs (among those that have been recently filled by employers) are available to those with very poor basic skills (e.g. reading/writing, arithmetic, computer use, and the ability to interact with customers), or job related skills (e.g. specific experience or previous training in the job).

Given this insight, some authors have attempted to explicitly compare the demand and supply sides of the labor market. Carlson and Theodore (1995) use the average skill content on jobs, as measured by the Dictionary of Occupational Titles, to determine the extent to which jobs might be available to AFDC recipients.[7] Holzer and Danziger (1997) use the household and employer surveys in the Multi-City Study of Urban Inequality (MCSUI) for Atlanta, Boston, Detroit and Los Angeles to calculate the degree of job availability facing various groups of disadvantaged workers, such as blacks, high school dropouts, and welfare recipients. Results from simulations that "match" workers with jobs on the basis of skills, location/transportation, and racial characteristics suggest that Black workers, high school dropouts, and welfare recipients will have the greatest difficulty finding work.[8] Furthermore, to the extent that many less-skilled workers do find jobs, many receive low starting and few benefits.

Thus, space and skill both matter and intersect. Yet another facet of the dilemma is "social": residents living in areas of concentrated poverty and joblessness may never develop the "network"

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[5]This is particularly problematic since many inner-ring suburbs now suffer from employment challenges and poverty rates that rival those of the inner city (see Orfield 1997 for a general argument and Pastor, Dreier, Grigsby, and Lopez-Garza 1997 for evidence on Los Angeles).

[6]Using data from the 5% PUMS, Raphael compares the employment and activity outcomes of youths living in a low job-growth area to youths living in a high-growth area within the Oakland Primary Metropolitan Statistical Area. Results show that residing in a low employment growth area has a strong negative effect on both the probability of being employed and the probability of being active, defined as being employed or in school. The large negative effect remains when he controls for personal and family background effects. In an earlier paper, Raphael (1997a) establishes a strong correlation between neighborhood youth employment rates and spatial proximity to net employment growth which remains even after he controls for several measures of average neighborhood labor quality.

[7] "AFDC" (or "Aid to Families with Dependent Children") is the former Temporary Assistance to Needed Families program.

[8]The results also suggest that the mismatches will mostly be caused by difficulties that these workers have in gaining jobs that require large numbers of tasks or occupation-specific skills, as well as those located in establishments that currently hire only non-blacks.

contacts necessary to establish a toehold in the labor market.[9] Reviewing a variety of survey results, O'Regan (1993) notes that a vast majority of successful job seekers learn about job opportunities either because they themselves work at an establishment with vacancies or because they know someone who does.[10] Most critically, these networks "are largely determined by location" and "there is a negative externality associated with increased concentration of the poor" (O'Regan, 1993, p. 331). In short, network quality matters to individual job seekers and the economic outcomes of one's neighbors provide either positive or negative externalities (Mattingly 1999).

Building on these insights, Pastor and Adams (1996) try to test for the network effect in Los Angeles. The strategy they use involves a much finer-grained definition of neighborhoods than that in previous literature: instead of simply labeling areas city or suburb, Pastor and Adams (1996) break up L.A. County into fifty-eight different broad "neighborhoods." They then control for both the average travel time in the neighborhood, a standard measure of spatial mismatch, and network quality, proxied by the poverty of the neighborhood in which one lives.[11] The results suggest that network quality matters greatly and, in fact, may even dominate spatial employment gaps in the L.A. setting.

Unfortunately, the Pastor and Adams (1996) results are based on proxies for network. A superior approach is that of Oliver and Lichter (1996), who use the LASUI database to calculate direct measures of both neighborhood context and network quality. Parallel to the results in Pastor and Adams (1996), Oliver and Lichter (1996) find that living in medium and high poverty neighborhoods has an independent negative effect on employment. Controlling for personal characteristics, Oliver and Lichter (1996) also find that certain network characteristics (particularly ties across race and connections to employed individuals) affect employment.[12] These network characteristics are, however, less significant when used to predict wages.

In summary, the literature suggests that spatial, skill, and social mismatches affect individuals economic outcomes. In what follows, we attempt to look at all three of these sorts of mismatches in L.A. County, building on the locational specificity of Pastor and Adams (1996), the focus on job growth found in Raphael (1997a,b), the skill mismatch focus of Holzer and Danziger (1997), and the network quality calculations of Oliver and Lichter (1996). As noted in the introduction, we look at wages for two reasons: (1) wages are a general signal of the condition of the labor market and so should also be positively related to employment;[13] and (2) our attempt to appropriately test for effects shared by individuals in our sample (such as local job growth or the skill mismatch for the neighborhood as a whole) requires the use of a random effects technique which has not been developed for the logistic-style regressions used in estimating employment probabilities.

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[9]An additional factor produced by concentrated poverty is what Acs andWissoker (1991, p. 1) call "a self-perpetuating sub-culture isolated from mainstream society" which may encourage behavior less appropriate at the workplace. Wilson (1996) also stresses the adaptations that occur in communities where work has become increasingly rare.

[10] Employers in, turn, may rely on current employees to provide referrals of new employees, partly to reduce their own cost of information gathering. Montgomery (1991) develops an adverse-selection model that explains why well-connected workers receive higher wages and why firms that hire through referrals earn higher profits. Thus, network reliance maximizes utility on both sides of the labor market: firms minimize costs even as networked workers receive wages beyond what would be predicted based on their individual human capital or skills. For more on networks and job search, see Simon and Warner 1992.

[11]In one set of regressions, Pastor and Adams (1996) use a simultaneous equations (two-stage least squares) approach to control for the fact that economic outcomes, such as wages, determine neighborhood choice as well; the network quality results hold even in that specification.

[12]They also find that ties to those on social welfare have a negative impact on the probability of employment. Another study which finds a strong impact of networks on labor market outcomes, in this case for females, is Johnson et al (1999).

[13] Moreover, at least one key group residing in the inner city of Los Angeles, Latinos, exhibits extremely high rates of labor force participation—and hence a high probability of employment—but also very high rates of poverty (Marcelli, Pastor and Joassart, 1999; Pastor, 1993). In this case the relevant measure of economic well-being may be worker income.

