

Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration

David Card, *University of California, Berkeley*

This article uses 1990 census data to study the effects of immigrant inflows on occupation-specific labor market outcomes. I find that intercity mobility rates of natives and earlier immigrants are insensitive to immigrant inflows. However, occupation-specific wages and employment rates are systematically lower in cities with higher relative supplies of workers in a given occupation. The results imply that immigrant inflows over the 1980s reduced wages and employment rates of low-skilled natives in traditional gateway cities like Miami and Los Angeles by 1–3 percentage points.

Over the past 3 decades, immigration rates into the United States have risen while the real wages of younger and less-educated workers have fallen (Levy and Murnane 1992). Despite the coincidental timing, a growing body of research finds only modest evidence that immigrant competition has hurt the labor market opportunities of low-wage natives. A series of studies has correlated the fraction of immigrants in different

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cities with native wages, employment rates, and unemployment rates.¹ Typically, a 10-percentage-point increase in the fraction of immigrants (roughly the difference between Detroit and Houston) is estimated to reduce 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 raised the fraction 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 comparing labor market outcomes across cities has come under attack, most notably by Borjas, Freeman, and Katz (1992, 1996) and Borjas (1994). There are three key conceptual problems in the cross-market approach: (1) an increase in the fraction of immigrants in a city does not necessarily raise the supply of low-skilled labor, since natives may move out 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) in the long run, an immigration-induced increase in the supply of labor to a particular city can be diffused across the economy by intercity trade. In light of these problems, Borjas et al. (1992, 1996) and Borjas (1994) downplay findings from the cross-market studies, and they rely instead on *a priori* theoretical models to deduce the effects of immigration on native opportunities.²

In this article I attempt to reassess 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 population of U.S. immigrants. As noted by Butcher and DiNardo (1998), an average immigrant worker is only slightly less skilled than an average native worker. 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 immi-

¹ For recent surveys of this literature, see Borjas (1994) and Friedberg and Hunt (1995). Grossman (1982) is one of the earliest studies of immigrant impacts on local labor markets. Subsequent research includes Borjas (1987); Altonji and Card (1991); and Schoeni (1996). LaLonde and Topel (1991) use a somewhat different strategy that is closer in spirit to the analysis here.

² A similar approach is followed by Jaeger (1995) who simulates the effects of immigration on the relative wages of different education groups under various assumptions about technology.

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

grants 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 local labor markets are stratified along occupation lines. Assuming a constant elasticity of substitution (CES) technology, the fraction of a city's population who would normally be expected to work in a given occupation provides a summary measure of relative local labor market competition facing that group. Within this framework, immigrant inflows affect the structure of wages by raising or lowering the relative population shares of different occupation groups. An inflow of immigrants that raises the fraction of the population in a particular group would be expected to put downward pressure on wages and employment rates for workers in the group. On the other hand, a balanced inflow of immigrants that leaves the relative population shares unchanged would not be expected to affect the relative wage structure.

This framework also clarifies the role of mobility in offsetting the effects of immigrant inflows. In the absence of offsetting mobility flows, each newly arriving immigrant in a particular occupation group adds one person to the local population of that group. To the extent that immigrant inflows lead to outflows of natives or earlier immigrants in the same skill group, however, each newly arriving immigrant contributes less than one person to the net population of his or her skill group.

To operationalize the notion of occupation-specific labor markets, while recognizing that individuals have some flexibility in choosing occupations, I assign nationally based probabilities for working in different occupations to each person. These probabilities are estimated for a standardized national labor market, using observed characteristics such as education, age, ethnicity, and country of origin. The local supply of workers in a given occupation is defined as the sum of the probabilities for working in that occupation across all individuals in the local labor market. Conceptually, this is an estimate of the number of people who would be expected to work in the occupation in the absence of any distortions caused by local demand or supply pressures. Similarly, city-specific wages and employment rates for the occupation group are defined as weighted averages across all individuals in the local labor market, using the occupation-specific probabilities as weights.⁴

A second novel feature of the analysis in this article is a focus on recent immigrants—individuals who have moved to the United States within the past 5 years. This focus is motivated by two considerations. First, as will be shown below, recent immigrants are concentrated in the same occu-

⁴ This procedure is a generalization of the more standard procedure of assigning each individual to a specific skill group with a probability of one.

pations as low-skilled native workers. Much of the policy concern over higher immigration is, therefore, naturally directed toward the labor market impacts of newly arrived immigrants. Second, because many newly arriving immigrants settle in 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 demand 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.

I. Theoretical Framework

A useful benchmark model for analyzing the effect of relative supplies of different skill groups on the structure of wages is one with a single output good in each city. Assume that output in city c (Y_c) is produced by a competitive industry with a production function

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

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

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

For the moment, assume that individuals are assigned to unique occupations and ignore any variation in hours per worker, so N_{jc} is just a count of the number of individuals in occupation group j employed in city c . The variables e_{jc} represent city- and occupation-specific productivity shocks, while the parameter σ is the elasticity of substitution between different occupations. If w_{jc} represents the wage rate of occupation group j in city c and q_c is the selling price of output from city c , then the first-order condition that equates the marginal product of an occupation group with its real product wage can be written as

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

where $\theta_c = \sigma \log [q_c F_L(K_c, L_c) L_c^{1/\sigma}]$ represents a common city-specific component shared by all groups. Although equation (1) is not a proper labor demand function, it nonetheless captures the effect of the local wage structure on the relative demands for different occupations, holding constant citywide factors.

Let P_{jc} represent the population of individuals in occupation j in city c ,

and assume that the labor supply function (or participation function) for the group is log-linear:

$$\log (N_{jc}/P_j) = \varepsilon \log w_{jc} \quad (2)$$

where $\varepsilon > 0$. Equations (1) and (2) lead to the following expressions for the wage rate and employment-population rate of occupation j in city c :

$$\begin{aligned} \log w_{jc} = & 1/(\varepsilon + \sigma)\{(\theta_c - \log P_c) \\ & + (\sigma - 1) \log e_{jc} - \log (P_{jc}/P_c)\}, \end{aligned} \quad (3)$$

$$\begin{aligned} \log (N_{jc}/P_j) = & \varepsilon/(\varepsilon + \sigma)\{(\theta_c - \log P_c) \\ & + (\sigma - 1) \log e_{jc} - \log (P_{jc}/P_c)\}, \end{aligned} \quad (4)$$

where P_c is the total population in city c . These equations show that wages and employment rates are determined by three factors: a common city-specific component, an occupation and city-specific productivity component, and the relative population shares of the groups. The CES functional form implies that each group's relative wage depends only on its population share and on the group-specific productivity component.

