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IMMIGRANT INFLOWS, NATIVE OUTFLOWS, AND THE LOCAL LABOR MARKET IMPACTS OF HIGHER IMMIGRATION

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ABSTRACT

This paper uses 1990 Census data to study the effects of immigrant inflows on the labor market opportunities of natives and older immigrants. I divide new immigrants, older immigrants, and natives into distinct skill groups and focus on skill-group-specific outcomes within cities. An important first question is whether inflows of new immigrants lead to outflows of natives or earlier immigrants in the same skill groups. Even after accounting for endogenous mobility decisions I find that inter-city migration flows of natives and older immigrants are largely unaffected by new immigrant inflows. Inflows of new immigrants are associated with lower employment rates among natives and earlier immigrants, but with relatively small effects on the relative wage structure. The estimates imply that immigrant arrivals between 1985 and 1990 depressed the employment rate of low-skilled natives in major U.S. cities by 1-2 percentage points on average, and by substantially more in high-immigrant cities.

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The rapid rise in U.S. immigration over the past two decades has coincided with a period of stagnating average wages and widening wage inequality (Levy and Murnane, 1992), fueling concern that higher immigration may be responsible in part for the downward trend in labor market opportunities for less-skilled and minority workers. Despite the presumption that immigrant inflows necessarily harm at least some native workers, a growing body of research finds only modest evidence of this effect.[1] The conventional approach in the literature is to correlate the fraction of immigrants in different cities (or changes in this fraction) with corresponding measures of native wages, employment, and unemployment rates.[2] Most studies conclude that a 10 percentage point increase in the fraction of immigrants (roughly the difference between Detroit and Houston) reduces native wages by no more than 1 percentage point. This evidence seems to confirm the rather surprising experiences of Miami in the aftermath of the 1980 Mariel Boatlift. Although the Boatlift instantaneously affected the number of low-skilled workers in the Miami labor force, there was no discernable effect on wages or unemployment rates of less-skilled natives in the city (Card, 1990).

Nevertheless, the entire strategy of estimating the impact of immigration by relating native wages to the fraction of immigrants in different cities has come under criticism, most notably by Borjas, Freeman and Katz (1992, 1996) and Borjas (1994). There are three key conceptual problems in the conventional "cross-market" approach: (1) an increase in the fraction of immigrants in a city does not necessarily imply a net increase in the supply of labor, since natives may move <u>out</u> in response to immigrant inflows; (2) the cross-sectional correlation between immigrant inflows and native wages may be upward-biased by local demand shocks that raise wages and attract in-migrants; (3) any immigration-induced increase in the supply of labor to a particular city can be diffused across the economy by inter-city trade -- a "Heckscher-Ohlin" effect. In light of these problems, Borjas, Freeman

[1]For recent surveys, see Borjas (1994) and Friedberg and Hunt (1995).

[2]Grossman (1982) is one of the earliest studies along these lines. Subsequent research includes Borjas (1987), Lalonde and Topel (1991), Altonji and Card (1991), and Schoeni (1996).

and Katz (1992, 1996) and Borjas (1994) downplay the findings from cross-market studies, and rely instead on a priori theoretical models to deduce the effects of immigration on native opportunities.

In this paper I attempt to re-assess the effect of immigration on the local labor market opportunities of native workers, while addressing some of the limitations of earlier cross-market studies. My starting point is a recognition of the enormous heterogeneity in the pool of U.S. immigrants. As noted by Butcher and DiNardo (1996), the population of immigrants is only slightly less "skilled" than natives, and includes significant numbers of highly-skilled workers. In many cities, immigrants actually earn higher wages than natives. For example, in 66 of the 175 major cities analyzed below, the mean log hourly wage of immigrant men (based on data from the 1990 Census) is higher than the mean log hourly wage of native-born men.[3] Given this heterogeneity, the overall fraction of immigrants in a city is simply too crude an index of immigrant competition for any particular subgroup of natives.

To proceed, I make the simplifying assumption that natives compete most directly with immigrants who would be expected to earn "similar" wage rates in the national labor market. I fit a series of wage equations to samples of native-born and immigrant male and female workers, and stratify individuals into deciles of the resulting predicted wage distribution. Under some simplifying assumptions on technology and tastes, the fraction of a city's population in a particular skill group provides a summary measure of relative local labor market competition. In this framework, immigrant inflows affect the structure of native wages and employment only to the extent that they distort the relative population shares of different skill groups. If immigration leads to a rise in the fraction of workers in a particular skill group, one would expect lower wages for all workers in the group, and a concomitant reduction in the employment-population rate of the group. But a "balanced" inflow of immigrants would not be expected to affect the relative wages of any particular group.

[3]Cities where immigrant men earn more than native men include Baltimore, Buffalo, Cincinnati, Cleveland, Louisville, Memphis, St. Louis, and Wilmington.

This simple model provides a framework for evaluating the role of native out-migration in offsetting the effects of immigrant inflows. In particular, the key parameter of interest is the net number of people in a given skill group added to a city's population when an immigrant moves in. To the extent that immigrant inflows lead to native outflows, or deter natives or other immigrants from otherwise moving into the city, each newly-arriving immigrant will contribute less than one person to the net population of his or her skill group. An analysis of native out-migration patterns also provides an important check on any conclusions about the labor market effects of immigration. If immigrant inflows have a strong effect on the native wage structure, one would expect native out-migration rates to be relatively sensitive to immigrant inflows. Conversely, if native migration patterns are not very sensitive to immigration inflows, one might infer that newly-arriving immigrants exert only modest pressure on local labor market opportunities.

A second departure in this paper is an explicit focus on the impacts of recent immigrants -- individuals who have moved to the U.S. within the past 5 years. This focus is motivated by two factors. On the one hand, recent immigrants tend to earn very low wages and to compete with the most disadvantaged native-born workers. Much of the policy concern over higher immigration is therefore directed toward the labor market impacts of newly-arrived immigrants. On the other hand, because many new immigrants are drawn to "enclaves" established by earlier immigrants from the same source countries, it is possible to develop a measure of the supply-push component of recent immigrant inflows to a particular city that is arguably exogenous to local labor market conditions. Such a measure is needed to identify the causal effect of immigrant inflows in the presence of unobserved city- and skill-group-specific demand shocks.

A final reason for focusing on newly-arriving immigrants is that their impacts may be relatively localized. Given the rapid rise in immigrant inflows over the 1980s, most employers surely did not anticipate the sheer numbers of recent immigrants living in their local labor markets at the end of the decade, and could not have adjusted their product mixes and capital stocks to take advantage of these numbers. Under these circumstances, shifts in the relative supplies of different skill groups induced by recent immigrant inflows would be expected to exert some influence on the local wage structure, even with the inter-city trade and product specialization predicted by standard trade-theoretic models.[4]

I. Theoretical Framework

A convenient framework for analyzing the effect of relative supplies of different skill groups on the relative structure of wages in a local labor market is to treat each city c as an competitive economy with a single output good (Y_c).[5] Assume that Y_c is produced with a production function of the form

$$Y_c = F(K_c, L_c),$$

where K_c is a vector of non-labor inputs (capital, etc.) and L_c is a CES-type aggregate of the quantities of labor N_{jc} in various skill categories j=1,...J:

$$L_c = [\ \Sigma_j\ (e_{jc}\ N_{jc})^{(\sigma-1)/\sigma}\ ]^{\sigma/(\sigma-1)} .$$

The variables e_{jc} represent city- and skill-group-specific productivity shifters, while the parameter $\sigma > 0$ is the elasticity of substitution between different skill classes. If w_{jc} represents the wage rate of skill group j in city c and q_c is the selling price of output from city c, then the condition that the marginal product of each type of labor is equal to its real product wage can be re-written as

$$\text{(1)} \qquad \log N_{jc} = \theta_c + (\sigma-1) \log e_{jc} - \sigma \log w_{jc} ,$$

where

$$\theta_c = \sigma \log [\ q_c\ F_L(K_c,L_c)\ L_c^{1/\sigma}\ ]$$

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[4]There is surprisingly little evidence on the extent of product-mix specialization at the city level. Altonji and Card (1991) show that low-wage manufacturing industries increased their relative employment <u>shares</u> between 1970 and 1980 in high-immigrant cities relative to low-immigrant cities. The actual changes in the <u>levels</u> of employment in these industries, however, are small (and in some cases even negative), suggesting that low-wage industries could not have absorbed large inflows of immigrants.

[5]I discuss the important conceptual limitations of the single good assumption below.

represents a common city-specific component shared by all skill groups.[6] Notice that equation (1) is not a "proper" labor demand function because the common component θ_c is itself a function of the full set of city-specific wages and the prices of non-labor inputs and outputs. Nevertheless (1) expresses the effect of the local wage structure on the relative demand for different skill groups, taking as given the level of output, total aggregate labor input (L_c), and the price of output.

Let P_{jc} represent the population of workers in skill group j in city c, and assume that the employment-population rate of a skill group is a simple function of its wage:

(2) $\log (N_{jc}/P_{jc}) = \epsilon \log w_{jc}$,

where $\epsilon>0$. Combining equations (1) and (2) leads to the following expressions for the wage rate and employment-population rate of skill-group j in city c:

(3) $\log w_{jc} = 1/(\epsilon+\sigma) \{ (\theta_c - \log P_c) + (\sigma-1) \log e_{jc} - \log (P_{jc}/P_c) \}$,

(4) $\log (N_{jc}/P_{jc}) = \epsilon/(\epsilon+\sigma) \{ (\theta_c - \log P_c) + (\sigma-1) \log e_{jc} - \log (P_{jc}/P_c) \}$,

where P_c is the total population in city c. In this model the structure of relative wages and employment is determined by three factors: a common city-specific component (which is itself endogenous); a skill-group and city-specific productivity component; and the relative population shares of the various skill groups. The CES functional form implies that deviations of each group's relative wage from the city-wide average depends only on the group-specific productivity component, and on the group's relative population share.

Equations (3) and (4) are used as the basis for the empirical work in this paper. Specifically, assume that the productivity effect can be decomposed as

$$\log e_{jc} = e_j + e_c + e_{jc}',$$

[6] If other factors are ignored (i.e. $Y_c=L_c$) then $\theta_c = \sigma \log q_c + \log L_c$. Alternatively, if $F(K_c,L_c) = K_c^{1-\gamma}L_c^{\gamma}$ then $\theta_c = \sigma \log(\gamma q_c Y_c/L_c) + \log L_c$.

where e_j represents a common skill-group effect, e_c is a shared city-effect, and e_{jc}' represents a skill-group- and city-specific productivity term. Let $f_{jc} = P_{jc}/P_c$ denote the fraction of the population of city c in skill group j. Then (3) and (4) can be re-written as simple regression models of the form

(3') $$\log w_{jc} = u_j + u_c + d_1 \log f_{jc} + u_{jc},$$

(4') $$\log (N_{jc}/P_{jc}) = v_j + v_c + d_2 \log f_{jc} + v_{jc},$$

where u_j, v_j, u_c, and v_c are skill-group and city "fixed effects",

$$u_{jc} = (\sigma-1)/(\epsilon+\sigma)\, e_{jc}'$$

$$v_{jc} = \epsilon\, (\sigma-1)/(\epsilon+\sigma)\, e_{jc}'$$

are unobserved error components, and the coefficients d_1 and d_2 are functions of the elasticities of substitution and supply: d_1=-1/(ϵ+σ); d_2=-ϵ/(ϵ+σ). Note that the city effects absorb any city-wide variables that might otherwise influence the levels of wages or employment in the local labor market. Any skill-group-specific local productivity shocks, however, still appear in the error components. This fact must be kept in mind in estimation, since one might expect a positive local productivity shock to both raise wages <u>and</u> attract in-migrants in the particular skill group. In this case, the error components in equations (3') and (4') will be positively correlated with the population shares f_{jc}, leading to a positive bias in the estimates of the coefficients d_1 and d_2. As discussed in more detail below, this bias can be reduced or eliminated if there is an instrumental variable that is correlated with f_{jc} but uncorrelated with the city- and skill-group-specific productivity shock. The "supply-push" component of the immigrant inflows to a particular city is a potential candidate for such a variable.

<u>Allowing for Heterogeneity within Skill Groups</u>

The model developed so far assumes that individuals in a given skill group are all identical. While this may be a reasonable assumption in some contexts, here I combine native and immigrant men and women who earn similar hourly wage rates into the same skill groups (see below). A problem then arises because men and women who earn similar hourly wages tend to work different hours on average, implying that a simple "head count" is an incomplete measure of the supply of labor in a particular skill group.[7] A relatively simple extension of the model suggests a way to correct for heterogeneity within skill groups. Specifically, suppose that there are K subgroups within each skill group, and that the relative productivity of the kth subgroup of the jth skill class is α_{jk}, with $\alpha_{j1}=1$ as a normalization. (Differences in α may reflect differences in average hours of work and/or differences in productivity per hour). Assuming that individuals in different subgroups of the same skill class are perfect substitutes in production, the annual wages of different subgroups must satisfy

$$w_{jck} = \alpha_{jk}\, w_{jc}\ ,$$

where w_{jc} is the wage of the 1st subgroup of the jth skill class in city c. If N_{jck} workers of the j,kth group are employed in city c, the total number of efficiency units of labor of the jth skill class is

$$N_{jc} = \Sigma_k\, \alpha_{jk}\, N_{jck}\ .$$

Since employers are indifferent between hiring individuals from different subgroups within any skill group, the marginal productivity condition (1) continues to describe the relationship between the number of efficiency units of labor of skill group j and the standardized wage for the skill group.