Data Sources and Variable Construction

The basic data source in this analysis is the Los Angeles Survey of Urban Inequality (LASUI). Part of a four-city study, the LASUI includes unique data on network connections as well as educational level, race/ethnicity, and English language skills. While some of these traditional human capital and social category variables are available from the Census and other data sources, the LASUI measures are often better: work experience, for example, need not be proxied by substracting years of schools from age since the LASUI includes information both on when individuals actually began working and on what percent of the time since that start date they have, in fact, been engaged in employment.[14]

Unfortunately, the LASUI also suffers from certain key problems. First, the data base was constructed in such a way that the sample would consist of roughly equivalent numbers of African-Americans, Latinos, Anglos, and Asians; this does not reflect the actual demographics of L.A. County and so the sample must be appropriately (and complexly) weighted in order to do valid cross-tabs and pooled regression analysis.[15] Second, the researchers used a stratified sampling technique to both minimize the costs of data collection on specific ethnicities and to insure that they oversampled the poor; they therefore "clustered" on 91 of the available 1652 census tracts in the County. Because of both problems, regressions using LAUSI generally employ both weighting corrections and a robust standard errors technique to control for the clustering by tract.[16]

Aside from these technical problems, the LASUI is also woefully short on variables which can capture spatial and/or skill mismatch. While individuals are tagged by census tract, the actual character of the census tract location must be constructed through linking various census materials. Unfortunately, the U.S. census files have information on the jobs and incomes of residents that live in a tract but they do not have data on the sort of jobs that exist within the tract. Even if the census did include such job data, the tract is not the right level of analysis: surely, the spatial range for a job search and employment placement is not so constrained that it would fit into the typical Los Angeles census tract of a half-square mile and around five thousand people.

To correct for these problems and build toward some useable measure of spatial and skill mismatch, we decided to combine LASUI with other databases. The first was the Public Use Microdata Sample (PUMS). PUMS consists of detailed census questionaire responses by five percent of the County's population and can be used to calculate certain characteristics by Public Use Microdata Area (PUMA). These PUMAs enjoy a median population of 140,578, and tend to be identifiable neighborhoods (see Table 1 and Figure 1). In our view, such PUMAs are probably the right scale when thinking about accessible local labor markets.[17]

Table 1. 1990 Public Use Microdata Areas in Los Angeles County

PUMA	**POPULATION**	**DESCRIPTION** (Table 1; PUMAs in LA County)

[14]For a good description of the LASUI data set, see Johnson, Oliver, and Bobu(1994).

[15]In our analysis, we use the race normalized person weight, which also corrects for differences in household size as well as racial differentials in the tendency to respond to the survey.

[16]The robust standard errors technique tends to (appropriately) diminish the value of t-statistics.

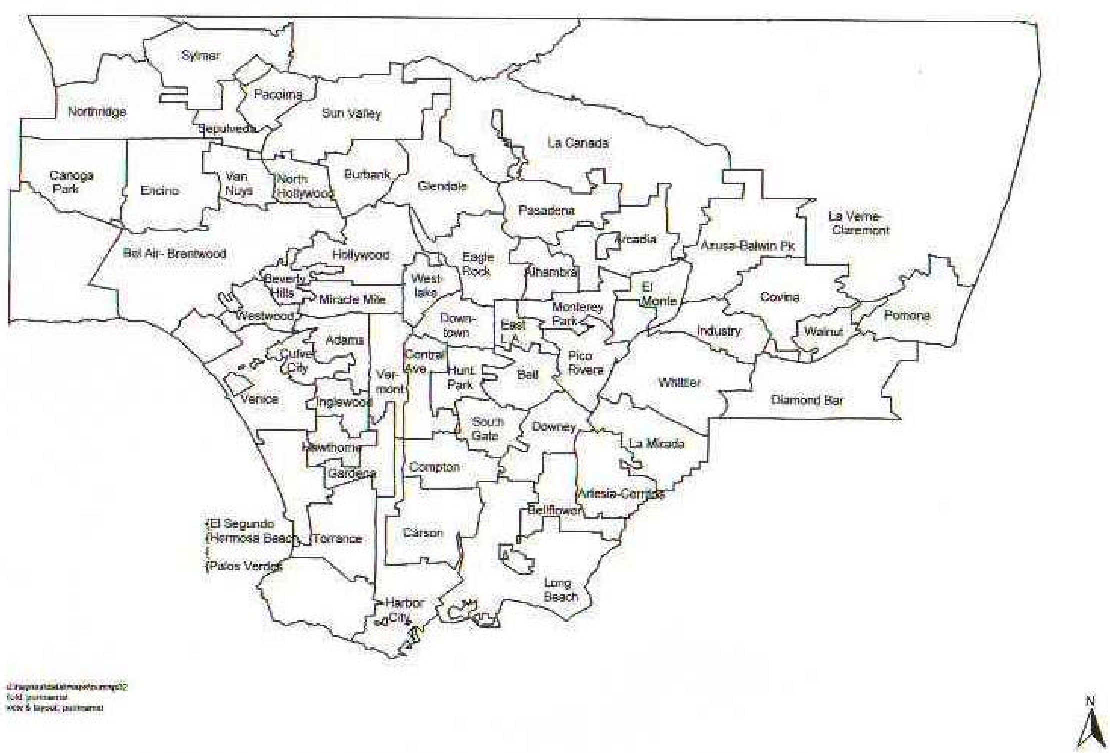
[17]The LASUI database also includes a breakdown of seven job and housing search areas (West San Fernando Valley, Downtown L.A., South Bay, Harbor/Long Beach, Burbank/Glendale, Covina/Industry, and the Westside) but these are rather large as "neighborhoods" and do not cover the whole county.