Equations (3) and (4) are used as the basis for the empirical work in this article. I assume that the productivity component can be decomposed as

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

where e_j represents a common occupation effect, e_c is a city-effect, and e'_{jc} represents an occupation and city-specific productivity term. Let $f_{jc} = P_{jc}/P_c$ denote the fraction of the population of city c in occupation group j . Then equations (3) and (4) lead to simple regression models of the form

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

and

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

where u_j , v_j , u_c and v_c are occupation- and city-fixed effects, u_{jc} and v_{jc} are unobserved error components that depend on e'_{jc} (and other factors, such as sampling errors), and the coefficients d_1 and d_2 are functions of the elasticities of substitution and supply: $d_1 = -1/(\varepsilon + \sigma)$; $d_2 = -\varepsilon/(\varepsilon + \sigma)$. City fixed effects absorb any citywide variables that might otherwise influence the levels of wages or employment in the local labor

market.⁵ Any occupation-specific local productivity shocks, however, remain in the error terms. To the extent that local productivity shocks raise wages and lead to an increase in the population of a particular occupation group, the error components in equations (3') and (4') will be positively correlated with the population shares, leading to positive biases in the estimates of d_1 and d_2 . 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 occupation-specific productivity shock. As discussed in more detail below, the supply-push component of the immigrant inflows to a particular city, which is based on historical settlement patterns and the total number of newly arriving immigrants from different source countries, is a potential candidate for such an instrumental variable.

The assumption that all individuals in a given occupation supply the same units of labor and earn the same wage is obviously quite restrictive, and this is unlikely to hold when men and women are pooled in the same occupations (as they are below). In an earlier version of this article (Card 1997), I showed how this assumption can be relaxed by assuming that different demographic subgroups within each occupation are perfect substitutes in production but supply different efficiency units of labor (e.g., by working more hours per period) or have different intercepts in their labor supply functions. This assumption leads to versions of equations (3) and (4) that depend on an adjusted count of the relative populations of different occupation groups, where the adjustment factors vary by demographic subgroup within occupations, reflecting differences in the relative efficiency and relative tastes of different subgroups. It is important to note that if the subgroup composition of different occupations is roughly constant across cities, then the adjustment factors will be constant, and equations (3') and (4') will continue to hold with a reinterpretation of the occupation-specific fixed effects. Otherwise, it is necessary to estimate the relative adjustment factors using data on per capita earnings for each subgroup in a given occupation.

Limitations of the Model

Before proceeding to the data analysis, it is useful to underscore the limitations of the theoretical framework underlying equations (3) and (4). Perhaps the most important limitation is the assumption of one output good. More generally, the demand for labor in a city is generated by many

⁵ Many previous studies (e.g., Altonji and Card 1991; Schoeni 1996) focus on a single skill group in each city and therefore rely on longitudinal data to eliminate permanent city effects. Lalonde and Topel (1991) compare the relative wages of different cohorts of immigrants within cities: their approach is, therefore, quite similar to the one in this article.

different industries, some of which produce goods or services that can be exported to other cities. In this situation, the impact of an increase in the relative fraction of the population in a given skill group can be mitigated by the expansion of export industries that use the relatively abundant skill-group more intensively.⁶ Such an endogenous shift in industry structure is observationally equivalent to occupation-specific local demand shocks that are positively correlated with the relative supplies of different occupation groups. However, since the market signal that triggers an endogenous change in local industry structure is a shift in relative wages, one would expect an exogenous rise in the local population share of a given occupation group to exert at least a short-run impact on wages.

In particular, consider the responses of different local labor markets to inflows of new immigrants over the 1980s. Given the unprecedented magnitude of these flows, it seems unlikely that employers could have adjusted their product mixes and capital stocks to fully accommodate the shifts in relative labor supplies. Nevertheless, employers in some immigrant gateway cities could have anticipated some fraction of the relative supply shifts that actually occurred, leading to some specialization and a lessening of impacts on the relative wage structure. Ordinary least squares estimates of the effects of relative population shares derived from equations (3') and (4') are, therefore, likely to be smaller in magnitude than the effects that would arise with a fixed industry structure, but they are likely to be larger than the effects that would emerge in the very long run if the industry structure could fully adjust. Instrumental variable estimates based on exogenous short-run supply shifts (such as the supply-push component of immigrant inflows to each city) should be larger in magnitude and closer to the parameter values that would arise with a fixed industry structure.

A second limitation of the model is the assumption (arising from the CES functional form) that the relative wage of a particular skill group depends only on the relative population share of that group. This assump-

⁶ Standard trade theory results imply that if each industry has the same production function in all cities, 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 Johnson and Stafford (1999) and Leamer (1995) for rigorous statements. 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 shares between 1970 and 1980 in high-immigrant cities relative to low-immigrant cities. The actual changes in the levels of employment in these industries, however, are small (and in some cases even negative), suggesting that low-wage manufacturing industries could not have absorbed large inflows of immigrants.

tion is widely used in the wage inequality literature (e.g., Bound and Johnson 1992), and it provides a natural starting point for analyzing the effect of relative supply shifts.⁷ As a specification test, I conduct some analysis using only a subset of occupations. As long as two or more groups are included per city, equations (3') and (4') are estimable, and under the CES assumption, the parameter estimates should be invariant to the choice of which occupation groups are included. On the other hand, if some subset of occupations are closer substitutes to one another, one would expect the magnitude of the estimated elasticity of substitution to rise when only those groups are included in the analysis.⁸

II. Data Description and Implementation Issues

The empirical analysis in this article is based on 1990 census data pertaining to labor market outcomes in 1989. Throughout the article, I restrict attention to men and women between the ages of 16 and 68 with at least 1 year of potential labor market experience in 1989. (The latter restriction is meant to eliminate students.) I use total annual earnings (including self-employment and wage and salary earnings) along 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. The appendix provides more detailed information on the sample extracts. I use 100% of all foreign-born individuals in the 5% public use micro sample of the 1990 census (roughly 840 thousand observations) and a 25% random sample of all U.S.-born individuals (roughly 1.8 million observations).

A. Defining Local Labor Markets

An immediate issue that arises in any study of local labor markets is the definition of individual 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 article, I consider each metropolitan statistical area (MSA) as an indepen-

⁷ Katz and Murphy (1992) consider a more general technology in their analysis of the role of demand shifts in wage inequality, although they reach substantially the same conclusions as Bound and Johnson (1992). Moreover, they do not simultaneously consider supply and demand shocks.

⁸ For example, suppose that labor input in each city can be decomposed as $G(L_{Ac}, L_{Bc})$, where L_{Ac} is a CES subaggregate of low-skill labor (with substitution with parameter σ_A) and L_{Bc} is a CES subaggregate of high-skill labor (with substitution with parameter σ_B). Then, estimation of eqq. (3') and (4') on the subset of low-skill occupations will recover σ_A and a corresponding labor supply elasticity for these groups.

dent labor market. I also consider individually identified cities within larger agglomeration of cities as separate local labor markets.⁹ A total of 324 individual MSAs and subcities within consolidated metropolitan statistical areas (CMSA) are identified on the 1990 census public-use files.¹⁰ Since the sample sizes for many of the smaller cities are limited, I restricted attention to the 175 largest cities, ranked by the number of native-born adults in the city. Using this criterion, the smallest city included in the sample is Ann Arbor, Michigan, while the largest city excluded from the sample is Naples, Florida. A list of included cities is available on request.