The labor supply equation can also be modified to allow for heterogeneity with skill groups. In particular, assume that the fraction of individuals in group j,k who work in a given year is

$$\text{(5)} \qquad \log\,(N_{jck}/P_{jck}) = a_{jk} + \epsilon \log w_{jck}\ .$$

Then the aggregate supply of efficiency units of labor of skill level j is

$$\text{(6)} \qquad \begin{aligned} N_{jc} &= \Sigma_k\, \alpha_{jk}\, N_{jck} \\ &= P_{jc}\, w_{jc}^{\epsilon} \times \Sigma_k\, a_{jk}\, \alpha_{jk}^{\epsilon+1}\, S_{jck}\ , \end{aligned}$$

where $S_{jck} = P_{jck}/P_{jc}$ is the relative fraction of subgroup k in the jth skill class. Equation (6) differs from equation (2) by an "adjustment factor"

$$A_{jc} = \Sigma_k\, a_{jk}\, \alpha_{jk}^{\epsilon+1}\, S_{jck}$$

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[7] In addition, women have lower employment-population rates, violating the homogeneity assumption implicit in the labor supply equation (2).

which reflects the composition of the jth skill group in a particular city, and the productivity and taste variables a_{jk} and α_{jk}. Combining equations (1) and (6) and decomposing the productivity term e_{jc} as above leads to the following modified versions of equations (3') and (4'):

$$\text{(3'')} \qquad \log w_{jck} = u_{jk} + u_c + d_1 (\log f_{jc} + \log A_{jc}) + u_{jc},$$

$$\text{(4'')} \qquad \log (N_{jc}/P_{jc}) = v_{jk} + v_c + d_2 (\log f_{jc} + \log A_{jc}) + v_{jc},$$

where u_{jk} and v_{jk} are now subgroup-specific intercepts. Consideration of within-group heterogeneity leads to an augmented measure of relative supply, but otherwise leaves the basic implications of the model unchanged.

Notice that if the sub-group composition of different skill classes is approximately constant across cities, then the adjustment factor A_{jc} will be roughly constant. Otherwise, it is necessary to estimate the relative productivity "weights" $a_{jk}\,\alpha_{jk}^{\epsilon+1}$. Simple estimates can be formed by taking mean annual earnings for each subgroup in a given skill class and subtracting mean earnings over all subgroups in the skill class.[8] In the analysis below I use estimates of this form, along with information on the shares of different subgroups in different cities, to estimate the supply-correction terms A_{jc}.

Limitations of the Model

Before proceeding to the data analysis it is useful to underscore some of the limitations of the theoretical framework underlying equations (3) and (4). Perhaps the most important conceptual issue is the assumption of only one output good per city. More generally, the demand for labor in any city is generated by many different industries, some of which produce goods or services that can be exported to other cities. In this situation, one would expect some of the local impact of an increase in the relative fraction of the population in a given skill group to be mitigated by the expansion of export industries that use the relatively abundant skill-group more

[8]This follows from the observation that the labor supply equation (5) can be re-written as

$$\log (w_{jck} N_{jck}/P_{jck}) = \log (a_{jk}\,\alpha_{jk}^{\epsilon+1}) + (1+\epsilon) \log w_{jc} .$$

The left-hand side of this expression can be interpreted as the log of per-capita earnings of subgroup k in skill class j in city c (including 0's for non-workers). Thus, intra-city differences in the log of mean per-capita earnings between subgroups of a given skill class are proportional to the relative productivity "weight" $a_{jk}\,\alpha_{jk}^{\epsilon+1}$.

intensively.[9] As noted earlier, it seems unlikely that employers could have fully adjusted their product mixes by the late 1980s to accommodate all the changes in relative labor supplies induced by immigration over the decade. Nevertheless, employers in many "immigrant gateway" cities could have anticipated some fraction of the inflows and relative supply shifts that actually occurred, leading to some product specialization and a lessening of any immigrant impact on the relative wage structure. Estimates of the effects of immigrant inflows derived from equations (3') and (4') are therefore likely to be smaller than the effects that would emerge with a fixed industry structure.

A second limitation of the model is the assumption (implicit in the CES functional form) that the relative wage of a particular skill group depends only on the relative population share of that group. More generally, one might expect a rise in the share of any given skill group to exert some influence on the wages of "similar" skill groups.

A final limitation of the theoretical framework is that by focussing on relative skill-group shares and the relative wage structure, the model provides little guidance on the magnitude of the effect of an increase in the supply of a particular skill group on the level of wages.[10] Estimates of the parameters of equations (3') and (4'), which contain unrestricted city effects, are not strictly comparable to estimates of the impact of higher immigration in the existing literature, which are based on comparisons of the levels of wages and employment rates of different groups across cities.

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[9]Standard trade theory results imply that if each industry has the same production function in all cities, and there are enough different tradeable goods with sufficiently diverse production technologies, and relative supplies of different skill groups are not "too" unbalanced, then in the long run one would expect the same wages in all cities regardless of the skill proportions in particular labor markets. See Leamer (1995) for a rigorous statement.

[10]Estimates of the parameter σ provide only part of the information needed to evaluate the elasticity of labor demand for a particular skill group. Altonji and Card (1991) present a model with 2 skill groups that illustrates the full effect of an inflow of labor on the level of wages.

II. Data Description and Implementation Issues

The empirical analysis in this paper uses individual micro data from the 1990 Census. All labor market outcomes refer to 1989. Throughout the paper, I restrict attention to men and women between the ages of 16 and 68 in 1990 with at least one year of potential labor market experience as of 1989. I use total annual earnings information (including self-employment and wage and salary earnings) together with data on weeks worked and hours per week over the year to construct an hourly wage measure and a simple indicator for employment status (based on reporting positive earnings and hours for 1989). The Data Appendix provides more detailed information on the sample extracts: I use 100 percent of all foreign-born individuals in the 5-percent public use micro samples (roughly 840 thousand observations), and a 25 percent random sample of all U.S.-born individuals (roughly 1.8 million observations).

Defining Local Labor Markets

An immediate issue in any study of local labor markets is how to define separate markets. Large urban agglomerations (such as the New York metro area) pose a particular problem: at one extreme, the entire area can be considered as a single labor market; at the other, individual cities within the metro area can be treated separately. In this paper I consider each Metropolitan Statistical Area (MSA) as an "independent" labor market. I also consider individually-identified cities within any larger agglomeration of cities as separate local labor markets. For example, New York City, Nassau and Suffolk Counties, and Newark are each considered as separate cities, although all three belong to the New York Consolidated Metropolitan Statistical Area (CMSA).[11]

[11]Other examples include Dallas and Fort Worth; and San Francisco, Oakland, and San Jose. There is some degree of arbitrariness in whether larger areas are broken into separately identified sub-units. According to the Census Bureau, metro areas with a million or more people may be subdivided if population and commuting criteria are met and if there is local political support for the separate entities. (US Census Bureau, 1996).

A total of 324 individual MSA's and sub-cities within CMSA's are identified on the 1990 Census public-use files.[12] Since the sample sizes for many of the smaller cities are limited, I decided to restrict attention to the 175 largest cities, ranked by the number of native-born adults in the city. Using this criterion, the three smallest cities included in the sample are Burlington (North Carolina), Des Moines (Iowa), and Ann Arbor (Michigan), while the three largest cities excluded from the sample are Naples (Florida), Boulder (Colorado), and Fort Pierce (Florida). A list of the cities included in the sample is presented in Appendix Table 1 of an earlier version of this paper (Card, 1996).

Table 1 presents some descriptive information on the characteristics of U.S. adults who lived in the largest 175 cities and elsewhere, along with comparisons between natives and immigrants in the larger cities. About 65 percent of the adult population resided in larger cities in 1990.[13] Residents of larger cities are more likely to be black, Hispanic, and foreign-born, and are slightly better-educated than other adults. The employment-population rate and average hours of work of big-city residents and other adults are very similar, although hourly wages are about 25 percent higher in larger cities.

In 1990, 13 percent of the adult population of the 175 largest U.S. cities were born abroad. Of these, about one-fifth arrived in the U.S. between 1985 and 1990. The three right-hand columns of Table 1 illustrate some of the similarities and differences between natives, recent immigrants, and immigrants who arrived before 1985. Two major differences between the native-born and either immigrant group are ethnicity and education: immigrants are 10 times more likely to be of Hispanic ethnicity, and have 1-2 years less education on average. Differences in ethnicity and education between newer and older cohorts of immigrants are much narrower.

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[12]Some individuals who live in geographic areas that straddle an MSA boundary (or boundaries) are not assigned an MSA in the public use micro samples. As explained in the Data Appendix, in cases where more that one-half of the population of such an area live in one MSA, I assigned all the individuals in the geographic area to that MSA.

[13]The rest of the population consists of individuals who do not live in MSA's or CMSA's (25 percent of the population) and individuals who live in smaller MSA's (10 percent of the adult population).

In terms of their labor market outcomes natives and pre-1985 immigrants fare about as well, whereas recent immigrants fare relatively poorly. The similarity in labor market status of older immigrants and natives is illustrated by the wage distribution data in Table 1. Although pre-1985 immigrants earn slightly lower wages than natives, the degree of overlap between the two groups' wage distributions is substantial. By comparison, over 40 percent of recent immigrants earned wages in the bottom two deciles of the overall wage distribution.[14]

Another difference between native workers, on one hand, and immigrants, on the other, is geographic distribution. Over one-third of all immigrants in the U.S. lived in the four "traditional gateway" cities of Los Angeles, New York, Chicago, and Miami in 1990, compared with only about 10 percent of natives. Immigrants and natives also differ in their inter-city mobility rates. As shown in the bottom row of Table 1, about 20 percent of the adult population reported living in a different city in 1990 than in 1985.[15] Even though natives are better-educated and slightly younger than pre-1985 immigrants (both factors that normally increase migration rates), a smaller fraction of natives left their 1985 city of residence by 1990. The mobility patterns of both groups are discussed in more detail below.

<u>Defining Skill Groups</u>

A second issue in any study of the labor market impacts of immigration is the choice of skill categories. Much of the existing literature distinguishes between immigrants, on one hand, and various sub-groups of natives, on the other (e.g. Borjas 1987, Altonji and Card 1991, Lalonde and Topel 1991, Schoeni 1996). As noted in the discussion of Table 1, however, immigrants as a whole are remarkably diverse. Even among the population of recent immigrants there is a significant minority of highly educated workers who compete most directly with

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[14]Butcher and DiNardo (1996) graph the densities of wages for natives, all immigrants, and recent immigrants in 1960, 1970, 1980, and 1990. Their findings are consistent with those in Table 1.

[15]The Census form asks each individual where they lived in 5 years ago, and the public-use micro data samples report "Public Use Micro data Area" (PUMA) identifiers for 1985 place of residence. I assigned these to MSA's using the mapping between PUMA's and MSA for 1990 place of residence.

native workers at the top of the skill distribution. An alternative to treating immigrants and natives as different skill groups is to define skill categories within which immigrants and natives are substitutes, and to consider immigrant inflows as shifting the supply of labor in particular skill categories. This approach narrows the focus of the analysis to the particular groups of natives most directly competitive with immigrants, at the cost of some arbitrariness in the definition of skill groups.

A particularly simple way to define skill groups is to assume that individuals who earn similar hourly wage rates are close substitutes. This is clearly an over-simplification: for example, 1990 census data show that business services sales representatives and electricians earn very similar average wages, although one might not expect individuals in the two occupations to compete for the same jobs. At the bottom of the labor market, however, it may be more reasonable to assume that individuals in low-skill manufacturing jobs, food services, child care, and various personal services occupations are in more-or-less direct competition. I present some direct evidence on this hypothesis below.

To operationalize the notion of skill categories based on "similar" wages, I first estimated a series of wage prediction models using national samples of native and immigrant men and women in the largest 175 cities. The native wage models (one for each gender) included dummy variables for individual years of education, a fourth-order polynomial in potential labor market experience, dummies for black, Asian, and aboriginal race and Hispanic ethnicity, dummies for marital status, disability status, and veteran status, and interactions between education and experience, education and race, and race and marital status. The models also include a complete set of unrestricted intercepts for the 175 individual cities. The models for male and female immigrants included the same basic covariates, plus dummy variables for 17 different origin countries (or groups of countries), a full set of interactions of the origin dummies with a quadratic function of the number of years since immigration to the U.S., and interactions of various origin groups with education.[16] I then used the estimated coefficients from these four models to assign a predicted wage to each adult (workers and nonworkers). In forming the predicted

[16]The origin groups are explained below. See Appendix A for a full description of these models.

wage I used a weighted average of the intercepts for the 175 individual cities, with weights equal to the fractions of native men in each city. This procedure assigns each person a predicted wage in a fixed "national" labor market. Finally, I determined the deciles of the predicted wage distribution for the entire population of workers, and assigned each individual to a particular decile.

Table 2 summarized the characteristics of individuals in each "skill group". As expected, individuals in higher skill groups are older, better-educated, and less likely to be black or Hispanic. A more surprising result is that the fraction of women follows an inverted U-shape across the deciles. This pattern arises because even though the mean predicted wage is higher for men, the distribution of predicted wages is less variable for women, leading to relatively fewer women in the lower tail of the predicted wage distribution.[17] The employment-population rate, average annual hours of work, and mean wages all increase steadily across the predicted wage deciles.

The fraction of immigrants is highest in the lowest skill groups but remains relatively constant across the top 5 skill categories. The composition of immigrants in the different skill groups varies dramatically, however, with many fewer recent immigrants and Mexican-born immigrants in the higher skill categories. Finally, it is worth noting that the delineation of skill groups based on the predicted wage distribution for workers leads to slightly more than 10 percent of the overall population in each of the four lower skill categories (see the bottom row of Table 2).

Do Natives Compete with Immigrants in the Same "Skill Group"?

For "skill groups" to be interpreted in the framework of the theoretical model presented in Section I, individuals in the same skill group must compete directly for the same jobs. Contrary to this assumption, some

[17]The standard deviation of predicted wages for men is about 0.42; the standard deviation of predicted wages for women is about 0.32. The gap arises because men have slightly more variable wages than women and because the prediction equations have higher R-squared's for men (0.37 for both native and immigrant men) than women (0.26 for both native and immigrant women).

researchers have argued that less-skilled immigrants do not compete for the same jobs as less-skilled natives.[18] How realistic is the supposition that natives and immigrants with similar wages actually compete with one another? One way to answer this question is to consider the extent to which they work in similar occupations. Assuming that people compete for jobs with other individuals in the same occupation, a higher degree of similarity in occupational distributions of two groups suggests a higher degree of competition between the groups.

Altonji and Card (1991) develop an index that provides an interpretable measure of occupational similarity between immigrant and native workers. Let f_i^1 and f_i^2 denote the fractions of groups 1 and 2 (e.g. natives and recent immigrants) employed in occupation i, and let f_i denote the fraction of the overall workforce employed in this occupation. Now consider an increase in the population of group 1 that generates a 1 percentage-point increase in the total workforce. Assuming that the new members of group 1 adopt the same occupation distribution as the existing members of the group, the percentage increase in the workforce of occupation i is f_i^1/f_i. For members of group 2, the weighted average increase in the supply of labor to their occupation-specific labor markets is

$$I_{1,2} = \Sigma_i f_i^2 f_i^1 / f_i .$$

Note that if $f_i^2 = f_i^1 = f_i$, corresponding to the situation in which both groups have the same occupational distribution as the overall workforce, the index takes a value of 1. On the other hand, if groups 1 and 2 work in completely different occupations, then the index is 0. Finally, $I_{1,2}$ can be bigger than 1 if groups 1 and 2 have similar occupation distributions and if both groups are concentrated in a subset of occupations.[19]

To evaluate the relative degree of competition between groups 1 and 2, consider the normalized index

$$R_{1,2} = I_{1,2}/I_{1,1}.$$

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[18] See e.g. Bailey (1985,1987). Fix and Passell (1994, Table B-7) review some of the ethnographic studies of native/immigrant competition.