PUMA	POPULATION	DESCRIPTION (Table 1; PUMAs in LA County)
5200	166,223	Burbank and San Fernando
5300	180,038	Glendale
5400	120,076	Monterey Park and Rosemead
5500	126,379	East Los Angeles
5600	127,934	Huntington Park, Florence-Graham* and Walnut Park*
5700	148,229	Lynwood and South Gate
5800	106,209	El Monte
5900	131,723	Pomona
6000	104,138	Carson and West Carson*
6100	109,602	Inglewood
6200	132,398	Beverly Hills, Culver City, West Hollywood, Ladera Heights*, Marina del Rey*, and View Park-Windsor Hills*
6300	131,591	Pasadena
6401	236,084	Lancaster, Palmdale and various areas in northern central L.A. county*
6402	141,472	Santa Clarita, Val Verde*, and various areas in northwestern L.A. County
6403	139,618	La Canada Flintridge, Monrovia, Sierra Madre, Altadena*, and La Crescenta-Montrose*
6404	106,042	Alhambra and South Pasadena
6405	145,597	Arcadia, San Gabriel, San Marino, Temple City, East Pasadena*, and North El Monte*
6406	139,685	Bell Gardens, Bell, Commerce, Cudahy, Maywood, and Vernon
6407	144,089	Compton, East Compton*, and Willowbrook*
6408	144,711	Azusa, Baldwin Park, Bradbury, Duarte, Irwindale and Citrus*
6409	156,380	Claremont, Glendora, La Verne, San Dimas, and Charter Oak*
6410	103,653	Diamond Bar, La Habra Heights, and Rowland Heights
6411	157,437	Covina, West Covina, and Vincent*
6412	111,998	Industry, La Puente, South El Monte, Avocado Heights*, Valinda*, and West Puente Valley*
6413	159,220	Whittier, Hacienda Heights*, and West Whittier-Los Nietos*
6414	118,741	Montebello and Pico Rivera
6415	114,853	La Mirada, Santa Fe Springs, East La Mirada*, and South Whittier*
6416	163,405	Artesia, Cerritos, and Norwalk
6417	139,113	Downey and Paramount
6418	149,011	Bellflower, Hawaiian Gardens, and Lakewood
6419	152,489	Lomita and Torrance
6420	195,581	Avalon, El Segundo, Hermosa Beach, Manhattan Beach, Palos Verdes Estates, Ranchos Palos Verdes, Redondo Beach, and Rolling Hills Estates
6421	129,410	Gardena, Lawndale, Alondra Park*, West Athens*, and Westmont*
6422	102,219	Hawthorne, Del Aire*, and Lennox*
6423	159,644	Agoura Hills, Hidden Hills, Santa Monica, Westlake Village, and other small parts of Western L.A. County*
6424	103,341	Signal Hill, Walnut, East San Gabriel*, Palmdale East*, and South San Jose Hills*
6501	237,315	Eagle-Rock Glassell, El Sereno, Highland Park, and Lincoln Heights
6502	134,932	Boyle Heights, Downtown, and parts of Wholesale
6503	234,621	Central Avenue-South, Green Meadows, and Watts
6504	169,397	Adams-La Brea and Crenshaw
6505	257,469	South Vermont, Vermont Square, and West Adams-Exposition Park
6506	240,908	Miracle Mile North, Wilshire Center North and South
6507	247,665	Hollywood and part of Los Feliz
6508	188,661	Westlake and Silverlake-Chinatown
6509	150,525	Bel Air, Brentwood Hills, Studio City, Pacific Palisades, and parts of other areas in West L.A. San Fernando Valley
6510	120,242	North Hollywood
6511	100,672	Pacoima
6512	130,700	Van Nuys-Sherman Oaks
6513	103,378	Sepulveda and part of Mission Hills
6514	120,016	Sun Valley and Tujunga-Sunland
6515	111,882	Sylmar, parts of Mission Hills, and Granada Hills

PUMA	POPULATION	DESCRIPTION (Table 1; PUMAs in LA County)
6516	150,541	Canoga Park and Woodland Hills
6517	146,056	Chatsworth, Northridge, and part of Granada Hills
6518	152,805	Encino-Tarzana and Reseda
6519	104,101	Westwood-West Los Angeles, and parts of Brentwood-Sawtelle and Palms
6520	195,481	Barnes City, Mar Vista, Venice, and Westchester
6521	188,031	Harbor City, North Shoestring, and San Pedro
6600	429,433	Long Beach

Notes to table: Areas marked with an asterisk (*) are unincorporated areas of the County, defined here by the names used by the L.A. County Office of Regional Planning. PUMAs 6501 to 6521 are all part of the City of Los Angeles; we offer their neighborhood names which are again taken from the regional planning authorities. When a PUMA includes a very small portion of a neighborhood (and most of the neighborhood is another PUMA), we drop mention here in order to focus on the central character of each PUMA.

Figure 1
Los Angeles County--PUMAs in 1990



Of course, to link the LASUI to PUMS required that we attach to each of the LAUSI tracts its PUMA location. However, we went beyond this limited task and recoded all of the tracts in L.A. County into their respective PUMAs. This allowed us to connect up to tract-level data on employment location available from Southern California Association of Governments (SCAG) and aggregate this to the PUMA level.[18]

This SCAG employment database had both the aggregate number of jobs in each tract in 1990 and the number of jobs in eighty-two different occupations in each tract in that year. We also obtained the 1980 SCAG job count by whole tract; while the 1980 figures did not include the eighty-two industry breakdown available for 1990, this did give us a starting base to calculate a measure of previous local job growth (explained below).[19]

To give an idea of the simplest way in which these various sorts of data were combined to provide for testable measures of spatial and skill mismatch, consider *JOBDENSE*, a measure of "job density" by PUMA. To construct it, we used PUMS to sum up the number of working age individuals in each PUMA; we then took the tract-level SCAG data on jobs, re-tagged all tracts into their PUMAs, aggregated them to obtain the total number of jobs per PUMA, and divided this by the previously determined size of the working age population. Each of the resulting *JOBDENSE* scores were then allocated to individuals in the LASUI database based on their tract, and hence PUMA, location. Note that this implies that many individuals receive the same score because they share the same neighborhood; this created the need for an estimation strategy which could control for "grouped effects" (see below).

As we shall see below, the *JOBDENSE* variable is not actually of much use in explaining economic outcomes. As both Raphael (1997a,b) and Stoll (1997) argue, the more appropriate measure is job growth since this indicates that new vacancies are being created (a circumstance under which wages are more likely to rise). To capture this, we constructed a variable called *JOBGROW* by taking the aggregate 1980 job count by PUMA, comparing it to the 1990 job count by PUMA, and calculating the rate of growth of employment.

Of course, even growth in the aggregate number of jobs does not mean that the resulting jobs are suited to the local residents: one can easily imagine a situation in which there is rapid employment growth but in occupations unlikely to employ low-skill individuals. We therefore sought to create a "dissimilarity index" of jobs and residents entitled *JOBDISSIM*. We began by reworking the industry categories in the SCAG data into seventy-eight industries that were also identifiable in the PUMS data.[20] We then collected by each PUMA the percent of residents employed in each of our industries and compared that to the percent of jobs in each industry in the PUMA. Following the usual logic of dissimilarity measures, the resulting variable is the percent of employed residents that would have to be reallocated such that the percentage of jobs by industry would exactly match the percent of residents identified as being employed in each industry. Note that this variable could equal zero even if the total number of jobs fell far short of

[18]The PUMA designations given by the Census are for partial tract; however, the employment data was only available at the whole tract level. Thus, we recoded at the partial tract level, attached to the partial tract version of the Summary Tape Files to obtain population figures, aggregated these by PUMAs, and double-checked our work by making sure the resulting figures squared with the reported tracts and populations in the PUMS materials. We then ran a program aggregating the partial-tract figures by whole tract, using an algorithm which assigned the PUMA names of the most populous tract in a partial split; this was then connected to the whole tract employment and aggregated by PUMA.