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% of the adult population resided in larger cities in 1990.¹¹ Residents of larger cities are more likely to be black, Hispanic, and foreign-born, and they 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% higher in larger cities.

In 1990, 14% of the adult population of the 175 largest U.S. cities were born abroad. Of these, about one-fifth arrived in the United States 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. Immigrants differ from natives in several dimensions: for example, immigrants are 10 times more likely to be of Hispanic ethnicity, and they have 1–2 years less education on average. Recent immigrants tend to be younger than the other two groups. The labor market outcomes of natives and pre-1985 immigrants are surprisingly similar, whereas recent immigrants have significantly

⁹ 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). The classification of large urban areas into separate entities is somewhat arbitrary. Areas with over a million people may be subdivided if population and commuting criteria are met and if there is local political support for creating separate entities (U.S. Bureau of the Census 1994).

¹⁰ Some individuals who live in geographic areas that straddle an MSA boundary (or boundaries) are not assigned an MSA in the public use micro data samples. As explained in the appendix, in cases where more than 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.

¹¹ The rest of the population consists of individuals who do not live in MSAs or CMSAs (25% of the population) and individuals who live in smaller MSAs (10% of the adult population).

Table 1
Characteristics of Natives and Immigrants

	All United States	In 175 Largest Cities	Outside of Largest Cities	In 175 Largest Cities		
				Natives	Pre-1985 Immigrants	Recent Immigrants
Weighted count (millions)	160.0	102.0	58.0	87.9	11.1	3.0
Immigrants (%)	10.2	13.9	3.7	.0	100.0	100.0
Immigrated, 1985-90 (%)	2.1	3.0	.7	.0	.0	100.0
Black (%)	9.9	11.5	7.0	12.3	6.8	6.8
Hispanic (%)	8.0	10.1	4.3	4.7	42.3	48.4
Average education (years)	12.6	12.9	12.2	13.1	11.6	11.1
Average age	39.9	39.6	40.3	39.7	40.7	31.9
Labor market outcomes:						
Worked in 1989 (%)	77.9	78.7	76.6	79.6	76.0	63.5
Average hours worked in 1989	1,403	1,427	1,360	1,445	1,390	1,025
Average hourly wage in 1989	11.92	12.82	10.25	12.99	12.30	9.20
Distribution of workers: By hourly wage (%):						
<\$6.00	25.6	21.8	32.8	20.8	24.6	44.3
\$6.00-\$9.99	28.4	27.4	30.4	27.1	29.2	29.3
\$10.00-\$15.00	22.0	23.1	19.8	23.6	21.4	13.1
>\$15.00	24.0	27.7	17.0	28.5	24.8	13.2
By location (%):						
Living in Los Angeles, New York, or Chicago	8.4	13.1	.0	10.0	31.6	35.1
Major city residents who lived elsewhere in 1985*	...	20.5	...	19.6	27.6	...

NOTE.—Figures are based on tabulations of the 1990 Census sample. Samples include men and women ages 16-68 with 1 or more years of potential experience in 1989.

* Percent of current residents of larger cities who did not live in the same city 5 years ago. Post-1985 immigrants were excluded from the calculation.

lower wages and employment rates. For example, 21% of natives and 25% of pre-1985 immigrants earned less than \$6 per hour in 1989, as compared with 44% of recent immigrants. Similarly, 29% of natives and 25% of pre-1985 immigrants earned over \$15 per hour, as compared with only 13% of recent immigrants.

Another difference between native workers and immigrants is geographic location. In 1990, about 28% of all immigrants lived in the three largest cities (Los Angeles, New York, Chicago), as compared with only 6% of natives. Immigrants and natives also differ in their intercity mobility rates. As shown in the bottom row of table 1, about 20% of the adult population of larger cities reported living in a different city in 1990

than did so in 1985.¹² 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.

B. Defining Occupation Groups

A second issue that arises in estimating the impact of immigration is the question of "who competes with whom?" Specifically, which groups of workers are perfect substitutes for each other, and how many independent types of labor are present in any local labor market? Most existing studies treat immigrant workers as one factor of production and various subgroups of natives as separate factors (a notable exception is Jaeger 1995). As noted in the introduction, however, the immigrant workforce is remarkably diverse, and it varies widely across cities. An alternative to treating immigrants and natives as separate skill groups is to define skill categories within which immigrants and natives are perfect substitutes and to classify individual immigrants and natives into these groups. This approach allows a more precise characterization of the degree of competition between natives and immigrants in different cities, but it does so at the cost of some arbitrariness in the definition of skill groups.

One potentially appealing assumption is that labor markets are stratified along occupation lines and that individuals who work in the same occupation are perfect substitutes with each other regardless of their gender or national origin.¹³ A problem with this assumption is that individuals can move between occupations, and they would be expected to do so if there is a relative oversupply of workers in a particular occupation. Another difficulty is that occupations are only observed for those who work: thus, it may be difficult to measure the population of individuals in a given city who could potentially work in an occupation. Both of these problems can be solved by considering an individual's occupation as a probabilistic outcome that depends on underlying characteristics such as age, education, race, gender, national origin, and length of time in the country. Suppose that occupations are partitioned into a set $j = 1, \dots, J$ and that a given individual, i , has probabilities $\pi_{i1}, \pi_{i2}, \dots$,

¹² The census form asks each individual where they lived 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 MSAs using the mapping between PUMAs and MSA for 1990 place of residence.

¹³ This assumption is built in to U.S. immigration law, which requires employers who sponsor applicants for permanent residence status to certify that the applicant is not undercutting wages of workers in the same occupation in his or her local labor market.

π_{ij} of working in the different occupations in some reference labor market (e.g., a nationally representative city). Then, the number of people who would be expected to work in occupation j in any particular local labor market is just the sum of the π_{ij} 's across the local population.¹⁴ (Of course, the number who actually work in the occupation could depend on conditions in the local market, such as the wage for the occupation.) Moreover, estimates of the employment rate and mean wages for individuals who would be expected to work in occupation j can be obtained by forming weighted averages of employment and wages across the population of the city, using the π_{ij} 's as weights.

To implement this idea, I estimated a set of multinomial logit models (by gender and immigrant status) for the probabilities of working in six different broad occupation groups, using a sample of individuals from the 175 largest cities. The models for native men and women included identical flexible functions of age and education, race, marital status, and disability status in each branch of the logit model. To abstract from any distortions in the occupation distribution in high-immigrant cities, the models also include dummies for the 30 largest cities and dummies for living in California, Texas, Florida, New York, or other northeastern states. The models for immigrants included the same basic covariates, plus dummy variables for 17 different origin countries (or groups of countries), a polynomial in the number of years in the United States, and interactions of four broad origin groups with education.¹⁵ The estimated coefficients from these four models were then used to assign probabilities of working in different occupations assuming that an individual lives in an average smaller city outside the four major immigrant-receiving states and the northeast.