[19] Holding constant the fraction of groups 1 and 2 in the entire workforce, the maximum value of the index occurs when groups 1 and 2 both work in only one occupation, and no other groups work in this occupation.

If $R_{1,2}$ is close to 1, then an expansion of the workforce of group 2 has about the same effect on occupation-specific labor markets for group 1 as an expansion in the labor force of group 1 itself. By comparison, if $R_{1,2} = 0.5$, then an increase in the population of group 2 has only one-half as big an effect on group 1 as an expansion of group 1 itself. Note that $R_{1,2}$ can be bigger than 1 if group 2's occupational distribution is even more concentrated in those occupations in which group 1 is relatively concentrated.

The first three columns of Table 3 present estimates of the own-indexes I_{gg} for native workers, older (pre-1985) immigrants, and recent immigrants, based on the 3-digit occupation distributions of the three groups.[20] Columns 4 and 5 of the table present the cross-indexes of competition between recent immigrants and natives and older workers, respectively, while columns 6 and 7 present the normalized cross-indexes for natives and older immigrants with respect to an increase in the number of recent immigrants. Each row of the table pertains to individuals in one of the 10 skill groups formed from the deciles of the predicted wage distribution.

An interesting feature of both the own-indexes (columns 1-3) and the cross-indexes of competition (columns 4-5) is the tendency for higher values at either end of the predicted wage distribution. This arises because workers at the extremes of the skill distribution are more highly concentrated in specific occupations than the overall workforce. As one might expect, the normalized cross-indexes in columns 6 and 7 indicate that recent immigrants are slightly more competitive with older immigrants than natives in the same skill group. On balance, however, the simple occupationally-based indexes in Table 3 suggest that recent immigrants compete fairly directly with both earlier immigrants and natives in the same skill groupings. There is little indication of occupational segmentation between natives, older immigrants, and recent immigrants with similar predicted wages.

[20]Indexes using courser occupation categories are fairly similar to those reported in Table 3.

III. Immigrant Inflows and Inter-city Mobility Patterns

One of the most important unresolved questions about the effect of immigration is whether immigrant inflows to particular cities lead to significant out-migration of natives. To the extent that natives and earlier immigrants respond to inflows of new immigrants by moving to other cities, the effect of immigration is quickly diffused across the national labor market. To the extent they do not respond, inflows of new immigrants directly shift the relative supplies of different skill groups in immigrant-receiving cities, leading to pressure on the relative wage structure in those cities.

In this section I analyze city-specific patterns of new immigrant inflows and the net migration responses of natives and earlier immigrants. The analysis uses information collected in the 1990 Census on each individual's current location and place of residence in 1985. The resulting 5-year interval provides a reasonable time window for individuals to respond to changes in local conditions. To fix ideas, let N^{90} represent the adult population of a given city in 1990, let N^{85} represent the population in 1985[21], and let N_1^t, N_2^t, and N_3^t represent the populations of three mutually exclusive groups in period t (t=85 or 90): natives (N_1^t); immigrants who arrived in the U.S. before 1985 (N_2^t); and immigrants who arrived in the U.S. after 1985 (N_3^t). By definition, $N_3^{85} = 0$. For natives and older immigrants,

$$N_1^{90} = N_1^{85} + N_1^J - N_1^L ,$$

$$N_2^{90} = N_2^{85} + N_2^J - N_2^L ,$$

where the superscript J denotes "joiners" -- people who moved into the city between 1985 and 1990 -- and the superscript L denotes "leavers" -- people who left the city between 1985 and 1990. Finally, let s_1 denote the fraction of natives in the city's population in 1985. Then the overall population growth rate of the city between 1985 and 1990 can be decomposed as:

[21]Notice that the retrospective nature of the 1985 location information means that the 1985 population count refers to the count of individuals who lived in a city in 1985, were interviewed in the 1990 census, and who met the requirements to be included in the 1990 sample (age 16-68 and at least 1 year of labor market experience as of 1989).

(7) $N^{90}/N^{85} = 1 + s_1(J_1 - L_1) + (1-s_1)(J_2 - L_2) + R$,

where $J_g=N_g^J/N_g^{85}$ is the inflow rate of group g (g=1,2), expressed as a fraction of its 1985 population, $L_g=N_g^L/N_g^{85}$ is the outflow rate of group g (g=1,2), and $R=N_3^{90}/N^{85}$ is the inflow rate of new immigrants to the city, expressed as a fraction of the total 1985 population of the city.

Equation (7) is a simple accounting identity that expresses net population growth as a weighted average of the net population growth rates of natives and older immigrants, plus the inflow rate of new immigrants. If immigrant inflows have no effect on the location decisions of natives or older immigrants, equation (7) shows that the population growth rate of a city will vary one-for-one with the immigrant inflow rate. Graphically, this means that observations on city-specific population growth rates will lie on a line with intercept 1 and slope 1 when plotted against the recent immigrant inflow rate. On the other hand, if previous residents of a city respond to inflows of new immigrants by moving away, or if natives and older immigrants who might otherwise move to the city choose other places to go, then immigrant inflows will generate less-than-proportionate increases in the city's population, leading to a scatter of points below the "reference line" with intercept 1 and slope 1.

An important feature of equation (7) is that it can be applied "within skill groups". At the skill-group level, the 1985 population count represents the number of people who would be assigned to the skill group as of 1990. Thus, a 26-year old male in 1990 who reports 16 years of completed education is included in the 1985 population in a relatively highly-skilled group, even though this individual was presumably still in school and competing in a different segment of the labor market in 1985. The use of a classification based on 1990 characteristics is appropriate if individuals are "forward looking" and choose a 1990 location based on their anticipated skill characteristics as of that date.

Figure 1 graphs skill-group-specific net population growth rates for the 175 largest U.S. cities between 1985 and 1990 against the immigrant inflow rates of the appropriate skill groups. In each panel I have super-imposed a reference line with intercept 1 and slope 1, representing the benchmark case of no offsetting migration by natives or earlier immigrants. Note that immigrant inflow rates for the lowest skill group range from 0 to over

50 percent[22], while inflow rates for the higher skill groups are under 5 percent. Thus the axes are scaled differently for the various skill groups. Despite wide differences across cities in immigrant inflow rates, the observed skill-group-specific population growth rates tend to cluster around the reference line.

The upper panel of Table 4 presents estimates from a series of OLS regression models that give more precise estimates of the responsiveness of the various components of city- and skill-group-specific population growth to inflows of recent immigrants. The models are fit to pooled samples of observations on 175 cities and 10 skill groups, and take the form

(8) $y_{jc} = Z_{jc}\beta + \gamma R_{jc} + d_j + \theta_c + e_{jc}$,

where Z_{jc} represents a vector of average characteristics of individuals in city c and skill group j in 1985, R_{jc} is the inflow rate of recent immigrants in skill group j and city c (i.e., the number of 1985-90 immigrants in skill group j living in city c in 1990, divided by the number of people in skill group j living in city c in 1985), d_j is a skill-group fixed effect, θ_c is a city-specific fixed effect, and e_{jc} is a error term. For example, the first column of Table 4 reports estimates of equation (8) with the dependent variable equal to L_1, the leaving rate of natives. In this set of models the Z's are the means of age, age-squared, education, and the fraction of blacks among the sample of natives in skill group j who lived in city c in 1985, as well as the fraction of immigrants in 1985. The other dependent variables in the table are an adjusted outflow rate for natives (explained below), the inflow rate of natives (J_1), the net population growth rate of natives ($J_1 - L_1$), the raw and adjusted outflow rates of pre-1985 immigrants (L_2), the inflow rate of pre-1985 immigrants (J_2), the net population growth rate of pre-1985 immigrants ($J_2 - L_2$), and finally the total population growth rate (N^{90}/N^{85}). In each case, the entry in the table is the estimate of the parameter γ in equation (8).[23]

[22]The maximum immigrant inflow rate for skill group 1 is 0.58 in Anaheim-Santa Ana California. Other cities with high inflow rates are Miami (0.48), Los Angeles (0.47), San Francisco (0.44), Santa Barbara (0.40), San Jose (0.40), Jersey City (0.38), and Fresno (0.35).

[23]The covariates in models for pre-1985 immigrants include means of age, age-squared, and education, the fraction black, and mean of years in the U.S. among pre-1985 immigrants in the city, as well as the fraction of immigrants in the city/skill-group in 1985. The covariates in the models for overall population growth include

An important conceptual distinction between equation (8) and the simple graphs in Figure 1 is the addition of city effects. These absorb any unobserved city-wide factors that might be correlated with new immigrant inflows and the average migration behavior of natives or older immigrants -- e.g., location-specific demand shocks. With city effects included, the coefficient γ is identified by the covariation between the relative inflow rates of new immigrants in different skill classes and the relative migration rates of natives or older immigrants.

Rows 1-5 of Table 4 report alternative OLS estimates of equation (8) using different estimation methods or samples. Row 1 contains unweighted estimates of γ using all 175 cities and 10 skill groups. Row 2 presents weighted OLS estimates, using as a weight for skill group j in city c the 1985 population of city c.[24] The motivation for the weighted estimates is the fact that the number of observations in the sample ranges from over 100,000 for Los Angeles to around 2,000 for some of the smaller cities. If the variances of the estimated flow rates are proportional to the sample sizes for each city-skill group cell, then the weighted estimates are more efficient. An alternative check on the sensitivity of the estimates to sampling errors for the smaller cities is to estimate the model on a subset of larger cities, as is row 3.

An important assumption underlying equation (8) is that the coefficients are similar for all skill groups. This is clearly an over-simplification: one would not necessarily expect migration flows of low-skilled individuals to exhibit the same responsiveness to immigrant inflows as the migration flows of more highly-skilled individuals. As a simple check on potential heterogeneity, the estimates in row 4 are derived from subsamples of the 3 lowest skill groups in each city. Finally, the estimates in row 5 are obtained from models that exclude city effects. Any discrepancy between these estimates and the baseline estimates in row 1 indicates the presence of unobserved

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all the mean characteristics for both natives and pre-1985 immigrants.

[24]The reduce the risk of a correlation between the weight for each city/skill-group cell and the dependent variables, I use the 1985 city population as a weight for each skill group in the city.

city-wide factors that affect both average immigrant inflows and average migration rates of natives or older immigrants.

The addition of average population characteristics to the right-hand side of equation (8) is meant to adjust for differences in the observable characteristics of the populations of different cities that may be correlated with mobility rates and immigrant inflow rates. In the case of the outflow rates, however, a finer adjustment may be useful. As motivation for this procedure, suppose that the probability of leaving city c for individual i in skill group j is:

$$P_{jci} = X_{jci} B_j + Z_{jc}\beta + \gamma R_{jc} + d_j + \theta_c + \zeta_{jc},$$

where X_{jci} is a vector of characteristics of individual i, B_j are a set of skill-group-specific coefficients, Z_{jc} is a set of other group-level characteristics that affect the mobility rate of group j in city c (such as the fraction of immigrants or non-whites in 1985), d_j and θ_c are skill-group and city dummies, and R_{jc} is the inflow rate of new immigrants in skill group j to city c. It is well known that γ can estimated in two steps by first estimating a micro-level linear probability model for the event of leaving one's city of residence in 1985 that includes unrestricted city and skill-group effects

(9) $$P_{jci} = X_{jci} B_j + \mu_{jc},$$

and then regressing the estimated μ_{jc}'s on city dummies, skill-group dummies, the other group-level controls Z_{jc}, and the inflow rate of new immigrants:

(8a) $$\mu_{jc} = Z_{jc}\beta + \gamma R_{jc} + d_j + \theta_c + \zeta_{jc} .$$

The "adjusted outflow rates" in Table 4 are simply the first-stage estimates of the μ_{jc}'s, derived from linear probability models fit by skill group to samples of natives and pre-1985 immigrants. These models include a much richer set of covariates than the limited number included at the aggregate level, allowing for very detailed adjustments to the raw outflow rates.[25]

[25]See Appendix A for a description of the first-stage models.

In principle it is possible to derive an analogous set of adjusted inflow rates for each skill group and city. In practice, however, the population at risk to move into a given city between 1985 and 1990 (i.e. the population who lived somewhere else in 1985) is more or less the same for all cities. Thus there is no real advantage in attempting to construct adjusted inflow rates.

The estimated effects of recent immigrant inflows on the raw or adjusted outflow rates of natives in rows 1-4 of Table 4 are uniformly negative, and are relatively similar across specifications. The effects on the outflow rates of pre-1985 immigrants are also mostly negative, although there is more variation in the point estimates across specifications. With respect to inflow rates, the estimated effects are slightly negative for natives, but tend to be positive for pre-1985 immigrants. For both groups, the estimated effects of recent immigrant inflows on net migration (inflows minus outflows) are therefore positive. The estimated marginal population effects of each additional recent immigrant, shown in the right-most column of Table 4, uniformly exceed 1.

Comparisons across rows 1-4 suggest that the estimated impacts of immigrant inflows are relatively insensitive to minor changes in specification, such as differences in weighting, exclusion of smaller cities, or consideration of only the three lowest skill groups. Changes in the list of group-level covariates included in the models (the Z_{jc}'s in equations (8) and (8a)) also tend to have relatively small effects on the estimates. An exception arises in the models for the inflow rate of older immigrants. Without controlling for the fraction of immigrants in 1985, recent immigrant inflows are estimated to lower the inflow rate of older immigrants, whereas the estimates in Table 4 show the opposite sign.[26] Nevertheless, the estimated effects of recent immigrants on total population growth do not change very much with changes in the list of other controls.