[19]Unfortunately, 1980 and 1990 tracts do not match perfectly, with some 1980 tracts combining into a single 1990 tract, some 1980 tracts splitting into two 1990 tracts, and a smaller number of tracts being created or spliced in a variety of different ways. We tackled this problem by creating a reallocation program which placed 1980 measures into the relevant 1990 tracts and then aggregated these measures by PUMA.

[20]A superior approach would probably consider occupation of residents and local jobs rather than industry but the SCAG data are collected by industry.

the number of employed residents; in short, we are referring here to the composition of employment, not the absolute gap, and hence it is quite appropriate to enter *JOBDISSIM* in regressions which also include *JOBGROW*.[21]

Another measure of spatial mismatch attempts to incorporate skill in its calculation. This is especially important since *JOBDISSIM* could be misleading; consider, for example, an extreme example in which jobs in any industry require exactly the same skills, implying that any “mismatches” in the composition of jobs and residents by industry would actually pose no drag to employment or wages. We therefore constructed a variable entitled *EDGAP* which essentially compares the "supply side" - the average education level of the labor force residing in each PUMA - with what term the “demand side” - employer-required skills in each PUMA.[22] When the gap is larger, the available local jobs are not well-suited for local residents and so wages will be lower.

To give the reader a sense of the parameters of these key variables, we ranked each of L.A.'s 58 different PUMAs by *JOBDENSE*, *JOBGROW*, *JOBDISSIM*, and *EDGAP*. The bottom third of the sample averaged 50 jobs per 100 working age residents, job growth over the 1980s of -6.5 percent, a dissimilarity index of 39, and an education gap of 2.1 years; for the top third, there was an average of 132 jobs per working age resident, job growth of nearly 75 percent, a dissimilarity index of 28, and an education gap of -1 years (that is, the residents were "overeducated" relative to the jobs).[23] That most of these variables may be helpful in explaining economic outcomes is revealed by a simple correlation between each and the poverty rate in each PUMA: with the exception of *JOBDENSE*, every variable is significant in the expected direction (for example, higher job growth, less poverty) at the .01 level.

Regression Results

[21]Of course, *JOBDISSIM* could also be entered with *JOBDENSE* and was in a series of regressions that go unreported here, mostly because *JOBDENSE* was insignificant and the results parallel those we see in the regressions with *JOBDISSIM* and *JOBGROW*.

[22]To determine the supply-side involved a straightforward calculation of the average education levels of the employed and unemployed workers in each PUMA with data taken from PUMS. For the demand-side, we first used the PUMS data to calculate the average educational level of those working in all of our 78 “common” (between SCAG and PUMS) industries in L.A. County, yielding a simple, albeit imperfect, proxy for the educational requirement for each industry. We then combined these County-wide education requirements by industry with weights derived from the SCAG data on the industrial composition of employment within each PUMA to calculate the average education of those working (and not necessarily living) in the PUMA. Subtracting the earlier supply side measure from this demand side proxy, we obtain a spatially-based measure of skill mismatch, *EDGAP*.

[23]Each of the thirds in this sentence is determined separately, that is, the job growth rate is the average for the bottom third when PUMAs are ranked by job growth, the dissimilarity index is the average for the bottom third when PUMAs are ranked by the dissimilarity index, etc.

Of course, correlations between poverty and our spatial variables do not account for either individual-level human capital nor do they directly capture the impact of social networks. We therefore decided to estimate the effects of our various mismatches in a multivariate model of wage determination. The sample consisted of all male, permanent, full-time employees in the LASUI database. The base equation to be estimated was fairly conventional and took the following form:

$$LNWAGE = f(MARRIED, IMMIG, AFAM, LATINO, ASIAN, EDUC, WORKEXP, WORKEXP2, ENGLIMIT),$$

where *LNWAGE* is the log of hourly wages; *MARRIED* is a dummy variable to account for marital status; *IMMIG* is a measure which ranges from 1 to 4 depending on whether the individual is U.S.-born, immigrated prior to the 1970s, immigrated during the 1970s, or immigrated during the 1980s and 1990s (with higher values indicating more recent immigration); *AFAM*, *LATINO*, and *ASIAN* are dummy variables for ethnicity; *EDUC* refers to years of education; *WORKEXP* is work experience in years (properly accounting for any time spent out of the labor market); *WORKEXP2* is the former variable squared (a specification which indicates that returns eventually diminish for each additional year of work experience); and *ENGLIMIT* is a dummy variable that takes on the value of one for those individuals who indicated that they cannot speak English well or very well.[24]

To this base regression, we then added several of the spatial variables discussed above, including *JOBDENSE*, *JOBGROW*, *JOBDISSIM*, and *EDGAP*. We also tried a variable more common in previous literature (see, for example, Ihlanfeldt, 1992): the average commute time to work of the residents of a neighborhood/PUMA. This sort of variable, which we call here *TRAVELTIME*, has been criticized by both Raphael (1997a,b) and Stoll (1997) as a very weak proxy for spatial mismatch. The results below confirm a very weak relationship between wages and *TRAVELTIME*, even though more accurate mismatch measures suggest that space does indeed matter.

We also added a simple measure of network quality, *NETQUAL*. This measure is derived from an effort by Michael Lichter to capture the multidimensionality of network quality by ranking individuals by both the number and "quality" of their ties to others. The characteristics used by Lichter to determine "quality" included relationship, sex, age, race, marital status, employment, education, and welfare receipt; these were calculated for up to each of, then summed over, three friends, relatives, or other persons named by the respondent in LASUI. Lichter's original measure ranged from -4 to 21 in the sample we drew for our regression; given that such exactness draws finer lines of quality than might be appropriate, we decided to create a new variable, *NETQUAL*, which took natural breaks in the numbers and set up simply three categories of network quality (with the higher numbers indicating higher quality).

Given that LASUI has been used to explore network effects by other researchers, it is the use of the spatial and locationally-based skill variables derived from the Census and SCAG data that represents the most novel aspect of this exercise. However, such a combination of the LASUI and other data also presents some serious methodological challenges. Note that several of the key spatial variables are common to all individuals in a "neighborhood," suggesting a violation of the usual assumptions about individual-level variance and uncorrelated error terms necessary for OLS procedures.

The proper way to account for such "grouped effects" is a random effects regression.[25] Unfortunately, such random effects regressions - since they are already correcting to allow group

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[24] The results are not sensitive to drawing the English-limited definition at other levels of English proficiency.