Table 2 summarizes the characteristics of individuals in each of the six predicted occupation groups. The groups are laborers and low-skilled service workers; operatives and craft workers; clerical workers; sales workers; managers; and professional and technical workers. The six groups each represent 10%–20% of the national labor force, and they are ordered by the mean level of education in the group. The first group, laborers and less-skilled service workers, has the lowest average education and the lowest average hourly wages; this group also has the highest representation of blacks, Hispanics, and immigrants. At the other end of

¹⁴ A similar assumption is widely used in the wage inequality literature to measure the supply of high-school-equivalent and college-equivalent labor—see, e.g., Katz and Murphy (1992).

¹⁵ The origin groups are explained below. See the appendix for a fuller description of these models. In principle, the models could be estimated on weighted samples, where the weight for each individual represents his or her relative probability of working (since occupations are only observed for workers).

Table 2
Characteristics of Predicted Occupation Groups

	Occupation Group					
	I	II	III	IV	V	VI
Percentage female	53.9	23.8	81.8	55.9	45.8	53.8
Mean education	11.1	11.4	12.8	13.0	14.4	15.6
Percentage black	19.4	12.3	11.3	7.3	6.2	8.2
Percentage Hispanic	16.9	16.6	12.1	10.5	7.2	6.2
Percentage immigrant	19.1	16.9	11.9	11.5	9.4	10.6
Percentage recent immigrant	5.4	3.7	2.0	2.4	1.3	1.8
Percentage Mexican immigrant	4.7	5.5	2.3	1.8	.2	.1
Mean years in the United States among immigrants	14.4	15.5	18.3	17.4	20.5	18.7
Mean log wage	2.10	2.29	2.18	2.30	2.52	2.56
Percentage of workers	17.4	23.2	16.2	11.3	12.0	19.8
Percentage of population	19.5	22.8	17.2	11.4	11.0	18.1

NOTE.—Occupation groups are I, laborers, farm workers, and low-skilled service workers; II, operatives and craft workers; III, clerical workers; IV, sales workers; V, managers; and VI, professional and technical workers. Characteristics for each occupation group are formed as weighted averages over the entire adult population, where the weights are the predicted probabilities of working in the occupations. See text for further details.

the spectrum, professional and technical workers have the highest average education and the highest average wage, and they have the lowest fraction of Hispanics and Mexican immigrants. As shown in the bottom two rows of the table, the fractions of the overall adult population and of the employed adult population assigned to the six occupation groups are somewhat different, and there is a greater relative representation of nonworkers in the the lowest occupation group.¹⁶

The occupational composition of the local population varies widely across cities. Table A1 in the appendix shows the predicted fractions of the population in each occupation group for the 30 largest cities, normalized relative to the corresponding averages for all cities. Compared with the all-city average, Miami has 30% more of its local population in the lowest occupation group. Los Angeles and New York also both have relatively high fractions in the lowest occupation group (roughly 18% above the national average in each case). By comparison, Seattle and Denver have relatively low fractions in this group. At the other end of the skill distribution, the populations of Washington, DC, and San Francisco are overrepresented in the highest occupational category (roughly 40% above the national average), whereas Riverside and Miami have relatively low fractions in this group. Across all 175 major cities, St. Louis has a

¹⁶ While not shown in the table, the characteristics of workers in each predicted occupation group match very closely with the characteristics of actual workers in each occupation.

Table 3
Predicted Occupation Distributions of Natives, Older Immigrants, and Recent Immigrants

	Predicted Percentage of Occupation						Index of Competition
	I	II	III	IV	V	VI	
Natives:							
All	18.3	21.9	17.6	11.8	11.6	18.8	.98
Dropouts	37.5	36.5	12.7	9.1	2.6	1.6	1.31
High school	22.6	28.4	22.0	12.2	7.9	6.9	1.08
Some college	14.8	19.6	21.2	13.9	13.4	17.2	.93
College or more	3.3	5.2	9.7	10.2	21.1	50.5	.67
Pre-1985 immigrants:							
All	24.5	27.5	15.6	9.5	8.3	14.6	1.09
Dropouts	38.5	41.8	10.5	6.8	1.6	.8	1.35
High school	25.7	28.4	20.4	11.7	7.4	6.4	1.12
Some college	18.5	21.9	20.9	12.1	11.7	15.0	.99
College or more	6.9	9.0	11.7	8.0	16.4	48.0	.74
Recent immigrants (all)	35.1	28.3	11.8	9.2	4.8	10.8	1.22

NOTE.—Predictions are based on a multinomial logit model fitted to workers but applied to the entire population of individuals ages 16–68 with 1 or more years of labor market experience in 1989 who lived in one of the 175 largest cities in 1990. Occupations groups are I, laborers, farm workers and low skilled service workers; II, operatives and craft workers; III, clerical workers; IV, sales workers; V, managers; and VI, professional and technical workers. Index of competition measures the relative impact of an increase in the supply of recent immigrants on the particular group of natives or earlier immigrants. See text for details.

predicted occupation distribution closest to the national average. Other cities that are very similar to the national average include Columbus (Ohio), Indianapolis, Louisville, and Fort Worth. Looking across cities, the predicted fraction of the population in the lowest education group is highly correlated with the fraction of immigrants and with the fraction of recent immigrants (the population-weighted correlations are 0.46 and 0.42, respectively). It is interesting to note that mean log wages are also positively correlated with the fractions of immigrants or recent immigrants in the city (the weighted correlations are 0.41 and 0.42, respectively).

C. The Degree of Competition between Natives and Immigrants

The hypothesis that labor markets are stratified by occupation suggests a simple metric for assessing the degree of competition between subgroups of immigrants or natives. Intuitively, two groups with very similar predicted occupation distributions are in direct competition, whereas two groups with very different distributions are not. Table 3 shows the mean predicted occupation distributions for natives, pre-1985 immigrants, and recent immigrants, as well as for various subgroups of natives and pre-1985 immigrants. An examination of these distributions shows that natives and older immigrants are fairly similar, although the latter are slightly more likely to work in the two lowest occupations. By compar-

ison, the predicted occupation distribution of recent immigrants is heavily skewed toward blue-collar occupations (laborers, operatives, and crafts). Indeed, the occupation distribution of recent immigrants is quite similar to that of natives who did not finish high school.

More formally, the degree of competition between groups can be summarized by an index (I) that measures the effective increase in labor supply experienced by one group as the population of another group rises (Altonji and Card 1991). Let f_j^1 and f_j^2 denote the fractions of groups 1 and 2 (e.g., natives and recent immigrants) employed in occupation j , and let f_j 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 j is f_j^1/f_j . For members of group 2, the weighted average increase in the supply of labor to their occupation-specific labor markets is $I_{1,2} = \sum_j f_j^2 f_j^1 / f_j$. Note that if $f_j^2 = f_j$ or $f_j^1 = f_j$ (i.e., if either group 1 or group 2 has the same occupational distribution as the overall workforce), then the index takes a value of one. On the other hand, if groups 1 and 2 work in completely different occupations, then the index is zero. Finally, $I_{1,2}$ can be bigger than one if groups 1 and 2 have similar occupation distributions and if both groups are concentrated in a subset of occupations.