The estimates in row 5 of Table 4 are obtained from models that exclude city effects. These are somewhat different from the estimates in rows 1-4, indicating the presence of city-level factors that affect both

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[26]The estimates indicate that a higher fraction of immigrants in 1985 leads to lower inflow rates of older immigrants between 1985 and 1990. Since recent inflows are highly correlated with the fraction of immigrants in 1985, if the latter control variable is excluded the negative effect loads onto the coefficient of the recent immigrant inflow variable. Estimates reported in an earlier version of this paper (Card, 1996) did not control for the fraction of immigrants in 1985.

the inflow rate of new immigrants and the migration behavior of earlier residents. For example, the estimate in row 1 implies that each additional new immigrant is associated with a net increase of 1.12 people to the total population, whereas the estimate in row 5 implies a net increase of 1.30 people. Cities with higher inflows of new immigrants also tend to have lower leaving rates and higher joining rates among natives and earlier immigrants, leading to an upward bias in the estimated responses to new immigrant inflows in models without city effects.

Endogeneity of Immigrant Inflows

Even with the inclusion of city effects, the estimates in rows 1-4 of Table 4 show that net population growth rates of natives and earlier immigrants are slightly positively related to new immigrant outflows -- the opposite of what would be expected if new immigrants depress wages and force other people to move out. One explanation for this finding is that there are unobserved city- and skill-group-specific factors (like the productivity shocks introduced in the theoretical model of Section I) that attract recent immigrants of a particular skill group and at the same slow down the outflow of natives. In the presence of such "demand-pull" factors, the causal effect of recent immigrant inflows can only be identified if there is an exogenous determinant of the supply of recent immigrants to individual cities in particular skill groups.

The tendency of newly-arriving immigrants to move to "enclaves" established by earlier immigrants from the same source country (Bartel, 1989) suggests one such determinant. In particular, suppose that the total number of immigrants from a given source country moving into the U.S. from 1985 to 1990 is independent of skill-group and location-specific demand conditions in any one city. (Total immigrant inflows could still depend on national demand conditions for a particular skill group, or on aggregate economic conditions in any particular city). The actual inflow of immigrants from a given source country moving to a particular city can then be decomposed into an "expected" component, based on the fraction of immigrants from that country in an earlier cohort who live in that city, and an "unexpected" component. Multiplying the expected inflow component from a given source country by a factor reflecting the national fraction of immigrants from that country who fall in a certain skill group gives an estimate of the "supply-push" component of recent immigrant inflows of a given skill group to a particular city that can be used as an instrumental variable in the estimation of equation (8).

Formally, let M_g represent the number of immigrants from source country g who entered the U.S. between 1985 and 1990, and let λ_{gc} represent the fraction of immigrants from an earlier cohort of immigrants from country g who are observed living in city c in 1985. Finally, let τ_{gj} represent the fraction of all 1985-90 immigrants from source country g who fall into skill group j. A simple estimate of the number of immigrants from country g in skill group j who would be expected to move into city c between 1985 and 1990 is $\tau_{gj}\lambda_{gc}M_g$. If τ_{gj}, M_g, and λ_{gc} are independent of skill-group-specific demand conditions in city c over the 1985-90 period then this estimate is independent of any "demand pull" conditions in the city. Summing across source countries, an estimate of the "supply-push" component of recent immigrant inflows in skill group j and city c is:

(10) $SP_{jc} = \Sigma_g \, \tau_{gj}\lambda_{gc}M_g$.

Since $\Sigma_c\lambda_{gc} = 1$, the sum of SP_{jc} across all "cities" (including cities excluded from the 175 largest city sample and non-urban locations) is equal to the actual inflow of immigrants in the jth skill group.

To construct this supply-push flow I use a set of 17 "source country groups", identified in Table 5.[27] The first column of the table gives the number of 1985-90 immigrants from each source (i.e., M_g), while the second column shows the fraction of recent immigrants attributable to each source country group. Mexico is the largest single source country, accounting for 27 percent of the approximately 3.3 million adult immigrants who entered the U.S. between 1985 and 1990 and were counted in the 1990 Census. The Philippines are the second largest source country, accounting for 5.2 percent of all recent immigrants. The other source-country groups each accounted for 2-6 percent of recent immigrants.

The right-hand columns of Table 5 show the fractions of recent immigrants from each source group in the 10 skill groups formed from deciles of the predicted wage distribution (i.e., the τ_{gj} in equation 10). As other

[27]The groupings were selected on the basis of geography and ethnic similarity.

analysts have noted (e.g. Borjas, 1994) there are notable differences in the skill distribution of immigrants from different source countries. For example, 93 percent of Mexican immigrants and 86 percent of Central American immigrants are assigned to the lowest skill category, compared to only 3 percent of immigrants from Canada, England, Australia and New Zealand. Cities that receive most of their new immigrants from Mexico or Central America therefore tend to have very low-skilled inflows, whereas cities that receive a larger fraction of Canadian or European immigrants have more highly-skilled inflows.

The final set of unknowns in equation (10) are the city distribution shares for each source country -- the λ_{gc}'s. I use the 1985 geographic distribution of immigrants who entered the U.S. between 1975 and 1984 (reported retrospectively in the 1990 Census) to estimate these shares. The resulting estimates are presented in an earlier version of this paper (Card, 1996, Appendix Table 2), and show many interesting patterns. For example, Los Angeles attracted the largest share of 1975-84 immigrants (18 percent), with 41 percent of Central American immigrants and 28 percent of Mexican immigrants living there in 1985. New York City accounted for the next largest share (10 percent), with 43 percent of Caribbean immigrants, 28 percent of South American immigrants, and 22 percent of immigrants from the former Communist countries of Europe. Even cities that currently receive relatively few immigrants show long-established enclave patterns. For example, Detroit accounted for only 0.6 percent of total immigrants, but 5 percent of immigrants from the Middle East and North Africa.

How do observed immigrant inflows over the period from 1985-90 compare with the supply-push flows predicted by equation (10)? Figure 2 plots the actual immigrant inflow rates for the two lowest skill groups in each city against the corresponding supply-push flows.[28] For reference, I have super-imposed a 45 degree line on each figure. The correlation between the actual and supply-push inflows is strong, although there are many cities with bigger or smaller inflows than would have been predicted on the basis of earlier immigrant settlement patterns and total inflows over the 1985-90 period. A case in point is Texas. The 9 Texas cities in the sample

[28]The actual and supply-push inflows are divided by the city- and skill-group population in 1985.

are plotted with a different symbol in Figure 2 and in most cases lie well below the 45-degree line. The shortfall presumably reflects the unfavorable labor market in Texas following the collapse of oil prices in the mid-1980s.

The lower panel of Table 4 presents instrumental variables (IV) estimates of the effect of immigrant inflows on mobility rates of natives and earlier immigrants, using the supply push component of immigrant inflows as an exogenous determinant of the recent immigrant inflow rate. Rows 6 and 7 contain unweighted and weighted IV estimates corresponding to the OLS estimates in rows 1 and 2. While the differences are slight, the IV estimates point toward slightly smaller net population responses to new immigrant inflows, as would be expected if the OLS estimates are upward-biased by unobserved city- and skill-group-specific demand shocks.

Row 8 reports weighted IV estimates using data on only the 3 lowest skill groups. These are not much different from the weighted IV estimates for all 10 skill groups, although the point estimates indicate a small depressing effect of new immigrants on net native population growth, driven by a marginally significant negative effect of new immigrant inflows on the rate of inflow of natives from other cities. Even among the most unskilled groups, however, the migration responses of native and older immigrants are modest, implying that each newly-arrived immigrant in a particular skill group adds approximately one person to the local labor market.

The finding that natives and older immigrants do <u>not</u> relocate in response to inflows of new immigrants is consistent with some previous studies of city-level population growth rates over the 1980s (Butcher and Card, 1991; White and Liang, 1994). However, it is inconsistent with the findings in a series of papers by Frey (1995a, 1995b) which argue that out-migration rates of low-skilled natives were higher from cities that received larger immigrant inflow rates over the 1985-90 period -- particularly California cities.[29] In an effort to verify the results in Table 4 I performed a variety of checks. First, as shown in Figure 3, I plotted the outflow rates of natives in the lowest skill group for each city against the corresponding immigrant inflow rate. As the figure makes clear, the leaving rates of low-skilled natives from the 17 California cities in the sample are similar to the rates for other

[29]Studies by Filer (1992) and White and Hunter (1993) of migration patterns in the 1970s also point to a negative correlation between immigrant inflows and native out-migration.

cities. Consistent with the estimates from the more complex models in Table 4, the raw data in Figure 3 suggest that out-migration rates of low-skilled natives are not systematically higher in high-immigrant cities. Second, as shown in the bottom row of Table 4, I estimated the migration response models excluding the data from the 17 California cities in the sample. These estimates are very similar to the corresponding estimates formed from the overall sample (in row 7).[30]

One caveat to the conclusion that native migration patterns are insensitive to immigrant inflows is the time frame implicit in Table 4. At least one fifth of the recent immigrants measured in the empirical analysis entered the U.S. in 1989 or early 1990, leaving relatively little time for previous residents of a city to respond. More generally, the correlation of 5-year mobility flows of natives and earlier immigrants with 5-year immigrant inflow rates cannot capture subtle lags in any behavioral responses. Nevertheless, the evidence in Table 4 seems to rule out the hypothesis that immigrant inflows engender large offsetting migration flows of natives and/or earlier immigrants.

IV. Effects of Immigrant Inflows on Employment and Wages of Natives and Older Immigrants

Having established that inflows of new immigrants shift the relative supplies of different skill groups in a local labor market, it is interesting to evaluate the effect of these inflows on the wages and employment rates of natives and older immigrants. I conduct the evaluation in the framework of the theoretical model presented in Section I. Thus, the key parameters are coefficients representing the effects of a change in the population share of a particular skill group on the employment rate or average wage of individuals in that skill group. I allow for heterogeneity within skill groups in three ways. First, I analyze the wage and employment outcomes of 4 separate subgroups in each skill class: native-born women, native-born men, pre-1985 immigrant women, and pre-1985 immigrant men. Second, I control for city-specific variation in some key characteristics of the particular

[30] I also estimated models that excluded California and Texas cities, and models for the 3 lowest skill groups that excluded the California cities. These were all very similar to the estimated models reported in Table 4.

gender/origin group (average age, average education, fraction married, fraction black, etc.) Finally, I analyze both the raw employment and wage rates of the four demographic groups in each city/skill group, and adjusted rates that account for the characteristics of the subgroup populations in each city.

Table 6 presents estimates of the effect of the population share of a given skill group on the employment rates of the four demographic subgroups in each skill group. The format of the table is similar to that of Table 4: thus each column presents results for a different dependent variable and each row pertains to a different estimation method or sample. In addition to the population share variable, the models also include skill-group dummies and a set of mean characteristics for the subgroup in the regression model. With the exception of row 6, all the models also include unrestricted city effects. The upper panel reports OLS estimates, treating the population share of a skill group in a city as exogenous. The lower panel reports IV estimates using the predicted inflow rate of new immigrants as an instrument for the log of the share of the skill group.

The raw employment rates for each demographic group are simply the fractions who worked positive hours and reported positive earnings in 1989.[31] The adjusted employment rates are estimated city dummies taken from a set of 40 first-stage linear probability models for employment status, fit by skill class and subgroup to national samples of individuals. The first stage models include a rich set of individual-specific characteristics (see Appendix A), thus purging the adjusted employment rates of differences attributable to the observable characteristics of the labor force in each city.

The first two rows of Table 6 report basic OLS and weighted OLS estimates. Consistent with the theoretical model, the estimated effects of an increase in population share are uniformly negative and similar across the different subgroups. The use of raw or adjusted employment rates makes little difference to the point

[31] Although equation (4) specifies the log of the employment rate as the dependent variable, I use the employment rate itself, since this simplifies the procedure for obtaining adjusted employment rates. The coefficients can be translated into effects on the log employment rate by multiplying by the inverse of the average employment rate (0.85 for men, 0.75 for women).

estimates or their precision. Row 3 presents estimates derived from the subsample of larger cities. These are quite similar to the weighted OLS results for the entire sample of cities in row 2.

In row 4 the analysis is restricted to the three lowest skill groups in each city. The resulting estimates are somewhat smaller in magnitude than the overall estimates, and are only statistically significant for native women. Perhaps surprisingly, there is no indication that shifts in the relative supply of a particular skill group generate larger effects on less skilled groups.

Row 5 presents estimates that make use of an augmented skill-group share measure, as suggested by equation (4"). Specifically, the observed skill group fractions are adjusted for inter-city differences in the population shares of 6 subgroups: native men, native women, pre-1985 immigrant men, pre-1985 immigrant women, post-1985 immigrant men, and post-1985 immigrant women. As suggested in Section I, the weighting factor for each subgroup is the difference between the mean annual earnings of the subgroup and the mean annual earnings of all individuals in the skill class, estimated from national data. As it turns out, inter-city variation in the adjustment factor is small relative to the variation in the unadjusted skill fractions (based on a simple head-count of the different skill groups). Consequently, the estimates are virtually identical to those in row 1.

Finally, row 6 presents results from specifications that exclude the city effects. These estimates are slightly less negative than those in row 1, suggesting that unmeasured city-wide factors that lead to higher employment-population rates for all skill groups are slightly positively correlated with the average log population share in the city.[32]

The bottom panel of Table 6 presents IV estimates that use the predicted inflow rate of recent immigrants in a particular skill group as an instrument for the skill group's population share. Although not shown in the table, the first-stage equations for the IV results show a large and highly significant effect of the predicted immigrant inflow rate on the log of the population share, with coefficients in the range of 1.3-1.6 and t-ratios of

[32]Any city-wide effect is orthogonal to the average population share in the city, since the latter sum to 1 across all 10 skill groups. However, the log population shares are not necessarily orthogonal to a city-wide effect. The mean log population share is decreasing in the variation in shares across skill groups.

about 10.[33] The IV estimates are uniformly more negative than the corresponding OLS estimates (compare rows 7 and 8 to rows 1 and 2), suggesting the presence of skill-group-specific local demand shocks that raise employment rates and also attract new immigrants. As with the corresponding OLS results, the weighted IV results for the 3 lowest skill groups show no indication that immigrant inflows have a bigger (i.e. more negative) effect when attention is focussed on less skilled workers.