[25] Such a random effects procedure allows us to estimate the impact of the common group characteristic. The procedure is commonly used for time-series, cross-section regressions since a time-invariant cross-sectional characteristics would instead get

characteristics to have an impact - are not amenable to either the cluster/robust errors or weighting strategies generally employed by other researchers using LASUI.[26] To understand the differences between the two techniques in our particular case, Table 2 lays out two simple sets of estimations. The first is merely the base regression above; the second is the base regression with an estimate of job growth. We will come to a discussion of the significance of job growth relative to other spatial variables further below; here, the focus is on the differences between the two estimation techniques.

Table 2. Wage Determination in Los Angeles County
Sample = all male, year-round, full-time Dependent variable = log of hourly wages workers/

EQUATION	(2a) (weighted, clustered)	(2b) (random effects)	(2c) (weighted, clustered)	(2d) (random effects)
MARRIED	0.024 (0.339)	0.142 (3.531) ***	0.022 (0.302)	0.137 (3.397) ***
IMMIG	-0.048 (-1.636) *	-0.107 (-4.814) ***	-0.044 (-1.522) #	-0.104 (-4.714) ***
AFAM	-0.190 (-1.805) *	-0.216 (-3.540) ***	-0.176 (-1.657) *	-0.203 (-3.315) ***
LATINO	-0.217 (-2.709) ***	-0.079 (-1.226) ***	-0.208 (-2.573) ***	-0.072 (-1.114)
ASIAN	-0.036 (-0.253)	0.180 (2.685) ***	-0.031 (-0.216)	0.176 (2.629) **
EDUC	0.049 (2.942) ***	0.057 (8.204) ***	0.048 (2.822) ***	0.055 (8.010) ***
WORKEXP	0.031 (3.719) ***	0.020 (3.915) ***	0.032 (3.706) ***	0.020 (3.838) ***
WORKEXP2	-0.005 (-2.306) **	-2.8E-04 (-2.594) ***	-0.005 (-2.282) **	-0.003 (-2.511) ***
ENGLIMIT	-0.311 (-2.067) **	-0.195 (-3.263) ***	-0.319 (-2.129) **	-0.194 (-3.255) ***
JOBGROW			0.001 (2.074) **	0.001 (2.070) **
Adjusted/Overall R2	0.296	0.351	0.299	0.358
Number of obs.	951	951	951	951
F-value/Chi-square	18.8 ***	369.1 ***	16.7 ***	374.3 ***

*** p > .01. ** p > .05. * p > .10. # p > .20.

We should stress that the estimation of the base regression using random effects, (1b), is strictly speaking unnecessary since there are no grouped effects in that regression;[27] nonetheless, it does offer a baseline for comparing what we term the weighted, clustered approach (using the approach of other LASUI researchers, race-normalized weights to reflect the under- and over-sampling of certain groups and clustering by tract for a robust errors correction), and the random effects approach which employs no such weighting or cluster correction but does appropriately account for grouped effects. The main differences are quickly discernable: in the random effects regression, *MARRIED* is significant while it is insignificant in the weighted, clustered regression; *IMMIG* is more significant in the random effects

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absorbed into a dummy variable if one was to use the traditional, OLS-Dummy Variable (or "fixed effects") procedure. Moulton (1986) was among the first to point out that such a technique might have broad application in straightforward cross-section analysis when data are drawn from a population with a grouped structure. One test to see whether such a technique is appropriate to the data is the Hausman test; such a test was performed after each reported regression with satisfactory results.

[26]Such approaches have been dictated by the stratified sampling of LASUI, particularly because in such circumstances straightforward OLS can improperly swell t-statistics and thereby lead researchers to inappropriately attribute significance.

[27]On the other hand, Moulton (1986) suggests that even inadvertent grouping, such as when individuals in the sample share a particular level of education, could result in distorted results and suggests that random effects be used more frequently.

regression as is *AFAM*; *LATINO* is less significant in the random effects regression; *ASIAN* flips signs from insignificantly negative in the weighted, clustered regression to positive and significant in the random effects regression; and *EDUC* has roughly the same coefficient value in both regressions but is far more significant in the random effects regression.[28]

Interestingly, this pattern suggests that any differences between the random effects and weighted, clustered approach are more likely due to the lack of race-normalized weights than to a clustering problem. To see this, note that since African-Americans are oversampled, *AFAM* is bound to be more significant when race-normalized weights are not used; undersampled Latinos are similarly bound to have their dummy variable fall in significance in the unweighted random effects regression. The oversampled Asians are also likely to have significance increase; the sign flip is likely due to the fact that *IMMIG* is now doing more of the econometric “work” - and a very high percent of the Asians in this sample are immigrants, implying that controlling for that and other human capital variables could lead to a positive effect for being Asian *per se*. The shift in *MARRIED* may also occur because patterns of family formation differ between the ethnic groups while the increase in the significance for *EDUC* reflects the fact that in an unweighted sample, *EDUC* (which also differs systematically by ethnicity) is accounting for part of the divergence between ethnic groups.

Despite these differences, it is important to stress that the main human capital variables have the same sign and roughly similar significance levels in both the weighted, clustered and random effects regressions. Most significantly, this pattern for our individual-level variables holds when we introduce one of the key spatial mismatch variables, *JOBGROW*; note further that the coefficient and significance level on that “grouped” variable is quite similar across the two sorts of specifications. Therefore, with the caveat that the dummy variables for race shift a bit between the two approaches, we are generally safe using the random effects technique, particularly since it is best suited to our specially constructed spatial mismatch variables.[29]

Now that the estimation technique has been established, we turn in Table 3 to an evaluation of some basic measures of spatial mismatch. The first variable, *TRAVELTIME*, is the average commute time to work for the PUMA in which an individual resides; similarly constructed variables have been used elsewhere as a proxy for spatial mismatch (Ihlanfeldt, 1992; Pastor and Adams, 1996). Note that the result is nearly total insignificance; with the t-score scraping zero, one might have concluded that spatial mismatch is also insignificant in Los Angeles County.[30] *JOBDENSE*, the ratio of jobs to working age residents, actually has a perverse sign: where jobs are more plentiful, salaries are lower.

Table 3. Wage Determination in Los Angeles County
Sample = all male, year-round, full-time workers/ Dependent variable = log of hourly wages

EQUATION:	(3a)	(3b)	(3c)

[28]The adjusted R-squared also rises in the random effects (RE) approach, suggesting a better fit, but this is also partly because of the fact that the overall R-squared measure typical of the RE strategy is unadjusted for the number of variables entered.

[29]To double-check our instincts, we always used both approaches in the actual regressions and compared results; because the contrast between the two is nearly always similar to that noted above, we present only the more appropriate random effects results below.