The right-hand column of table 3 presents estimates of the index of competition between recent immigrants and the various subgroups of natives and pre-1985 immigrants. Note, first, that the own-index of labor market competition between recent immigrants and themselves is greater than one (1.22). This reflects the fact that recent immigrants are disproportionately crowded into occupations I–IV. It is interesting that the cross-indexes of competition between recent immigrants and the least-educated subgroups of natives and older immigrants are even higher. Thus, the supply pressure exerted by an inflow of new immigrants is even bigger for poorly educated natives than for new immigrants themselves. This arises because a sizeable fraction of recent immigrants are predicted to work in the two highest occupations, whereas poorly educated natives are largely confined to the four lowest occupation groups, which experience disproportionate increases in supply when there is an inflow of new immigrants. Both informal comparisons of predicted occupation distributions and the more formal index of competition therefore confirm that inflows of new immigrants put substantial supply pressure on labor markets for less-educated natives.

III. Immigrant Inflows and Intercity Mobility Patterns

One of the most important unresolved questions about U.S. immigration is whether immigrant inflows to particular cities lead to offsetting

mobility flows by natives and earlier immigrants (see, e.g., Filer 1992; Frey 1995*a*, 1995*b*; White and Hunter 1993; and Wright, Ellis, and Reibel 1997). To the extent that existing residents of a city respond to inflows of new immigrants by moving to other cities or that potential in-movers from other cities alter their migration plans and move elsewhere, the effect of new immigration is quickly diffused across the national labor market. In the absence of such flows, however, new immigrant inflows directly shift the skill distribution of local labor markets, and they can be used as instrumental variables for the shares of the local population in different occupation groups, potentially overcoming endogeneity issues arising from the presence of skill-group specific local demand shocks.

This section analyzes the effect of immigrant inflows on the migration behavior of natives and earlier immigrants and on net population growth. Unlike most of the previous literature, I focus on skill-group specific migration flows, in order to assess the effect of immigrant inflows on the composition (rather than the total population) of local labor markets. The analysis uses information collected in the 1990 census on each individual's current location and place of residence in 1985. To fix ideas, let N^{90} represent the 1990 population of a given city in a certain occupation group, and let N^{85} represent the 1985 population of the same skill group. Note that N^{85} represents the number of people who lived in the city in 1985 and would be assigned to the occupation group as of 1990. Next, let N_1^I , N_2^I , and N_3^I represent the numbers of city residents in the occupation in period t ($t = 85$ or 90) from three mutually exclusive groups: natives (N_1^I), immigrants who arrived in the U.S. before 1985 (N_2^I), and immigrants who arrived in the United States after 1985 (N_3^I). By definition, $N_3^{85} = 0$. For natives and older immigrants,

$$N_1^{90} = N_1^{85} + N_1^J - N_1^L \quad (5)$$

and

$$N_2^{90} = N_2^{85} + N_2^J - N_2^L, \quad (6)$$

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 occupation group in 1985. Then, the overall growth rate of the local population of the occupation group between 1985 and 1990 can be written as

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

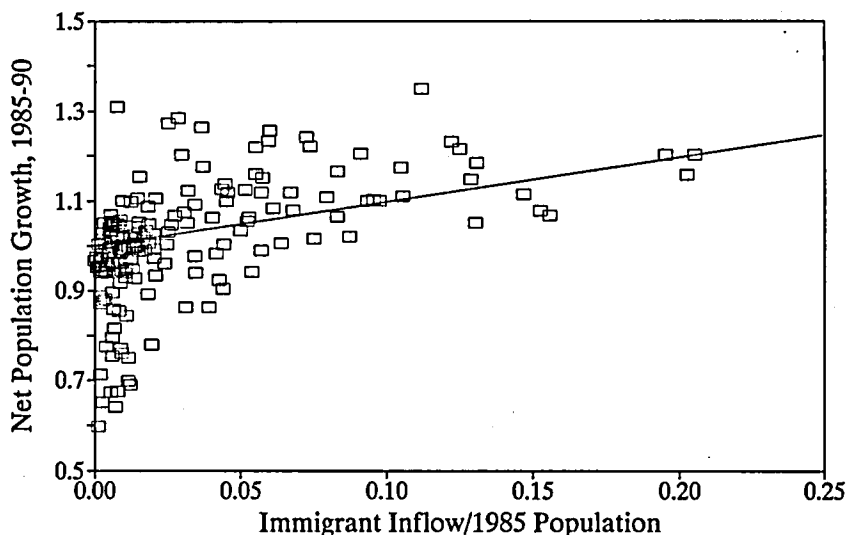


FIG. 1.—Recent immigrant inflows and net population growth of laborers and less-skilled service workers. Line shows population growth assuming no offsetting mobility.

where $J_g = N_g^I/N_g^{85}$ is the inflow rate of group g ($g = 1$ for natives and 2 for pre-1985 immigrants), expressed as a fraction of its 1985 population, $L_g = N_g^L/N_g^{85}$ is the outflow rate of group g , and $R = N_3^{90}/N^{85}$ is the inflow rate of new immigrants in the occupation group.

Equation (7) is a simple accounting identity that expresses the growth rate of the population of a specific occupation group as a weighted average of the net population growth rates of natives and older immigrants in the group, plus the inflow rate of new immigrants. If immigrant inflows have no effect on the location decisions of natives or older immigrants in the same skill group, this equation shows that the occupation-specific growth rate will vary one-for-one with inflows of new immigrants in the group. In terms of a graph, this means that observations on city-specific growth rates for a given occupation group will lie on a line with an intercept of 1 and a slope of 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 size of the occupation group, which will lead to a scatter of points below the line with intercept of 1 and slope of 1.

Figure 1 graphs the 1985–90 growth rates of the population of occupation group I (laborers and low-skilled service workers) for the 175 largest U.S. cities against the immigrant inflow rates of new immigrants in this occupation, along with a reference line that represents the benchmark

case of no offsetting migration by natives or earlier immigrants. Across cities, the 5-year immigrant inflow rate for the lowest occupation group ranges from 0 to over 20%.¹⁷ Even at these very high rates of new immigration, however, there is little indication of offsetting migration flows. In fact, a population-weighted OLS regression fit to the data in figure 1 yields a coefficient of 1.26 between immigrant inflows and population growth (with a standard error of 0.13).