The IV estimates in Table 6 point to a moderate effect of immigrant inflows on the employment rates of natives and earlier immigrants. In terms of the theoretical model, the estimated effects of the log population share on the adjusted employment rates in row 8 of Table 6 imply that the coefficient d_2 is in the range of -0.16 to -0.06. An alternative way to assess the size of the estimates is to consider the reduced-form effect of predicted immigrant inflows on the employment rate of natives and earlier immigrants. For example, the reduced-form coefficient of predicted immigrant inflows on the adjusted employment rate of native men corresponding to the weighted IV estimate in column 2 of row 8 is -0.20 (standard error = 0.02), while the corresponding coefficient for the bottom 3 skill groups is -0.15 (standard error =0.03). In the lowest skill group, the inflow rate of recent immigrants ranges from 0 to 0.5, with a mean of about 0.13. Thus the reduced form estimates imply that higher immigrant inflows reduced the <u>relative</u> employment rate of native men in larger U.S. cities by 1-2 percentage points on average, and by as much as 5-10 percentage points in cities like Los Angeles or Miami. The implied effects on the relative employment rates of native women and earlier immigrants are about 50-70 percent as big.

The correlation between the supply-push component of immigrant inflows and the employment-population rate of native men in the lowest skill group is illustrated in Figure 4. While there is substantial unexplained variation in average employment rates of unskilled native men across cities, the negative relationship between employment and immigrant inflows is discernable. Indeed, a weighted regression of the adjusted employment rates on the predicted immigrant inflows has a coefficient of -0.19 (standard error 0.03) -- very

[33]A coefficient close to 1 in the first-stage models is consistent with the finding that immigrant inflows have a coefficient close to 1 in models for the total skill group population in Table 4.

similar to the reduced form coefficient obtained for all 10 skill groups including city dummies.[34] As suggested by the coefficients in Table 6, the simple correlations between immigrant inflows and the employment rates of native women and older cohorts of immigrants in the bottom skill group are weaker than the one for native men, but uniformly negative.

Estimated Wage Effects

Table 7 presents a parallel analysis for the effect of skill group population shares on mean log wages of the four demographic subgroups. An important difference between the analysis of employment and wages is the fact that wages are only observed for workers. Thus there is a potential selectivity bias in the measured effect of population shares on wages. I return to this problem below and present some evidence on the likely magnitude of the bias. In the meantime, it should be recognized that the coefficient estimates in Table 7 may be biased toward zero if higher-wage individuals in a given skill class are more likely to remain employed in the face of declining demand conditions.

A comparison of the coefficients in Tables 6 and 7 reveals that the estimated impacts of higher population shares on wages are generally smaller in magnitude and less consistent across demographic groups than the impacts on employment. The largest wage effects are obtained for native and immigrant women, whereas the effects for native and immigrant men are small and often insignificantly different from 0. The IV estimates in rows 7 and 8, which one might expect to be more negative than the corresponding OLS estimates, are slightly more negative for men but actually more positive for women. On the other hand, the IV estimates for native women in the three lowest skill groups are moderately large, and the corresponding estimates for immigrant women are quite sizeable. In light of the very small estimated wage impacts for men in the three

[34]The unweighted regression coefficient is -0.12, with a standard error of 0.05.

bottom skill groups the estimates for immigrant women appear anomalous, although I have been unable to find any simple explanation for the very large implied effects of skill group shares on less-skilled immigrant women.[35]

Potential Selectivity Biases

Based on the estimates in Table 7 it is difficult to conclude that changes in the relative population shares of different skill groups lead to large systematic changes in the relative wage structure of a particular city. Nevertheless, it is possible that selectivity biases attenuate the measured effects of changing skill-group shares. To get a sense of the likely magnitude of such biases, I performed a very simple exercise using the predicted wage that was initially assigned to each individual to determine his or her skill category. Specifically, I computed the difference between the mean predicted wage for the subset of employed workers in each city/skill-group cell and the mean predicted wage for all individuals in the cell. This gap is an estimate of the observable component of the selectivity bias in the mean wages of employed workers.[36]

Analysis of the gap revealed a negative correlation between the observable selectivity bias component and the city-specific employment rate for individuals in the lowest skill group, but little or no correlation for individuals in higher skill groups. These patterns suggest that there is some selection bias in the observed wages of employed workers, but that the bias is confined to the lowest skill group. Assuming this is the case, consistent estimates of equation (3') can be obtained by using samples that exclude the lowest skill group. I therefore re-estimated the models in Table 7 using only the 9 highest skill groups. The OLS estimates from this subsample are very close to those in Table 7: for example, weighted OLS estimates corresponding to the ones in row 2 are 0.01 (standard error 0.01) for adjusted native male wages; -0.07 (standard error 0.01) for adjusted native female

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[35]I found no evidence that the results were driven by a few outliers or by noisy data. For example, median regression estimates of the reduced-form models underlying the IV estimates were very similar to the corresponding OLS estimates.

[36]Note that since the wage prediction models are fit with no allowance for selection bias, the coefficients of these models may be biased, implying that the gap in mean predicted wages between workers and the population is an inconsistent estimate.

wages; -0.04 (standard error 0.03) for adjusted immigrant male wages; and -0.05 (standard error 0.03) for adjusted immigrant female wages.[37]

An alternative way to evaluate the potential magnitude of any selectivity bias is to postulate a specific model of the joint determination of wages and employment, and calculate the implied bias directly. For example, suppose that individual wages are distributed within skill-group/city cells according to:

$$\log w_{jci} = \log w_{jc} + \xi_{jci},$$

where ξ_{jci}, the deviation of individual i's log wage from the mean log wage of the cell, is normally distributed with mean 0 and standard deviation $\sigma(\xi)$. Suppose that individual i's employment outcome is determined by a latent index of the from $d_{jc} + \alpha\xi_{jci} + \upsilon_{jci}$, where υ_{jci} is another normally distributed error. In this case, it is well known that the mean of observed log wages among workers in city c and skill group j is related to the unconditional mean by:

$$E(\log w_{jci} \mid \text{I works}) = \log w_{jc} + \rho\, \sigma(\xi)\, \lambda(\pi_{jc}),$$

where ρ is the correlation coefficient between ξ_{jci} and the composite error $\alpha\xi_{jci} + \upsilon_{jci}$, π_{jc} is the employment rate of group j in city c, and λ is the inverse Mill's ratio

$$\lambda(\pi_{jc}) = \phi(\Phi^{-1}(\pi_{jc}))/\pi_{jc}\,,$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ refer to the standard normal density function and cumulative density function, respectively (Gronau, 1974). For given values of ρ and $\sigma(\xi)$, the selectivity bias component in the mean of observed wages is $\rho\, \sigma(\xi)\, \lambda(\pi_{jc})$. Based on the observed dispersion of wages, a reasonable estimate of $\sigma(\xi)$ is 0.5. Treating $\sigma(\xi)$ as known, all that is needed is an estimate of ρ to form an estimate of the selectivity bias component.

Since the function $\lambda(\pi)$ is approximately linear over most of its range, the assumption of joint normality of the various error components implies that the degree of selectivity bias in the observed mean of wages for a

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[37]The IV estimation procedure breaks down when skill group 1 is excluded. In particular, the first stage equations fit to only the top 9 skill groups fail to show a significant positive effect of predicted immigrant inflows on the skill group shares. This problem arises because cities that have a higher inflow rate of immigrants in e.g. skill group 3 typically have an even higher inflow in skill group 1. Thus the population share of the higher groups is actually (weakly) negatively correlated with their inflow rates.

given city/skill group is approximately a linear function of the employment rate of the group. Indeed, for $.3 < \pi < 1$,

$$\lambda(\pi) \approx 1.6 - 1.6\pi .$$

Thus, assuming $\sigma(\xi)=0.5$, the implied selectivity bias component in the observed wages of employed workers in different city/skill group cells is approximately:

$$\text{Bias}_{jc} \approx 0.8\,\rho - 0.8\,\rho\,\pi_{jc} .$$

To illustrate the implications of this formula, note that the estimates in Table 6 suggest that the employment rate of different skill groups is negatively related to the log population share of the skill group with a coefficient of (roughly) -0.10. Using this estimate, the implied selectivity bias in a regression of observed mean log wages on log population shares is approximately 0.08ρ ($\rho \times -0.8 \times -0.10$). Since ρ cannot exceed 1, an <u>upper bound</u> on the selectivity bias is 0.08, and a more reasonable bound might be 0.04 (assuming $\rho < 0.5$).

Given that the bulk of the estimates in Table 7 range from -0.10 to 0, a reasonable lower bound on the coefficient d_1, taking account of potential selectivity biases, is -0.15, with a somewhat tighter bound (-0.10) for native and immigrant men. This range of estimates can be combined with evidence on the range for the coefficient d_2 from Table 6 to provide estimates of the theoretical parameters underlying equations (3') and (4') ---the participation elasticity ϵ and the substitution elasticity σ. Assuming that $-0.15 \le d_1 \le 0$ and $-0.16 \le d_2 \le -0.06$, the data point to an estimate of $\epsilon = d_2/d_1$ that is bigger than 1 -- on the order of 1.5 using midpoints for each range. The implied estimate of the substitution elasticity $\sigma = -(1+d_2)/d_1$ is very large -- at least 5, and probably more like 12, using the midpoint estimates.

In terms of implications for immigrant inflows, the reduced-form effects of predicted immigrant inflows on the adjusted wages of native men for the models in rows 7-9 of Table 7 range from -0.07 to -0.02, while the reduced-form effects for the adjusted wages of native women range from -0.12 to -0.02. Assuming an upper-bound selectivity bias of +0.05, the reduced-form models suggest that the corrected effect of immigrant inflows on native male wages ranges from -0.12 to -0.02, while the corrected effect for native female wages ranges from

-0.17 to -0.02.[38] For natives in the bottom skill group these effects imply that immigrant inflows during 1985-90 lowered mean wages by 0-2 percent on average, and by 0-8 percent in cities like Los Angeles and Miami. Given the imprecision in the reduced-form coefficients and the ad hoc nature of the selectivity adjustment, the upper bounds of these ranges must be interpreted very cautiously. One could easily infer from Table 7 that immigrant inflows have no systematic effect on the relative wage structure, at least for men.

V. Conclusions

The analysis in this paper points to three substantive conclusions. First, inflows of new immigrants to individual labor markets over the 1985-90 period did not generate large offsetting mobility flows by natives or earlier immigrants in the same skill groups. As a result, most cities that received large flows of recent immigrants experienced sharp increases in the relative size of their less-skilled populations. Second, shifts in the population shares of different skill groups are associated with systematic changes in relative employment. A 10 percent increase in the share of the population in a given skill group (say from 0.10 to 0.11 of city's population) leads to about a 1 percentage-point reduction in the employment-population rate of native men in the group, and slightly smaller reductions for native women and older immigrants in the same skill group. Taken together, these first two findings imply that inflows of new immigrants over the late 1980s reduced the employment rates of very low-skilled natives and earlier immigrants in a typical major city by 1-2 percentage points, and by 3-5 times as much in very high-immigrant cities like Los Angeles or Miami. The effects of immigrant inflows on moderately- or highly-skilled natives and previous immigrants were much smaller. Finally, increases in the population shares of different skill groups are associated with generally small changes in the relative wage structure.

In the context of the simple theoretical model developed in the paper, the estimation results suggest that the elasticity of substitution between different skill categories is very high, and that the elasticity of labor market

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[38]The regression coefficient of employment on the predicted immigrant inflow rate is roughly comparable to the coefficient on the log population share, implying a similar selectivity adjustment in the reduced-form models.

participation is moderately large. If skill groups are highly substitutable, inflows of immigrants in a particular skill group will not affect the relative wage structure very much, although they may lead to a shift in the general level of wages in a city.[39] An alternative possibility is that labor markets adjust slowly to the short-term immigrant inflows studied in this paper, with an influx of new immigrants leading first to employment losses and only in the longer run to changes in relative wages.

An unresolved issue is the extent to which the impacts of immigrant inflows (or other sources of skill-imbalances in local labor markets) are diffused across the national labor market by changes in the product-mix of employers in different cities. Standard models of international trade suggest that cities with relatively more unskilled workers will begin to specialize in the production of "low-skill-intensive" tradeables. To date there is relatively little evidence on the extent of such specialization. Nevertheless, the employment effects found here suggest that there is some localized impact of immigrant inflows.

Finally, it is useful to compare the findings from this analysis with the results in the existing literature. At the outset, it should be noted that most of the existing literature makes no distinction between older and more recent immigrants, and simply tries to measure differences in native wages or employment outcomes associated with differences in the overall fraction of immigrants in a local labor market. In contrast, the analysis here distinguishes rather narrowly between different subgroups of natives, older immigrants, and recent *immigrants*. Even with these distinctions, there is little evidence that immigrant inflows affect the native wage structure (at least in the short-run). The findings in this paper with respect to wages are therefore consistent with most of the existing literature. The conclusion that immigrant inflows reduce native employment rates is new. However, the implied effects <u>for natives as a whole</u> are very small. Even for workers in the bottom of the skill distribution I find relatively modest employment effects of recent immigrant inflows in all but a few high-immigrant cities. And even in these cities the magnitude of the implied employment effects is really a reflection of the

[39]It should be noted that a comparison of the wage models in Table 7 with and without city effects confirms that average wage levels are typically higher in cities with high overall immigrant inflow rates. This is consistent with the existing literature, e.g. Schoeni (1996).

extraordinarily high immigrant inflow rates in the latter half of the 1980s. Between 1985 and 1990 a handful of U.S. cities experienced immigrant inflows that expanded their unskilled labor forces by as much or more than the Mariel Boatlift affected the Miami labor market.[40] The results in this paper suggest that these massive expansions may have lowered native employment rates for the bottom skill decile by 5-10 percentage points.

[40]I estimate that the Boatlift expanded the relative population share of the least-skilled workers in Miami by 30-40 percent -- well within the sample range of the data analyzed here.

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Data Appendix

a. Basic Sample Criteria

I begin with a 25 percent random sample of all native-born individuals age 16-68 in the 5-percent public use samples of the 1990 census, and 100 percent of all foreign-born individuals in the same age range. The resulting sample sizes are: 965,132 native women; 921,034 native men; 428,789 foreign-born women; and 418,258 foreign-born men. I further restrict the sample to individuals whose potential labor market experience (age minus years of education minus 5) is greater than 1 in 1990. Years of education are assigned to the education codes used in the 1990 Census following Park (1995). The minimum age restriction eliminates about 4.5 percent of natives and 4 percent of immigrants from the sample.