[30]Indeed, in previous work by one of the authors (Pastor and Adams, 1996), we found nearly no impact of spatial mismatch as measured by *TRAVELTIME* in Los Angeles. The more sophisticated measures employed in this piece allow us to better pick up the spatial effect.

MARRIED	0.141 (3.515) ***	0.140 (3.495) ***	0.137 (3.397) ***
IMMIG	-0.107 (-4.801) ***	-0.106 (-4.780) ***	-0.104 (-4.714) ***
AFAM	-0.215 (-3.517) ***	-0.213 (-3.515) ***	-0.203 (-3.315) ***
LATINO	-0.079 (-1.218)	-0.085 # (-1.319)	-0.072 (-1.114)
ASIAN	0.180 (2.680) ***	0.177 (2.638) ***	0.176 (2.629) **
EDUC	0.056 (8.189) ***	0.056 (8.121) ***	0.055 (8.010) ***
WORKEXP	0.020 (3.190) ***	0.020 (3.920) ***	0.020 (3.838) ***
WORKEXP2	-2.8E-04 (-2.589) **	-0.003 (-2.596) ***	-0.003 (-2.511) ***
ENGLIMIT	-0.194 (3.260) ***	-0.192 (-3.221) ***	0.194 (-3.255) ***
TRAVELTIME	0.001 (0.052)		
JOBDENSE		-0.900 (-2.032) **	
JOBGROW			0.001 (2.070) **
Overall R-squared	0.351	0.357	0.358
Chi-square	366.0 ***	378.2 ***	373.9 ***
Number of obs.	951	951	951

*** p > .01. ** p > .05. * p > .10. # p > .20.

However, each sign may indicate less than meets the eye. Average travel time may be a poor measure of spatial mismatch in Los Angeles, a place where commuting long distances is a norm and residence in far-flung suburbs does not seem to dampen some individuals' labor market outcomes. Moreover, the static snapshot given by *JOBDENSE* may not be a good indicator of how spatial mismatch impacts labor market outcomes; wage hikes are more likely in a growing area and the better measure for this would be *JOBGROW*. And, as noted from the first table of regression results and repeated in the third column of Table 3, *JOBGROW* is indeed significant and positive.

Of course, job growth is not enough: vacant jobs in one's local labor market may still be "mismatched" on the basis of industry type and/or skill. We try to get at the former by adding *JOBDISSIM*, a measure that indicates the percentage of residents that would need to reallocate themselves to have a parallel distribution of residents and jobs by industry; we expect that where this is higher, mismatch is higher and wages are lower. When entered by itself, the variable attains a twenty percent level of significance; when entered in conjunction with *JOBGROW*, the t-score falls below one (see the first column of Table 4).

Table 4. Wage Determination in Los Angeles County
Sample = all male, year-round, full-time workers/ Dependent variable = log of hourly wages

EQUATION:	(4a)	(4b)	(4c)

MARRIED	0.134 (3.312) ***	0.128 (3.188) ***	0.127 (3.170) ***
IMMIG	-0.103 (-4.656) ***	-0.103 (-4.637) ***	-0.104 (-4.735) ***
AFAM	-0.191 (-3.061) ***	-0.167 (-2.681) ***	-0.148 (-2.378) **
LATINO	-0.065 (-1.009)	-0.038 (-0.587)	-0.022 (-.328)
ASIAN	0.180 (2.670) ***	0.189 (2.828) ***	0.213 (3.161) ***
EDUC	0.055 (7.905) ***	0.053 (7.637) ***	0.051 (7.382) ***
WORKEXP	0.020 (3.819) ***	0.020 (3.824) ***	0.019 (3.769) ***
WORKEXP2	-2.7E-04 (-2.491) **	-2.7E-04 (-2.525) ***	-2.6E-04 (-2.422) **
ENGLIMIT	-0.019 (-3.210) ***	-0.186 (-3.139) ***	-0.178 (-2.997) ***
JOBGROW	0.001 (1.742) *	0.001 (1.360) #	0.001 (1.500) #
JOBDISIM	-0.006 (-0.942)		
EDGAP		-0.052 (-2.646) ***	-0.052 (-2.811) ***
NETQUAL			0.052 (2.305) **
Overall R-squared	0.360	0.369	0.374
Chi-square	370.4 ***	386.3 ***	411.1 ***
Number of obs.	951	951	951

*** p > .01. ** p > .05. * p > .10. # p > .20.

EDGAP, which directly calculates the difference between the education requirements of local jobs and the educational achievement of local residents, fares better. On it own, it is highly significant and remains so with the inclusion of *JOBGROW* (see the second column of Table 4). Moreover, using both appropriately diminishes the significance of *JOBGROW*, a sensible result given that local job growth is less likely to help wages when there is a significant job-resident mismatch. This result has salience for enterprise zone-style strategies: simply putting the jobs in a neighborhood may not raise employment in the neighborhood itself. We consider such policy implications further in the conclusion.

Network quality also matters, as is evidenced in the last column in Table 4. *NETQUAL* is positively signed and significant when entered into a regression which controls for the spatial and skill mismatch via *JOBGROW* and *EDGAP*.[31] Indeed, the statistical significance of each of the latter variables rises, albeit slightly, when we control for network quality; this suggests that what matters is not only whether jobs are available at the right skill levels in the local labor market but also whether individuals have the proper connections to the world of employment.

Tables 5, 6, and 7 present selected regression results by different ethnic groups; in the case of Latinos and Asians, we also break out the respondents by recent immigrant and U.S.-born/less-recent (pre-1970s) immigrant. We determined a base regression for each group by first running a regression with the full range of the human capital variables, and then dropping those which failed to achieve significance

[31]This variable is significant when entered on its own, a result we do not report since *NETQUAL* enjoys roughly the same coefficient value and significance level as in the reported regression with other variables in Table 4.

(for example, *ENGLIMIT* is not important for Anglos or African-Americans). We then entered our various neighborhood/spatial variables; to conserve space, we report only those results that were significant or indicate important differences between groups.

Table 5 starts with the results for Anglos and African-Americans. For the former group, the entered conventional variables have a statistically significant impact on wages, with the negative impact of *IMMIG* being the weakest. In contrast, only *EDUC* and *WORKEXP* are found to be important in explaining wages for African Americans, with *MARRIED* and *IMMIG* consistently insignificant (in the latter case, probably because there are so few Black immigrants in the sample). Also, the standard specification - in which there are diminishing gains from each additional year of work experience *(WORKEXP2*) - applies to Anglos, but not to African Americans.