A problem with this regression is that favorable demand conditions in a city may stimulate inflows of both immigrants and natives, leading to an upward bias in the partial correlation between N^{90}/N^{85} and R . This can be overcome by pooling the data for all six occupation groups and including city-specific fixed effects that capture any unobserved characteristics of a particular city that lead to greater population inflows (or lower outflows) for both immigrants and natives. More generally, each of the components of occupation-specific local population growth can be modeled as a function of observable city- and occupation-specific factors, a general citywide effect, and the occupation-specific new-immigrant inflow rate:

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

where y_{jc} represents a particular component of population growth for occupation group j in city c (e.g., the out-migration rate of natives), Z_{jc} represents a vector of observable factors that affect this growth rate (e.g., the characteristics of the group measured in 1985), R_{jc} is the inflow rate of recent immigrants in skill group j to city c , d_j is a skill-group fixed effect, θ_c is a city fixed effect, and e_{jc} is a error term. In light of equation (7), the estimate of γ for total population growth will be a weighted average of the γ 's for the individual components, plus 1.

Table 4 reports a series of estimates of the coefficient γ for seven different population growth components: native outflow rates, native inflow rates, net native population growth, pre-1985 immigrant outflow rates, pre-1985 immigrant inflow rates, net population growth of pre-1985 immigrants, and, finally, total population growth (i.e., N^{90}/N^{85}). The covariates in these models include the means of age, age-squared, education, and the fraction of blacks among the particular group in the city in 1985, as well as the fraction of immigrants in 1985.¹⁸ Row A

¹⁷ The maximum immigrant inflow rates for occupation group I are 0.21 for Anaheim-Santa Ana, CA, and 0.20 for Los Angeles, CA, and Miami, FL. Other cities with high inflow rates are San Francisco, CA (0.16), Jersey City, NJ (0.15), San Jose, CA (0.15), Salinas, CA (0.13), and New York, NY (0.13).

¹⁸ The covariates in the models for overall population growth include all the mean characteristics for both natives and pre-1985 immigrants in the city in 1985.

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		Inflow Rate	Net Population Growth	Outflow Rate		Inflow Rate	Net Population Growth	
	Raw	Adjusted			Raw	Adjusted			
Ordinary least squares estimation:									
A. 175 cities weighted	.02 (.02)	.02 (.02)	.13 (.02)	.11 (.03)	.13 (.04)	.08 (.04)	.09 (.06)	-.04 (.07)	1.25 (.04)
B. 175 cities unweighted	.05 (.03)	.05 (.03)	.08 (.05)	.02 (.06)	.13 (.07)	.06 (.07)	-.16 (.10)	-.29 (.12)	1.19 (.06)
C. Top 50 cities weighted	.00 (.03)	.01 (.03)	.18 (.03)	.17 (.04)	.08 (.05)	.05 (.04)	.14 (.08)	.07 (.09)	1.30 (.05)
D. 158 cities outside California weighted	-.11 (.04)	-.08 (.04)	.11 (.05)	.22 (.06)	.16 (.07)	.04 (.07)	.19 (.10)	.03 (.12)	1.36 (.07)
Instrumental variables estimation (instrument is predicted immigrant inflow):									
E. 175 cities weighted	.02 (.02)	.03 (.02)	.13 (.03)	.11 (.03)	.14 (.04)	.10 (.04)	.14 (.06)	.00 (.07)	1.25 (.05)
F. Top 50 cities weighted	.00 (.03)	.01 (.03)	.16 (.03)	.16 (.04)	.10 (.05)	.07 (.04)	.24 (.09)	.13 (.09)	1.28 (.05)
G. Three least-educated occupations only	-.06 (.02)	-.03 (.03)	.11 (.03)	.15 (.03)	.08 (.05)	.00 (.05)	.26 (.07)	.19 (.08)	1.25 (.04)
H. Laborers/low-skill services and professional/technical only	-.12 (.05)	-.08 (.05)	.15 (.05)	.27 (.07)	.16 (.08)	.06 (.07)	.14 (.11)	-.02 (.13)	1.43 (.08)

NOTE.—Entries are estimated regression coefficients of recent immigrant inflow rate in models for dependent variable listed in column heading. Sample includes six occupation groups in 175 cities (1,050 observations) except as noted in rows G and H. All models include occupation group dummies, mean age, mean age-squared, mean education, and percentage black; and (for immigrants only) mean years in the United States for the skill group in the particular city in 1985. Adjusted outflow rates are obtained from a set of linear probability models fitted by occupation group to the event of leaving one's city of residence in 1985. See text for details. Standard errors are in parentheses.

reports weighted OLS estimates of equation (8) for each of the dependent variables, using the 1985 city population as a weight for the observations from occupation group j in city c .¹⁹ Row B reports corresponding un-weighted estimates, while row C reports estimates based on only the 50 largest cities. As a further check on the sensitivity of the results, row D reports results based on a subsample that excludes any California cities.

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 might be correlated with mobility rates and immigrant inflow rates. In the case of the outflow rates, a finer adjustment is potentially useful. As motivation for this procedure, suppose that the out-migration probability for individual i in occupation group j who lived in city c in 1985 is

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

where X_{ijc} is a vector of characteristics of individual i , b_j is 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 nonwhites in 1985), d_j and θ_c are skill-group and city dummies, R_{jc} is the inflow rate of new immigrants in occupation j to city c , and ζ_{jc} is a residual component. The coefficient γ can be 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 occupation-group effects:

$$P_{ijc} = X_{ijc}b_j + \mu_{jc}, \quad (9)$$

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

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

The adjusted outflow rates used in the models in table 4 are simply the

¹⁹ 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-occupation group cell, then weighted estimates are more efficient. To reduce the risk of a correlation between the weight for each city/occupation-group cell and the dependent variables, I use the 1985 city population for all occupation groups as a weight for each occupation group in the city.

first-stage estimates of the μ_{jc} 's, derived from linear probability models fit to samples of natives and pre-1985 immigrants.²⁰ 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.²¹ 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 very similar 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 A–C of table 4 are very modest in size and fairly similar across specifications. When California cities are excluded, the effects become slightly negative, suggesting that occupation-specific outmigration responses to immigrant inflows may be different for California cities. Nevertheless, the coefficients are still small in magnitude, implying that any native out-migration response is modest. The effects of new immigrant inflows on the outflow rates of earlier immigrants are also positive, but they are modest in magnitude and (in the case of the adjusted outflows) uniformly insignificant. With respect to inflow rates, the estimated effects of new immigrant inflows are generally positive for both natives and pre-1985 immigrants. For natives, the positive effect on inflows is larger than the positive effect on outflows, so that the estimated impact of recent immigration on net native population growth is positive. For pre-1985 immigrants, there is more variability across specifications, but, apart from the unweighted OLS estimates, the coefficients are not significantly different from zero. Finally, the estimated coefficients in the extreme right-hand column of the table for the overall population growth rate are uniformly above one, suggesting that the net mobility responses of natives and older immigrants do little to dampen the impacts of new immigrants and that they may actually complement recent immigrant inflows, even when citywide demand factors are taken into account by including city-fixed effects.²²

Even after accounting for unobserved city-specific factors, the estimates in rows A–D of table 4 suggest that the net mobility flows of

²⁰ For occupation j , the models are fitted over the entire population of the city but use as weights the probabilities that each individual works in occupation j .