Labor market outcomes are based on earnings and hours of work in 1989. Individuals are coded as employed if they reported positive earnings, including wage and salary and/or self-employment earnings, and positive weeks of work and positive usual hours per week in 1989. An hourly wage was assigned by dividing total earnings by the product of weeks worked and usual hours per week. I did not exclude allocated responses for earnings or hours. Wage rates less than $2.00 per hour, or greater than $90 per hour, were set to missing.

b. Assigning MSA Codes

The finest level of geographic information on the 1990 public use samples is the PUMA (public-use micro sample area). Most individuals who live in a metropolitan area are also assigned a metropolitan area identifier (i.e., an MSA or CMSA code). However, some PUMA's straddle the boundary of one or more MSA's, and in these "mixed" PUMA's an MSA code is not assigned. I used the Geographic Equivalency file to identify the MSA that contributed the largest fraction of the population to any such mixed PUMAs. If over 50 percent of the PUMA population was attributable to a single MSA, I then assigned all individuals in that PUMA to the majority MSA. The computer code for this assignment, which affects 213 PUMAs, is available on request.

c. Assigning 1985 MSA Codes

The public use samples also include information on place of residence in 1985, coded to the PUMA level. I used the Geographic Equivalency files to map 1985 PUMA codes into MSA's. The computer code for this assignment is available on request. A small fraction of immigrants who are coded as having arrived in the U.S. between 1985 and 1990 report data on their place of residence in 1985. For simplicity, however, I assume these individuals lived outside of the U.S. in 1985, and ignore them in constructing 1985 population counts for individual MSA's.

d. Final Sample Sizes

With the exception of Table 1, the analysis throughout the paper is restricted to individuals who lived in one of the 175 largest MSAs in either 1990 or 1985. The final sample sizes for the analysis of 1990 employment outcomes (which condition on 1990 place of residence) are shown in the first column of the Table A-1. The final sample sizes for the analysis of 1990 wage outcomes (which condition on 1990 place of residence and non-missing wage data) are shown in the column 2 of Table A-1. The final sample sizes for the analysis of 1985-1990 mobility (which condition on 1985 place of residence) are shown in the column 3 of Table A-1.

Table A-1

Final Sample Sizes of Overall Extracts

	In Large City in 1990:		
	All	Valid Wage	In Large City in 1985
Native Men	535,979	452,605	559,195
Native Women	563,238	395,003	586,476
Immigrant Men	333,122	274,404	252,149
Immigrant Women	338,160	105,936	263,396

Appendix A

I. Models Used to Determine Skill Group

Separate models were fit for native-born and immigrant men and women, using the samples of individuals living in the largest 175 cities with valid wages in 1990 described above. Each model included unrestricted dummies for the city of residence, along with 12 dummy variables for individual levels of education and a quartic function of potential experience.

The native models also included three race dummies (black, Asian, aboriginal), interactions of the race dummies with years of education and experience, interactions of years of education with experience and experience-squared, indicators for being married, being a veteran, and reporting a disability, and interactions of the three race dummies with the marital status and veteran status indicators. In addition, the model for native women included indicators for the presence of own children less than 6 years of age, and between 6 and 17 years of age.

The immigrant models included 17 origin dummies, origin-group-specific quadratic functions of years since arrival in the U.S., a dummy for having moved to the U.S. before age 6, an interaction of years of education with a quadratic function of years in the U.S., interactions of years of education with indicators for 3 main origin groups (immigrants from Mexico, Canada/Australia/Europe; and Asia), and dummies for black and Asian race, being married, and reporting a disability. Finally, the model for immigrant women included indicators for the presence of own children less than 6 years of age, and between 6 and 17 years of age.

Wage predictions were formed for each individual using the estimated coefficients from the appropriate model. The intercepts of the prediction models were obtained by taking a weighted average of the estimated city-specific intercepts, using the relative fractions of native men in each city as a weight. Finally, I obtained the deciles of the distribution of predicted wages for the entire sample of individuals with valid wages in 1990.

II. Models Used to Construct Adjusted Out-migration Rates

The adjusted outflow rates used in Table 4 are city dummies estimated from a set of linear probability models for the event of "moving out of the 1985 city of residence by 1990". A total of 20 models are fit by skill group and nativity (male or female natives in one set of models; male or female immigrants in another set) using the samples of individuals described in Table A-1 who lived in one of the 175 largest cities in 1985. For each skill - nativity group, I fit a linear probability model with unrestricted dummies for the particular city of residence in 1985. For natives, the other covariates included in the models were: a gender dummy; age, age-squared, and a dummy for age under 30; interactions of the three age variables with the gender dummy; years of education; interactions of education with indicators for gender, age under thirty, and gender*age under 30; a dummy for black race; and interactions of education with indicators for black men and black women. For immigrants the covariates included age, age-squared, and a dummy for age under 30; a gender dummy; years of education; interactions of education with indicators for gender, age under thirty, and gender × age under 30; 16 dummies for country of origin; interactions of the country-of-origin dummies with years since arrival in the U.S., and years since arrival squared.

III. Models Used to Construct Adjusted Employment Rates

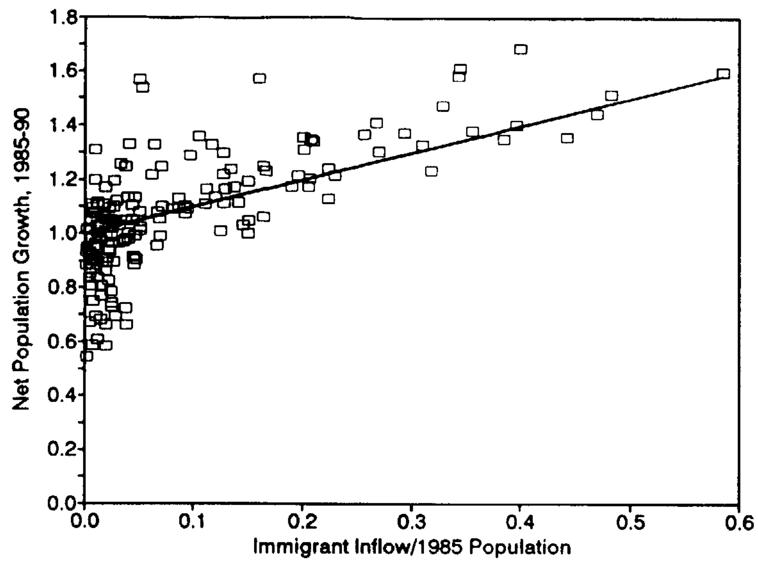
The adjusted employment rates used in Table 6 are city dummies estimated from a set of linear probability models for the event of "reporting positive earnings and hours in 1989". A total of 40 models are fit by skill group and gender × nativity (immigrant women, immigrant men, native women, native men) using the samples of individuals described in Table A-1 who lived in one of the 175 largest cities in 1990. For each skill - gender - nativity group, I fit a linear probability model with unrestricted dummies for the particular city of residence in 1990. For natives, the other covariates included in the models were: years of education and a dummy for 16 or more years of education; a cubic function of experience; a dummy for being married; and interactions of a dummy for black race with education, experience, the dummy for 16 or more years of education, and the dummy for marital status. For immigrants the other covariates included years of education and a dummy for 16 or more years of education; a cubic function of experience; a dummy for being married; 16 dummies for country of origin; interactions of the country-of-origin dummies with years since arrival in the U.S., years since arrival squared; and interactions of education with years in the U.S. and indicators for 3 main origin groups (immigrants from Mexico, Canada/Australia/Europe; and Asia).

IV. Models Used to Construct Adjusted Wage Rates

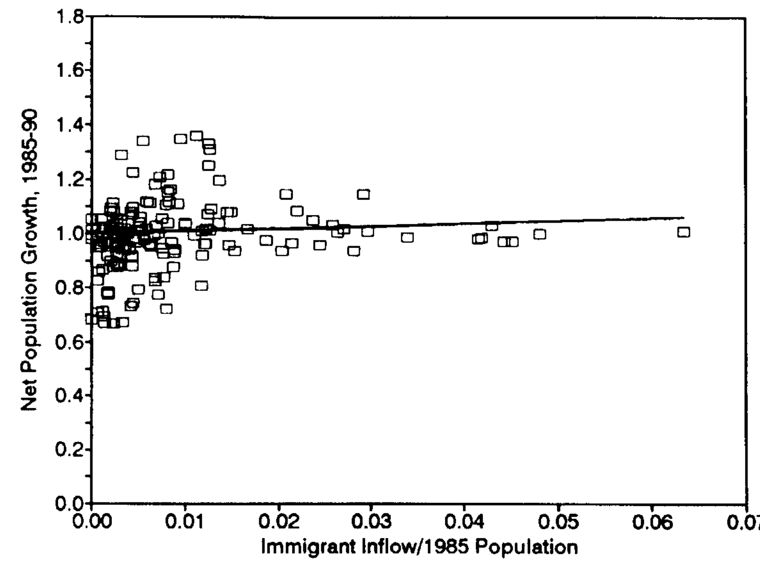
The adjusted wage rates used in Table 7 are city dummies estimated from a set of linear regression models fit to observed log wages. A total of 40 models are fit separately by skill group and gender × nativity (immigrant women, immigrant men, native women, native men) using the samples of individuals described in Table A-1 who lived in one of the 175 largest cities in 1990 and reported a valid wage. For each skill - gender - nativity group, I fit a model with unrestricted dummies for the particular city of residence in 1990. For natives, the other covariates included in the models were: years of education and a dummy for 16 or more years of education; a cubic function of experience; a dummy for being married; and interactions of a dummy for black race with education, experience, the dummy for 16 or more years of education, and the dummy for marital status. For immigrants the other covariates included years of education and a dummy for 16 or more years of education; a cubic function of experience; a dummy for being married; 16 dummies for country of origin; interactions of the country-of-origin dummies with years since arrival in the U.S., years since arrival squared; and interactions of education with years in the U.S. and indicators for 3 main origin groups (immigrants from Mexico, Canada/Australia/Europe; and Asia).

Figure 1: Recent Immigrant Inflows and Total Population Growth in Selected Skill Groups.