Table 5. Wage Determination for African-Americans and Anglos in Los Angeles County
Sample = all male, year-round, full-time workers/ Dependent variable = log of hourly wages

EQUATION	(5a)	(5b)	(5c)	(5d)	(5e)	(5f)
		Anglos				*African-Americans*
MARRIED	0.221 (2.920) ***	0.219 (2.968) ***	0.207 (2.786) ***			
IMMIG	-0.070 (-1.478) #	-0.072 (-1.541) #	-0.067 (-1.428) #			
EDUC	0.090 (5.696) ***	0.088 (5.655) ***	0.084 (5.331) ***	0.122 (4.929) ***	0.108 (4.372) ***	0.104 (4.112) ***
WORKEXP	0.033 (3.073) ***	0.032 (3.139) ***	0.033 (3.163) ***	0.012 *** (3.131)	0.011 (3.034) ***	0.011 (3.003) ***
WORKEXP2	-0.004 (-2.044) ***	0.000 (-2.182) **	0.000 (-2.071) **			
JOBGROW	4.2E-04 (0.586)		0.004 (0.664)	0.001 (0.293)	-4.5E-04 (-0.222)	-0.001 (-0.254)
JOBDISIM	-0.002 (-0.269)			-0.007 (-0.707)		
EDGAP		-0.077 (-2.221) **	-0.065 (-1.844) *		-0.101 (-3.109) ***	-0.098 (-3.027) ***
NETQUAL			0.112 (2.365) **			0.046 (0.776)
Overall R-	0.249	0.263	0.281	0.161	0.202	0.206
Chi-square	75.9 ***	82.0 ***	89.1 ***	34.4 ***	45.3 ***	45.8 ***
Number of	237	237	237	184	184	184

*** p > .01. ** p > .05. * p > .10. # p >

The Anglo and African-American regression also differ with regard to our spatial and network quality variables. For Anglos, *JOBGROW* matters but is not significant; our skill-based mismatch variable, *EDGAP*, has the expected negative sign and is significant while our other mismatch variable, *JOBDISSIM*, is negative but not significant; and *NETQUAL* has a positive and significant effect. For African-Americans, *JOBGROW* is insignificant but *EDGAP* matters greatly, a pattern which squares with the notion that African-Americans in Los Angeles live in areas which are "job-rich" but in employment types not appropriate to the skill base of the residents (Johnson and Farrell 1996; Pastor, Dreier, Grigsby, and Lopez-Garza, 1997).

For Latinos and Asians, we broke each group into (1) U.S.-born and less-recent immigrants, and (2) more recent (post-1970s) immigrants; the results are given in Tables 6 and 7. Starting with Latinos, note that *MARRIED* and *EDUC* has an impact for both groups (1) and (2); for the more established residents, *ENGLIMIT* matters while it makes no significant difference for recent immigrants (and hence is unreported here).[32] *WORKEXP* matters for both groups (1) and (2) but *WORKEXP2* is statistically significant only for recent Latino immigrants. As for Asians, like African Americans, *MARRIED* and *WORKEXP2* were excluded from the regressions since they are statistically insignificant. The wage penalty for limited English ability is significant for both the recent and more established residents.

Table 6 Wage Determination for U.S.-born, Less- Recent Latino Immigrants and Recent Latino Immigrants
Sample = all-male, year-round, full-time workers Dependent variable = log of hourly wages

Equation:	(6a) *U.S.-born and less-recent immigrants*	(6b)	(6c)	(6d)	(6e) *Recent immigrants*	(6f)
MARRIED	0.180	0.156	0.153	0.204	0.203	0.204
	(2.119) **	(1.802) *	(-1.773) *	(2.687) ***	(2.855) ***	(2.824) ***
EDUC	0.047	0.044	0.044	0.022	0.021	0.021
	(3.510) ***	(3.223) **	(3.176) ***	(2.253) **	(2.145) **	(2.116) **
WORKEXP	0.009	0.008	0.008	0.017	0.016	0.015
	(2.408) **	(2.181) **	(2.169) **	(1.314) #	(1.254)	(1.191)
WORKEXP2				-0.001	-0.001	-0.001
				(-1.822) *	(-1.780) #	(-1.672) *
ENGLIMIT	-0.221	-0.210	-0.205			
	(-2.125) **	(-2.019) **	(-1.945) *			
JOBGROW			4.4E-04			0.002
			(0.429)			(0.710)
JOBDISIM				-0.012		
				(-1.026)		
EDGAP		-0.043	-0.040		-0.041	-0.039
		(-1.528) #	(-1.335) #		(-0.982)	(-0.875)
NETQUAL			0.016			-0.020
			(0.302)			(-0.487)
Overall R-squared	0.213	0.228	0.230	0.194	0.192	0.197
Chi-square	40.9 ***	43.2 ***	42.2 ***	27.6 ***	27.3 ***	27.5 ***
Number of obs.	162	162	162	144	144	144

*** p > .01. ** p > .05. * p > .10. # p > .20.

For recent Latino immigrants, all neighborhood variables are signed appropriately but insignificant; for more established Latino residents, *EDGAP* matters much as it does for Anglos and African-Americans. Network quality is positively signed but insignificant for established Latino residents; it is also insignificant but negatively signed for recent Latino immigrants, a result which squares with Falcón's (1995) finding that networks may help Latinos with job connections but not with wages.[33] As for Asians, *EDGAP* matters for the more established residents while both *JOBGROW* and *NETQUAL* matter in a statistically significant way for the more recent immigrants.

Table 7 Wage Determination for U.S.-born, Less Recent Asian Immigrants and Recent Asian Immigrants
Sample = all male, year-round, full-time workers Dependent variable = log of hourly wages

Equation:	(7a) *U.S.-born and Less-recent*	(7b)	(7c)	(7d)	(7e) *Recent Immigrants*	(7f)

[32] While this may not square with some observers' priors, note that: (1) immigrants in this sample are likely to be dominant in their home language, making distinctions by English ability difficult, and (2) many immigrants may not have moved on to employment where English skills matter greatly.

[33] A series of logistic regressions on employment confirm that network quality matters in the probability of employment; as noted in a previous comment, such regressions can only be suggestive since there is no established procedure for controlling for grouped effects in a logit.