²¹ See the appendix for a description of the first-stage models.

²² The estimate of γ for total population growth when city-fixed effects are excluded is larger than any of the estimates in table 4 (1.59, with a standard error of 0.10). Thus, it appears that unobserved city factors are positively correlated with new immigrant inflows and complementary mobility flows of natives and earlier immigrants.

natives and earlier immigrants may be positively related to new immigrant inflows—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 occupation-specific factors (like the productivity shocks introduced in the theoretical model of Sec. I) that attract recent immigrants of a particular skill group and at the same time slow down the outflow of natives. In the presence of such occupation-specific demand-pull factors, an instrumental variable for occupation-specific immigrant inflows is needed to identify the true causal effect of inflows.

The tendency of newly arriving immigrants to move to enclaves established by earlier immigrants from the same source country (Bartel 1989) suggests one such instrument. In particular, suppose that the total number of immigrants from a given source country who enter the United States is independent of occupation-specific demand conditions in any particular city. The actual inflow of immigrants from a given source country moving to a city can then be decomposed into an exogenous supply-push component, based on total inflows from the country and the fraction of earlier immigrants from that country who live in the city, and a residual component reflecting any departures from the historical pattern. Multiplying the total inflow from a given source country by a factor reflecting the national fraction of immigrants from that country who fall into a certain occupation group gives an estimate of the supply-push component of recent immigrant inflows of a given skill group 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 United States 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 occupation group j . In the absence of demand-pull factors, 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 occupation-specific demand conditions in city c over the 1985–90 period, then this estimate is independent of any demand-pull conditions in the city.²³ Summing across

²³ If city- and occupation-group specific productivity shocks are highly persistent and immigrant inflows from different source countries are persistently concentrated in specific occupation groups, then the fraction of earlier immigrants from a given source country who settled in a given city may be correlated with the current city- and skill-group specific productivity shock for the predominant skill group(s) from that country. In this case the proposed measures of supply-push immigration are not strictly exogenous. One could potentially overcome this

source countries, an estimate of the supply-push component of recent immigrant inflows in occupation group j and city c is

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

To construct this measure, I used a set of 17 source country groups, identified in table 5.²⁴ The first column of the table gives the fraction of all 1985–90 immigrants from each source (i.e., M_g/M , where M is the total inflow of new immigrants), while the second column shows the mean education of recent immigrants from each source country group. Mexico is the largest single source country, accounting for 26% of the approximately 3.4 million adult immigrants who entered the United States between 1985 and 1990. The Philippines is the second largest individual source country, accounting for about 5% of all recent immigrants. Other source-country groups account for 1%–8% of recent immigrants.

The right-hand columns of table 5 show the predicted fractions of recent immigrants from each source country group in the six occupation groups. There are notable differences in the skill distributions of immigrants from different source countries. For example, 81% of Mexican immigrants and 71% of Central American immigrants are predicted to work in the two lowest occupation groups, versus only 40% of immigrants from Canada, England, Australia and New Zealand, or from Korea and Japan. Cities that receive most of their new immigrants from Mexico or Central America, therefore, tend to have relatively 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 United States between 1975 and 1984 (reported retrospectively in the 1990 census) to estimate these shares. A table of the resulting estimates (available on request) shows many interesting patterns. For example, Los Angeles attracted the largest share of 1975–84 immigrants (18%), with 41% of Central American immigrants and 28% of Mexican immigrants living there in 1985. New York City accounted for the next largest share (10%), with 43% of Caribbean immigrants and 22% of immigrants from the former Communist countries of Europe, but a very small share of Mexicans (0.7%). Even

problem by finding a set of instruments that explain the location choices of earlier immigrants from different sources countries and using predicted settlement patterns of the earlier cohort to construct the supply push indexes.

²⁴ The groupings were selected on the basis of geography and ethnic similarity and are reported in order of population size.

Table 5
Countries of Origin and Predicted Occupation Distributions of Recent Immigrants

	Percent of Total	Mean Education (Years)	Predicted Fraction in Occupation Groups					
			I	II	III	IV	V	VI
All source countries	100.0	11.0	35.0	28.4	11.6	9.3	4.8	11.0
Mexico	26.2	8.0	39.3	41.9	10.3	7.5	.6	.4
Caribbean countries	8.4	11.1	37.6	26.0	17.7	8.3	4.4	6.0
Central America	8.2	9.0	39.9	31.3	13.2	8.3	3.4	4.0
China, Hong Kong, and Singapore	6.2	13.0	32.3	16.9	9.3	9.7	8.3	23.4
South America	6.0	12.2	32.0	26.0	18.1	8.7	6.2	8.9
Indonesia, Malaysia, and Brunei	6.0	11.3	42.5	23.7	9.8	8.4	4.3	11.1
Korea and Japan	5.9	13.6	29.9	18.0	8.5	17.0	9.0	17.6
Philippines	5.1	13.4	33.6	18.3	15.0	7.3	5.4	20.4
Burma, Laos, Thailand, and Vietnam	4.6	9.3	36.7	38.8	7.2	6.8	2.4	8.1
Australia, New Zealand, Canada, and United Kingdom	4.4	14.0	24.8	16.6	12.0	11.1	10.8	24.6
India, Pakistan, and Central Asia	4.1	14.0	21.9	17.1	12.2	12.8	8.0	28.0
Russia, Central Europe	4.0	13.0	33.3	28.3	7.1	7.2	5.7	18.3
Turkey, North Africa, and the Middle East	3.4	13.1	28.2	17.5	9.2	17.3	8.8	19.1
Northwestern Europe and Israel	2.9	14.3	27.5	15.9	11.3	11.7	9.6	23.9
Southwestern Europe	2.0	12.1	36.4	25.1	6.8	9.4	6.7	15.6
Africa (excluding North Africa)	1.7	13.3	29.9	24.0	18.7	7.0	6.8	13.7
Cuba	1.0	10.5	39.2	32.2	8.9	7.3	4.1	8.3

NOTE.—Figures are based on immigrants who entered the United States between 1985 and 1990, were ages 16–68 in 1990, and had more than 1 year of potential experience. The sample size is 171,233, representing a population of 3.43 million. See table 3 for descriptions of the occupation groups and the occupation prediction method.

cities that currently receive relatively few immigrants show long-established enclave patterns. For example, Detroit accounted for only 0.6% of total immigrants but for 5% of immigrants from the Middle East and North Africa.

How do the 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 rate for laborers and low-skilled service workers in each city against the corresponding supply-push flows. For reference, I have superimposed a 45-degree line on the 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 national immigration inflows over the 1985–90 period. The set of Texas cities is a case in point. The nine Texas cities in the sample are plotted with a different symbol in figure 2 and uniformly lie below the 45-degree line. The shortfall presumably reflects the relatively unfavorable labor market in Texas following the collapse of oil prices in the mid-1980s.