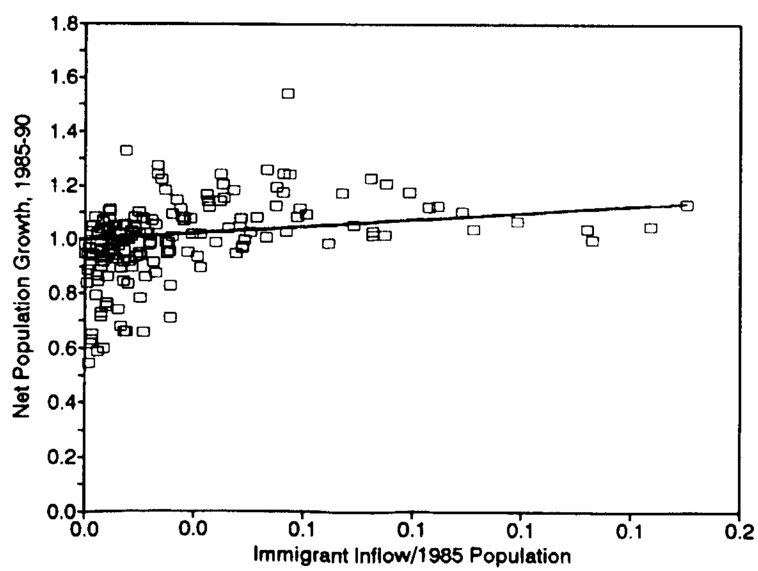
a. Skill Group 1



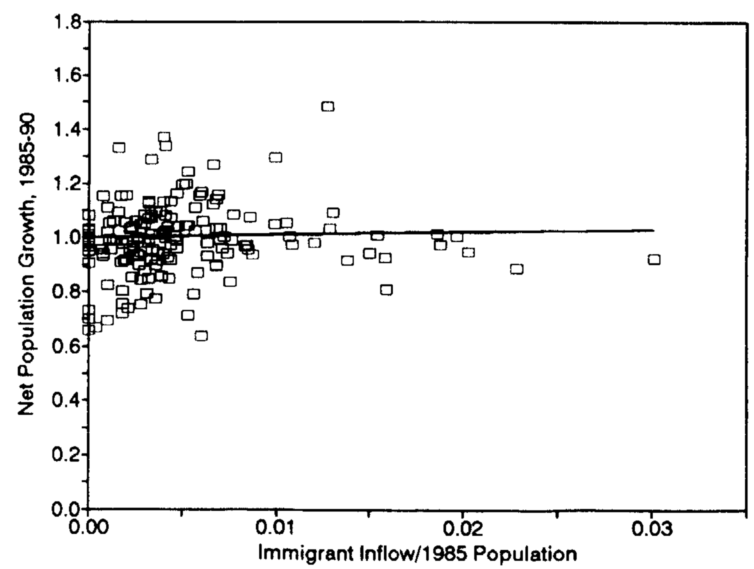
c. Skill Group 4



b. Skill Group 2



d. Skill Group 8



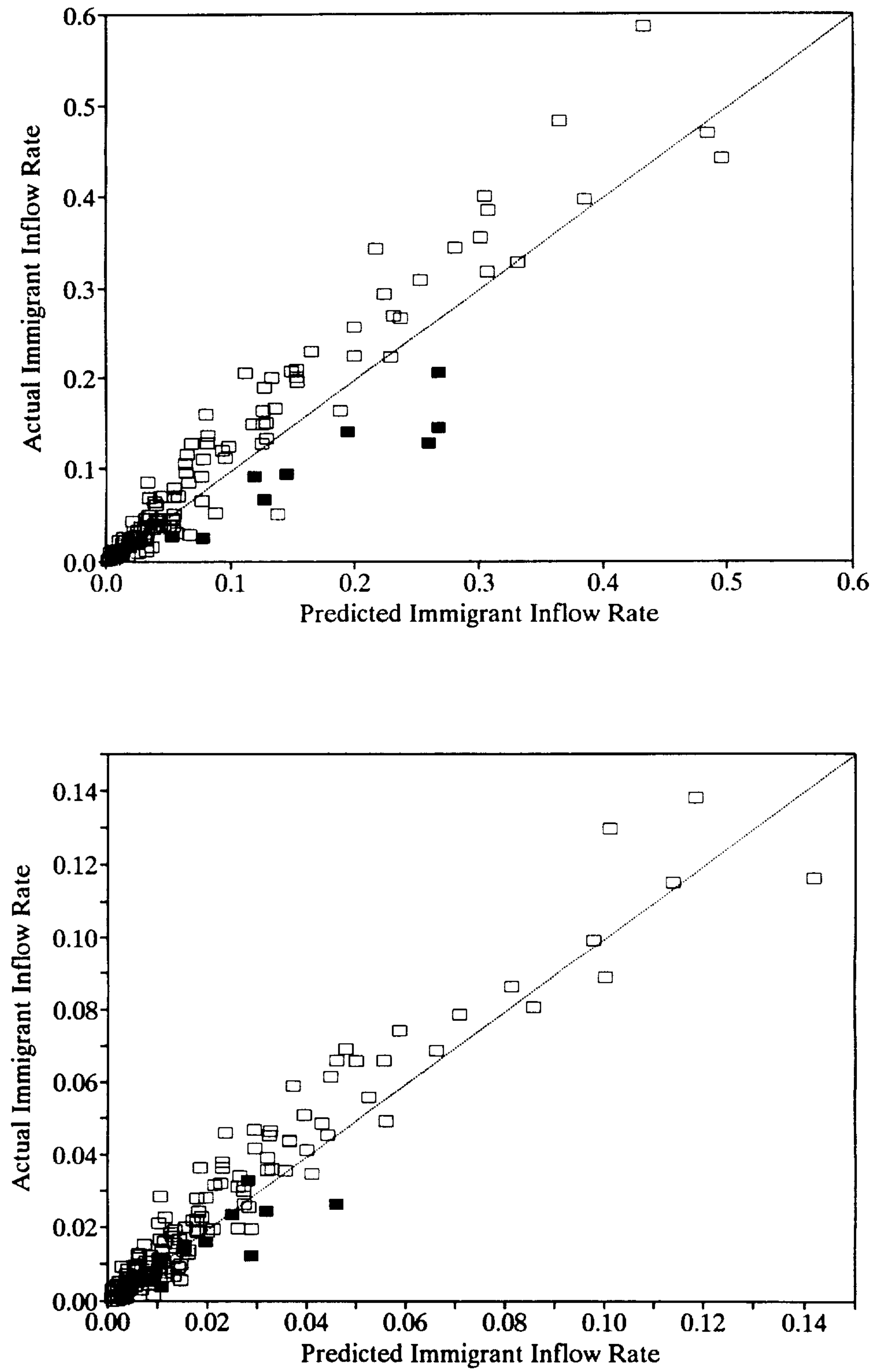
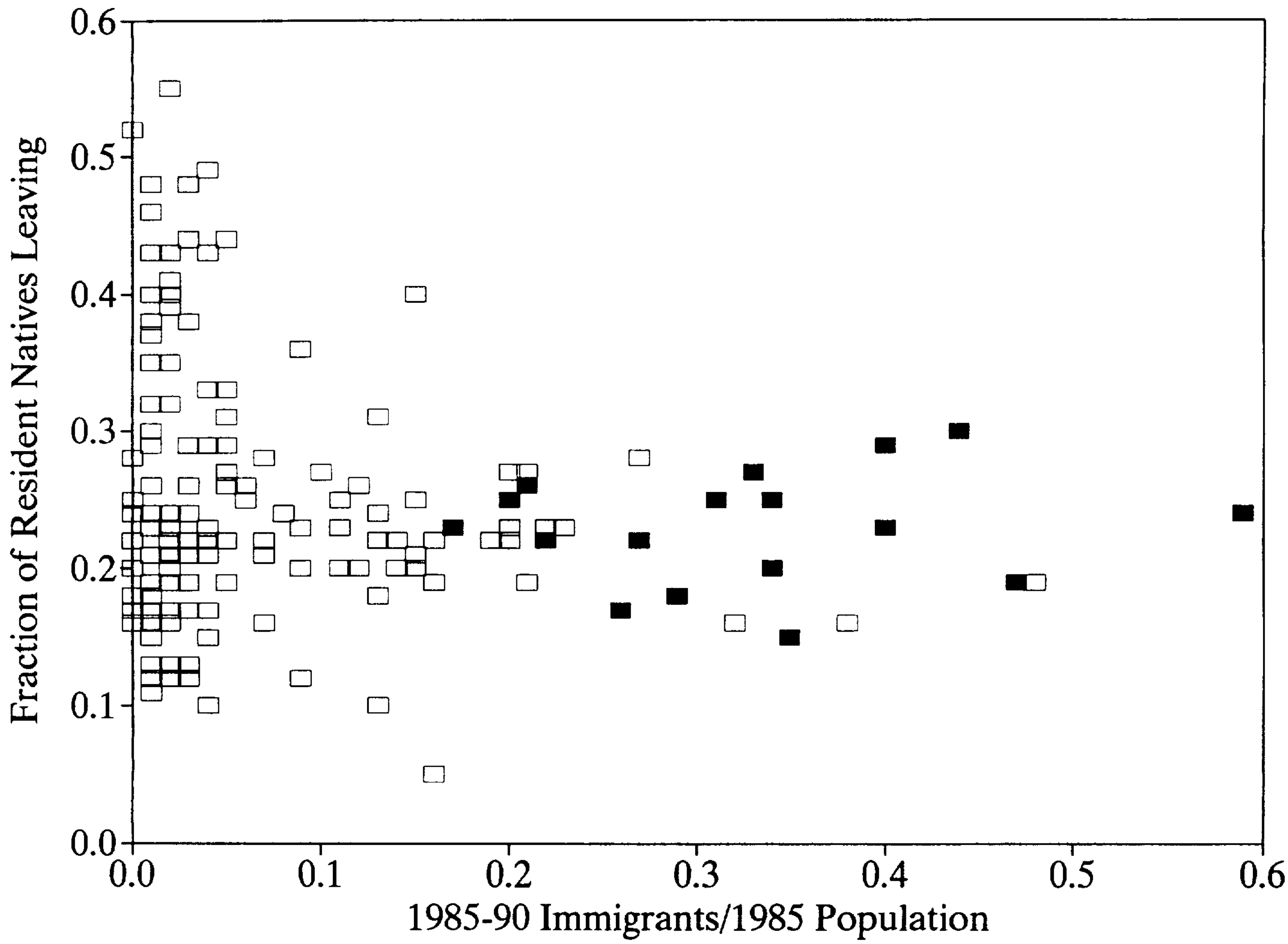


Figure 2: Actual and Supply-Driven Immigrant Inflows in Two Lowest Skill Groups (Texas Cities Highlighted)

Figure 3: Immigrant Inflow Rates and Native Outflows Rates for Individuals in Lowest Skill Decile in 175 Major Cities, 1985-1990.



Note: California cities shown with filled squares

Figure 4: Predicted Immigrant Inflow Rates and Adjusted Employment Rate of Native Men in Lowest Skill Decile in 175 Major Cities, 1989.

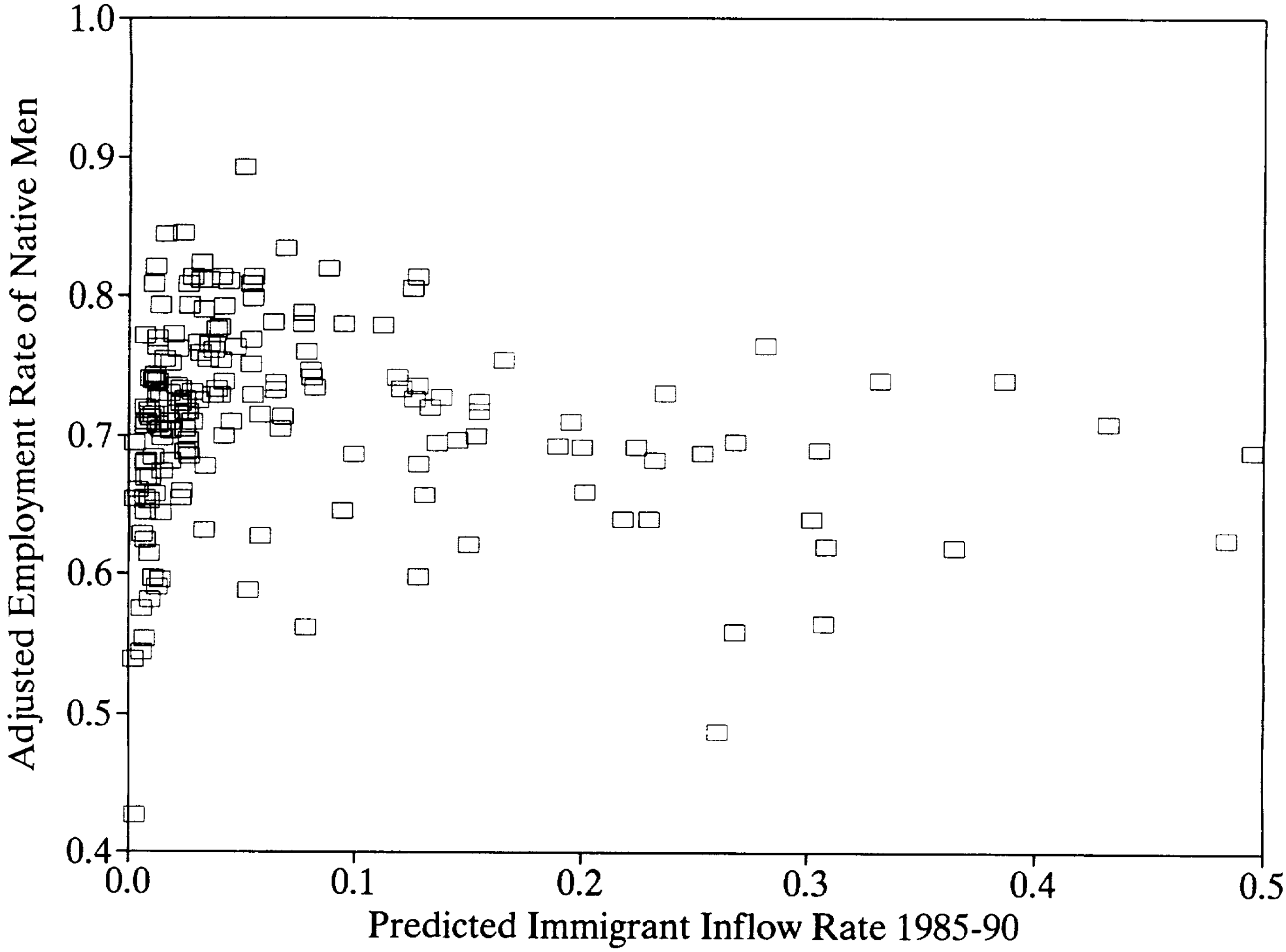


Table 1: Sample Characteristics, Natives and Immigrants Age 16-68 with Positive Labor Market Experience

	All U.S.	In 175 Largest Cities	Outside Largest Cities	In 175 Largest Cities: Natives	Pre-1985 Immigs	Recent Immigs
Weighted Count (thousands)	160,019	101,742	58,277	88,332	10,478	2,932
% Immigrants	10.2	13.2	3.7	0.0	100.0	100.0
% Immigrated 1985-90	2.1	2.9	0.7	0.0	0.0	100.0
% Female	51.0	51.2	50.6	51.2	51.0	48.1
% Black	9.9	11.6	7.0	12.3	7.0	6.9
% Hispanic	8.0	9.4	4.3	4.7	38.9	46.6
Average Education	12.6	12.9	12.2	13.1	11.7	11.1
Average Age	39.9	39.6	40.3	39.7	40.6	31.9
Labor Market Outcomes:						
% Worked in 1989	78.0	78.8	76.7	79.5	76.9	63.7
Average Hours in 1989	1403	1427	1363	1443	1408	1029
Average Hourly Wage in 1989	11.94	12.85	10.25	13.01	12.34	9.21
Distribution of Workers Across Wage Deciles[a]:						
% in deciles 1-2	24.1	20.0	31.2	19.6	23.2	42.3
% in deciles 3-4	20.4	20.0	22.6	18.8	20.7	23.2
% in deciles 5-7	29.6	30.0	27.7	31.1	29.5	20.3
% in deciles 8-10	25.8	30.0	18.5	30.5	26.3	14.1
Location:						
% Living in Four Major Cities[b]	9.2	14.0	0.0	10.6	36.0	39.9
% Lived in Different City in 1985[c]	20.7	20.4	22.1	19.7	26.3	--

Notes: Based on tabulations of 1990 Census sample. Samples include men and and women age 16-68 with 2 or more years of potential experience.
[a]Deciles of wage distribution among those in 175 largest cities.
[b]Los Angeles, New York, Chicago, Miami.
[c]Recent (post-1985) immigrants excluded from calculation.

Table 2: Characteristics of Adult Population by Predicted Skill Group

		Skill Group (Decile of Predicted Wage Distribution):									
	All	1	2	3	4	5	6	7	8	9	10
Percent Immigrants	13.2	29.7	17.6	12.2	9.5	11.7	11.0	9.6	8.5	6.4	7.6
Percent Born in Mexico	2.8	12.9	4.1	2.2	1.6	1.3	0.8	0.4	0.3	0.1	0.1
Percent Immigrated 1985-90	2.9	13.4	3.4	1.7	1.3	1.4	1.1	0.8	0.8	0.4	0.3
Average Years in U.S. Among Immigrants	16.2	8.5	14.5	18.2	19.2	19.4	19.0	21.9	23.2	24.1	26.3
Percent Female	51.2	60.7	69.7	78.4	77.5	63.7	43.4	36.4	25.8	23.0	5.4
Percent Native Female	44.5	40.7	59.6	71.3	72.4	57.9	39.1	33.1	23.8	21.9	5.0
Percent Native Male	42.3	29.5	22.8	16.5	18.1	30.4	49.9	57.3	67.7	71.8	87.5
Percent Black	11.6	18.1	18.3	14.6	12.8	13.1	12.3	8.7	5.1	3.6	2.0
Percent Hispanic	9.4	27.0	14.4	8.9	6.9	7.2	6.4	5.0	4.2	3.2	2.4
Average Years Education	12.9	10.0	10.9	12.0	12.4	13.0	13.1	13.8	14.0	15.1	17.3
Average Age	39.6	25.0	36.8	40.3	42.8	40.8	39.9	42.1	43.7	45.2	46.7
Percent Worked in 1989	78.8	64.9	66.9	69.4	75.4	79.3	83.7	84.3	89.6	93.4	95.5
Average Hours in 1989	1427	788	1061	1143	1307	1419	1586	1617	1830	1952	2133
Average Log Hourly Wage	2.33	1.71	1.93	2.05	2.15	2.25	2.35	2.47	2.59	2.73	3.02
Distribution of Adults Across Skill Groups:											
Percent of Workers in Skill Group	100.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
Percent of Population in Skill Group	100.0	12.6	11.8	11.3	10.4	9.8	9.4	9.3	8.8	8.3	8.3

Note: Individuals are assigned to a skill group on the basis of a wage prediction derived from a regression model fit to workers in 1989. Prediction models are fit separately for native and immigrant men and women: see text for more information.