	Immigrants					
EDUC	0.032 (1.564) *	0.027 (1.230)	0.027 (1.219)	0.046 (2.145) **	0.047 (2.115) **	0.040 (1.778) **
WORKEXP	-0.004 (-0.713)	-0.004 (-0.694)	-0.004 (-0.682)	0.006 0.973	0.006 (0.944)	0.006 (1.002)
ENGLIMIT	-0.429 (-3.015) ***	-0.401 (-2.758) **	-0.399 (-2.727) **	-0.267 (-2.332) **	-0.261 (-2.283) **	-0.209 (-1.764) **
JOBGROW		2.8E-06 (0.004)	-1.3E-05 (-0.016)	0.002 (3.571) ***	0.002 (3.447) ***	0.002 (3.554) ***
JOBDISIM	-0.030 (-2.268) **			0.010 (0.943)		
EDGAP		-0.111 (-2.114) **	-0.111 (-2.104) **		0.026 (0.590)	0.037 (0.839)
NETQUAL			0.010 (0.133)			0.111 (1.625) **
Overall R-squared	0.214	0.214	0.213	0.247	0.233	0.251
Chi-square	27.5	27.2	27.0	34.8	34.1	37.2
Number of obs.	106	106	106	118	118	118

*** p > .01. ** p > .05. * p > .10. # p > .20.

Stepping back to look at the full pattern of results, four trends stand out. First, the conventional variables used in wage regressions work best for Anglos, and do not fully explain wage determination for other ethnic groups. This suggests that there are different experiences in the labor market which make generalizing from the experience of one ethnic group to that of another somewhat problematic.

Second, among the mismatch variables, our spatially based measure of skill mismatch, *EDGAP*, is clearly an important determinant of wages -- it is statistically significant and robust for all groups, with the exception of recent Asian and Latino immigrants.[34] Skill-based spatial mismatch seems to matter.[35]

Third, note that *JOBGROW* may be correctly signed but it is not statistically significant in distinguishing the experiences of those within an individual ethnic groups (with the exception of Asian immigrants). This may seem puzzling since *JOBGROW* is significant for the full sample. However, note from Table 2 that the coefficients on the dummy variables for ethnicity in the full-sample regressions go down when *JOBGROW* is added to the base regression. This suggests that the growth of local employment is as highly segregated (as is the residential pattern); in the full sample, *JOBGROW* is picking up some of this racial difference or employment mismatch.

Finally, *NETQUAL* is significant only for Anglos and recent Asian immigrants. Moreover, Anglos have much better networks -- 33.3 percent of Anglos had "high quality" ties, compared to approximately 15 percent of African-Americans and Latinos, and 17 percent of Asians. Of course, this does not rule out the potential importance of networks: the ranking method used to construct this variable is somewhat arbitrary and we used it primarily because it is the only available measure of network quality

[34]It is not clear why these two groups would be less affected by an education gap, particularly given the likelihood that they are less likely to have private cars and hence more likely to depend on immediately local employment.

[35]Note, however, that *JOBDISSIM* -- the "dissimilarity index" of jobs and residents -- is consistently insignificant for all ethic groups, confirming the full-sample result that this particular specification of skill-based spatial mismatch is not useful in explaining wage patterns. While we do not report it in the tables, *JOBDENSE* is also found to be mostly insignificant. The only exception is Latinos -- recent as well as less recent immigrants -- for whom this variable is weakly significant with a negative sign. Recall that this was the result for the full-sample (Table 3).

and, having been developed for another project by Michael Lichter, is unpolluted by our own priors regarding the likely effect on network quality on the wages of different ethnic groups.[36]

Overall then, "pure" spatial mismatch (low job growth in one's own neighborhood) is not as significant as usually hypothesized, perhaps because Los Angeles County is a place where commuting is standard; in particular, such a mismatch has little impact on the highest wage earners (Anglos) and, while significant for the sample as a whole, is not particularly significant when distinguishing between the experience of minority workers.[37] This does not imply that space is unimportant: spatially-based skill mismatch is quite important for both African-Americans and longer-term immigrant and U.S.-born Latinos. As for "social mismatch," networks do seem to matter, but do not yield high rewards for most minority workers; they may help connect individuals to employment but the results may not be particularly "good" jobs.

Conclusions

Tackling poverty is a difficult challenge on many levels. The lack of political will is a serious problem, and stems in part from a view that perhaps little can really be done. To be effective, a new approach needs to start by understanding the broader determinants of economic outcomes. Like Wilson (1996), we believe that the broader macro economy is one of the most important factors. Yet differential results also occur because of a series of mismatches of skill, space, and network-based opportunities.

This paper has looked at these three sorts of mismatches in the Los Angeles context. As it turns out, all three matter in a pooled sample of male workers. In ethnic-specific regressions, network quality matters most for Anglos; for African-American workers, the spatially-based skill gap is more important than job growth or networks;[38] for recent Latino immigrants, individual characteristics are more important than space or skill; for longer-term immigrant and U.S.-born Latinos, individual variables (including English ability) play a large role but the locationally-based skill gap also matters; for recent Asian immigrants, being near where the jobs are matters to economic outcomes; for longer-term Asian-origin residents, the spatially-based skill gap matters most.

If job growth was the problem, then the remedy may involve attracting industries back to the inner city, perhaps through tax abatements.[39] But our results suggests that what as much as jobs *per se* is whether the jobs are appropriate to the population. If such skill-based mismatch is the problem, then skill upgrading through job training is necessary, perhaps targeted to the needs of localized firms.[40] Networks are also important although this problem is less amenable to public policy. Still, the creation of “substitute

[36]Preliminary results suggest that while network quality may not affect wages of minority groups, it does affect the probability of finding a job. This is however beyond the scope of this paper, and will be addressed in future work.

[37]This may be because the degree of residential segregation in Los Angeles and the stratified sampling strategy of LASUI - which tended to concentrate sampling of particularly ethnic groups in particular locations - does not allow for as much variation of local job growth within one ethnic group.

[38]This result is a bit surprising in light of the popular notion that African-Americans are being squeezed out of decent employment because of immigrant hiring networks.

[39]Another approach involves enhancing mobility to areas of high job growth; to do this, some suggest improved public transit or while others stress better access to suburban housing, perhaps through stricter enforcement of anti-discrimination laws and/or more mobile Section 8 rent vouchers.

[40]This has been the strategy of *RLA* in Los Angeles. Formed after the 1992 civil unrest, *RLA* initially tried to lure corporate investment to South Central; it subsequently shifted gears and began working on retaining small firms already in the area and redoing job preparation strategies to meet their needs.

networks," as in the sort of direct connections to employers evident in certain job placement and "linkage" programs, may be useful.[41]

Given this pattern, programs such as Center for Employment Training (CET) in San Jose - which worry less about attracting jobs and instead seek to combine hard skill development with improved network contacts to jobs anywhere in the region - might be quite useful in the Los Angeles context.[42] Certainly, a new approach is needed for a region where the economic tide may have come back but some boats remain marooned by decades of previous policy neglect.

[41]Here, mention Frida Molina's (1999) study on job linkage programs.

[42]For a fuller review of the Center for Employment Training, see Melendez (1996).

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