Table 3: Indexes of Occupational Competition

	Own-Group Indexes:			Cross-Group Indexes wrt Recent Immigrants		Normalized Cross-Indexes	
Skill Group:	Recent Immigs (1)	Older Immigs (2)	Natives (3)	Older Immigs (4)	Natives (5)	Older Immigs (6)	Natives (7)
1	3.4	3.7	2.2	3.3	1.7	0.9	0.8
2	1.7	2.1	1.4	1.7	1.3	0.8	0.9
3	1.4	1.5	1.3	1.2	1.1	0.8	0.8
4	1.4	1.3	1.3	1.1	1.0	0.8	0.7
5	1.6	1.2	1.2	1.1	1.0	0.9	0.8
6	2.0	1.3	1.2	1.1	1.0	0.9	0.8
7	2.4	1.3	1.3	1.2	1.0	0.9	0.8
8	3.1	1.4	1.3	1.5	1.1	1.0	0.9
9	4.7	1.9	1.5	2.2	1.4	1.2	0.9
10	7.3	5.2	2.7	4.2	2.7	0.8	1.0

Note: See text. Own-group indexes (columns 1-3) represent the effective percentage increase in supply of labor to occupations held by a specific group as a result of an expansion of the group that leads to a 1-percent increase in the overall workforce. Cross-group indexes with respect to recent immigrants (columns 4-5) represent the effective percentage increase in supply of labor to occupations held by a specific group (older immigrants or natives) as a result of an increase in the workforce of recent immigrants that leads to a 1-percent increase in the overall population. Normalized cross-indexes repesent the ratio of the cross-group index to the own-group index: i.e. column 6 = column 4 / column 2; column 7 = column 5 / column 3.

Calculations are based on employment distributions across 502 3-digit occupations.

Table 4: Effects of Recent Immigrant Inflows on Migration Rates of Natives and Earlier Immigrants in the Same Skill Group

	Native Out-and-Inflows				Earlier Immigrant Out-and-Inflows				Total Population Gain per New Immigrant
	Outflow Rate: Raw	Outflow Rate: Adjusted	Inflow Rate	Net Population Growth	Outflow Rate: Raw	Outflow Rate: Adjusted	Inflow Rate	Net Population Growth	
OLS Estimation									
1. All Skill Groups with City Effects Unweighted	-0.14 (0.03)	-0.14 (0.03)	-0.06 (0.05)	0.08 (0.06)	-0.15 (0.08)	-0.22 (0.08)	0.14 (0.13)	0.28 (0.15)	1.12 (0.05)
2. All Skill Groups with City Effects Weighted	-0.12 (0.02)	-0.12 (0.02)	-0.07 (0.03)	0.05 (0.03)	-0.01 (0.05)	-0.07 (0.04)	0.05 (0.07)	0.07 (0.08)	1.07 (0.03)
3. All Skill Groups with City Effects 100 Largest Cities Unweighted	-0.13 (0.03)	-0.14 (0.03)	-0.12 (0.04)	0.01 (0.05)	0.02 (0.06)	-0.05 (0.06)	0.05 (0.09)	0.03 (0.11)	1.05 (0.05)
4. 3 Lowest Skill Groups with City Effects Unweighted	-0.10 (0.04)	-0.11 (0.04)	0.02 (0.08)	0.12 (0.09)	-0.21 (0.11)	-0.25 (0.11)	0.03 (0.18)	0.25 (0.21)	1.13 (0.08)
5. All Skill Groups No City Effects Unweighted	-0.19 (0.06)	-0.19 (0.06)	0.10 (0.09)	0.29 (0.11)	0.04 (0.09)	-0.05 (0.09)	0.18 (0.15)	0.14 (0.19)	1.30 (0.12)
IV Estimation: Instrument is Predicted Immigrant Inflow Rate									
6. All Skill Groups with City Effects Unweighted	-0.15 (0.03)	-0.14 (0.03)	-0.10 (0.05)	0.05 (0.06)	-0.18 (0.09)	-0.24 (0.09)	0.11 (0.14)	0.29 (0.17)	1.09 (0.06)
7. All Skill Groups with City Effects Weighted	-0.12 (0.02)	-0.12 (0.02)	-0.15 (0.03)	-0.03 (0.04)	-0.02 (0.05)	-0.08 (0.05)	0.06 (0.08)	0.07 (0.09)	1.01 (0.04)
8. 3 Lowest Skill Groups with City Effects Weighted	-0.05 (0.03)	-0.06 (0.03)	-0.14 (0.06)	-0.09 (0.07)	-0.05 (0.07)	-0.08 (0.07)	0.03 (0.11)	0.08 (0.14)	0.96 (0.07)
9. All Skill Groups with City Effects Excluding 17 California Cities, Weighted	-0.14 (0.03)	-0.13 (0.03)	-0.15 (0.04)	-0.01 (0.05)	-0.09 (0.07)	-0.19 (0.07)	0.03 (0.11)	0.12 (0.13)	1.08 (0.05)

Notes: Entries are estimated regression coefficients of recent immigrant inflow rate in models for dependent variable listed in column heading. Sample includes 10 skill groups in 175 cities (1750 observations). All models include 9 skill group dummies, the fraction of immigrants in 1985, mean age, mean age-squared, mean education, percent black, and (for immigrants only) mean years in the U.S. for the skill group in the particular city in 1985. Adjusted outflow rates are described in text. Standard errors in parentheses.

Table 5: Countries of Origin and Skill Composition of Recent Immigrant Flows

Origin Group	Number of Immigrants (1000's)	Percent of Immigrant Flow	Fraction of Origin Group in Skill Range:				
			Lowest	2nd	3rd-4th	5th-7th	8th-10th
All Countries of Origin	3,311	100.0	58.7	13.9	11.4	11.3	4.6
Australia, New Zealand, Canada, United Kingdom	151	4.6	3.4	12.7	19.8	30.9	33.2
Northwestern Europe and Isreal	98	3.0	10.5	21.7	15.9	28.4	23.5
Southwestern Europe (Italy, Spain, Greece, etc)	68	2.1	11.9	25.8	20.9	32.4	9.0
Central Europe - Former East Block and Russia	137	4.1	35.5	16.3	22.0	19.9	6.2
India, Pakistan and Central Asia	140	4.2	37.8	16.8	20.1	21.1	4.1
Arab Countries including Turkey and N. Africa	116	3.5	33.3	19.9	21.0	19.8	6.0
Burma, Loas, Thailand, Viet Nam	157	4.7	70.5	14.7	8.6	5.4	0.8
Indonesia, Malaysia, Brunei	206	6.2	53.7	21.2	12.8	10.0	2.2
China, Hong Kong, Mongolia, Singapore	212	6.4	46.0	16.5	17.9	17.7	2.0
Korea and Japan	203	6.1	28.3	15.9	15.6	24.1	16.0
Phillipines	174	5.2	38.3	18.4	24.7	17.5	1.1
Cuba	34	1.0	66.6	19.8	7.9	4.8	1.0
Carribean Countries	173	5.2	59.4	22.2	12.8	4.8	0.8
Central America (excluding Mexico)	282	8.5	86.4	9.0	2.4	2.0	0.2
South America	205	6.2	53.7	21.1	14.6	8.9	1.7
Africa (except Algeria, Egypt, Morocco, etc)	60	1.8	33.3	23.5	20.5	19.2	3.5
Mexico	896	27.1	93.4	4.4	1.2	0.8	0.1

Notes: Based on individuals age 16-68 in 1990 who immigrated 1985-1990 with 2 or more years of potential labor market experience in 1990. Tabulations include immigrants who live in 175 major cities as well as those who live in smaller cities or non-urban areas.

Table 6: Effects of Skill Group Population Share on Employment-Population Rates of Natives and Earlier Immigrants

	Native Men		Native Women		Pre-1985 Immigrant Men		Pre-1985 Immigrant Women	
	Raw	Adjusted	Raw	Adjusted	Raw	Adjusted	Raw	Adjusted
OLS Estimation								
1. All Skill Groups with City Effects Unweighted	-0.06 (0.01)	-0.04 (0.01)	-0.06 (0.01)	-0.04 (0.01)	-0.03 (0.02)	-0.04 (0.02)	-0.01 (0.02)	-0.01 (0.02)
2. All Skill Groups with City Effects Weighted	-0.06 (0.01)	-0.05 (0.01)	-0.07 (0.01)	-0.06 (0.01)	-0.01 (0.01)	-0.03 (0.01)	-0.02 (0.02)	-0.03 (0.02)
3. All Skill Groups with City Effects 100 Largest Cities Unweighted	-0.06 (0.01)	-0.04 (0.01)	-0.07 (0.01)	-0.06 (0.01)	0.01 (0.02)	-0.02 (0.02)	0.02 (0.02)	0.01 (0.02)
4. 3 Lowest Skill Groups with City Effects Unweighted	-0.03 (0.02)	-0.02 (0.01)	-0.03 (0.01)	-0.03 (0.01)	0.01 (0.05)	-0.02 (0.05)	0.00 (0.04)	0.02 (0.03)
5. All Skill Groups with City Effects Adjusted Population Share Measure[a] Unweighted	-0.06 (0.01)	-0.04 (0.01)	-0.06 (0.01)	-0.04 (0.01)	-0.03 (0.02)	-0.05 (0.02)	-0.01 (0.02)	-0.01 (0.02)
6. All Skill Groups No City Effects Unweighted	-0.04 (0.01)	-0.02 (0.01)	-0.05 (0.01)	-0.03 (0.01)	-0.02 (0.02)	-0.03 (0.02)	0.01 (0.02)	0.00 (0.02)
IV Estimation: Instrument is Predicted Immigrant Inflow Rate								
7. All Skill Groups with City Effects Unweighted	-0.02 (0.02)	-0.09 (0.02)	-0.04 (0.03)	-0.06 (0.03)	0.09 (0.07)	-0.09 (0.07)	0.03 (0.10)	-0.03 (0.10)
8. All Skill Groups with City Effects Weighted	-0.08 (0.01)	-0.12 (0.01)	-0.08 (0.01)	-0.08 (0.01)	0.04 (0.03)	-0.08 (0.03)	-0.02 (0.04)	-0.10 (0.04)
9. 3 Lowest Skill Groups with City Effects Weighted	-0.05 (0.01)	-0.07 (0.01)	-0.02 (0.01)	-0.02 (0.01)	0.03 (0.04)	-0.05 (0.04)	0.00 (0.04)	-0.03 (0.03)

Notes: Entries are estimated regression coefficients of log skill-group population share in model for employment rate of group listed in column heading. Sample includes 10 skill groups in 175 cities (1750 observations). All models include 9 skill group dummies, mean age, mean education, percent black, percent married and (for immigrants only) mean years in the U.S. and fractions of immigrants from Western Europe, Asia, and Mexico for the gender/origin/skill group in the particular city in 1990. Adjusted employment rates are described in text. Standard errors in parentheses.

[a]Skill-group population share in city is adjusted for gender/origin composition. See text.

Table 7: Effects of Skill Group Population Share on Wage Rates of Natives and Earlier Immigrants

	Native Men		Native Women		Pre-1985 Immigrant Men		Pre-1985 Immigrant Women	
	Raw	Adjusted	Raw	Adjusted	Raw	Adjusted	Raw	Adjusted
OLS Estimation								
1. All Skill Groups with City Effects Unweighted	0.04 (0.01)	0.02 (0.01)	-0.08 (0.01)	-0.09 (0.01)	0.00 (0.03)	0.00 (0.03)	-0.02 (0.04)	-0.02 (0.04)
2. All Skill Groups with City Effects Weighted	0.02 (0.01)	0.00 (0.01)	-0.05 (0.01)	-0.05 (0.01)	-0.01 (0.02)	-0.01 (0.02)	-0.04 (0.03)	-0.05 (0.03)
3. All Skill Groups with City Effects 100 Largest Cities Unweighted	0.03 (0.01)	0.01 (0.01)	-0.05 (0.01)	-0.05 (0.01)	-0.03 (0.03)	-0.04 (0.03)	-0.05 (0.04)	-0.07 (0.04)
4. 3 Lowest Skill Groups with City Effects Unweighted	0.01 (0.02)	0.00 (0.02)	-0.07 (0.02)	-0.07 (0.02)	-0.04 (0.07)	-0.06 (0.07)	-0.13 (0.04)	-0.10 (0.04)
5. All Skill Groups with City Effects Adjusted Population Share Measure[a] Unweighted	0.03 (0.01)	0.02 (0.01)	-0.07 (0.01)	-0.08 (0.01)	0.00 (0.03)	-0.01 (0.03)	-0.01 (0.04)	0.00 (0.04)
6. All Skill Groups No City Effects Unweighted	0.07 (0.02)	0.06 (0.02)	0.00 (0.02)	-0.01 (0.02)	0.03 (0.03)	0.02 (0.03)	0.01 (0.04)	0.01 (0.04)
IV Estimation: Instrument is Predicted Immigrant Inflow Rate								
7. All Skill Groups with City Effects Unweighted	0.01 (0.04)	-0.01 (0.04)	-0.03 (0.04)	-0.02 (0.04)	0.17 (0.12)	0.01 (0.12)	0.08 (0.16)	0.06 (0.16)
8. All Skill Groups with City Effects Weighted	-0.01 (0.02)	-0.04 (0.02)	-0.02 (0.02)	-0.01 (0.02)	0.10 (0.05)	0.02 (0.05)	0.01 (0.07)	-0.01 (0.07)
9. 3 Lowest Skill Groups with City Effects Weighted	0.01 (0.02)	-0.01 (0.02)	-0.08 (0.02)	-0.06 (0.02)	0.03 (0.06)	0.00 (0.06)	-0.25 (0.06)	-0.22 (0.06)

Notes: Entries are estimated regression coefficients of log skill-group population share in model for mean log wage rate of group listed in column heading. Sample includes 10 skill groups in 175 cities (1750 observations). All models include 9 skill group dummies, mean age, mean education, percent black, percent married and (for immigrants only) mean years in the U.S. and fractions of immigrants from Western Europe, Asia, and Mexico for the gender/origin/skill group in the particular city in 1990. Adjusted wage rates are described in text. Standard errors in parentheses.

[a]Skill-group population share in city is adjusted for gender/origin composition. See text.