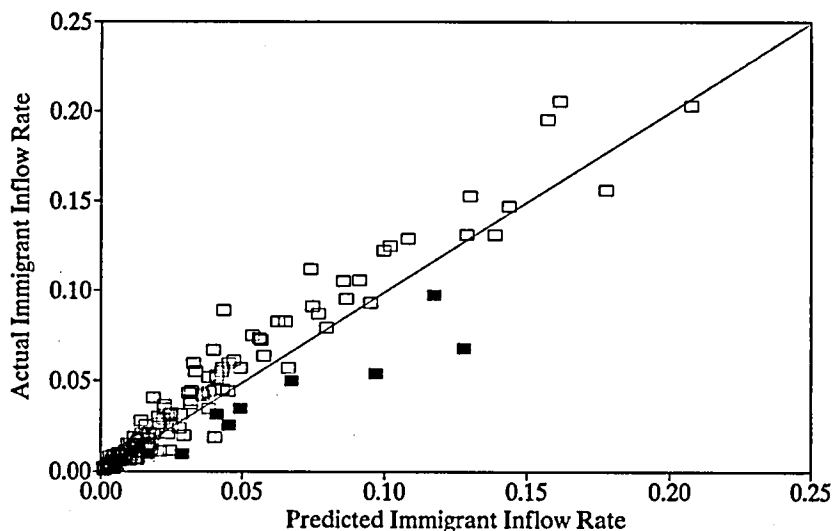


FIG. 2.—Actual and supply-driven immigrant inflows of laborers and less-skilled service workers. Texas cities shown with filled squares.

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. Row E reports estimates for the 175 largest cities, while row F reports estimates based on only the largest 50 cities. The point estimates of the coefficient γ are very similar to the corresponding OLS estimates (from rows A and C, respectively) providing no evidence of endogeneity bias attributable to occupation-specific local demand shocks that draw new immigrants and other migrants in specific skill groups to certain cities.

Another specification test is provided by the IV estimates in row G, which are based on mobility patterns for only the three lowest occupation groups. (The OLS estimates for these specifications are very similar to the IV estimates.) Based on the similarity of these estimates with the estimates in rows E and F, there is little indication that less-educated occupation groups have systematically different responses to new immigrant inflows than do other groups. Although not shown in the table, IV estimates for the subset of cities outside of California are very similar to the OLS estimates, which again suggests that the main results are quite robust.

A final set of models were estimated to assess the effect of immigrant inflows on the population shares of different occupation groups. This analysis is directly relevant to the theoretical model in Section I, since in that model wages and employment rates of different occupation groups vary with the log population shares of the groups. An analysis of the

effects of new immigrant inflows on population shares also provides a useful check on the implicit assumption underlying the models in table 4 that the mobility flows of an occupation group depend only on the immigrant inflows of people in that group. Specifically, if the population growth rate of a given occupation group varies one-for-one with the immigrant inflow rate of the group, then the log of the population share of the group will also vary one-for-one with group-specific immigrant inflows. More generally, however, inflows of one group could affect the mobility decisions of other groups, leading to a bigger or smaller effect of immigrant inflows on the log population share.²⁵ Ordinary least squares regression models similar to those in table 4 reveal that the elasticity of population share with respect to new immigrant inflows is close to one, with most estimates clustering somewhat above one. The IV estimates, using the supply-push component of immigrant inflows, are generally as big or only slightly smaller. These findings are consistent with the results in table 4, which suggests that mobility flows of natives and earlier immigrants are, if anything, slightly complementary to recent immigrant inflows.

Taken as a whole, the results in table 4 confirm that mobility flows of natives and older immigrants are not very sensitive to inflows of new immigrants. This conclusion is consistent with some previous studies of city-level population growth rates over the 1980s (Butcher and Card 1991; White and Liang 1994), but not with others. Most notably, Frey (1995*a*, 1995*b*) has argued 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.²⁶ 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

²⁵ I also fitted some models that included inflows of immigrants in the laborer and low-skilled service occupations as an additional explanatory variable for mobility flows of other occupation groups. The effects of the low occupation inflows were generally small and statistically insignificant.

²⁶ 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 outmigration. A recent paper by Wright, Ellis, and Reibel (1997) reexamines the connection between net internal migration and immigration inflows, using both 1975–80 and 1985–90 data. After comparing various specifications, these authors surmise that differences in findings across previous studies result from a failure to separate city size effects from immigrant flow effects. They conclude that “the net loss of native workers from large metropolitan areas in the United States in the late 1970s and late 1980s occurs for reasons other than mass immigration to these places” (Wright et al. 1997, p. 250).

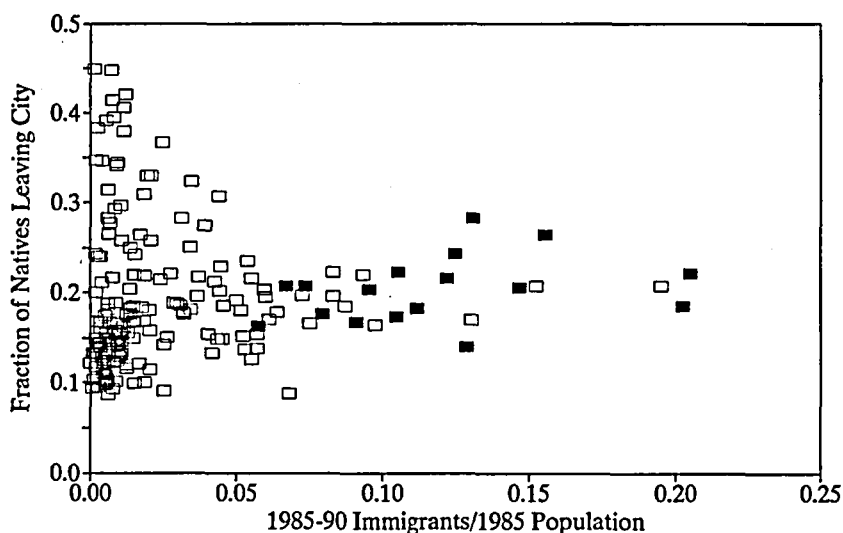


FIG. 3.—Immigrant inflows and native outflows for laborers and less-skilled service workers. California cities shown with filled squares.

cities in the sample are similar to the rates for other 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, I estimated the migration response models using only data from the 17 California cities in the sample. These estimates showed that even within California, occupation-specific mobility flows are relatively insensitive to immigrant inflows.²⁷

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 United States 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 long lags in any behavioral responses. Nevertheless, the evidence in table 4 suggests that immigrant inflows exert a powerful short-run effect on the relative supplies of different types of labor in different cities.²⁸

²⁷ For example, the coefficient of immigrant inflows on native outmigration is 0.05 (standard error 0.05); and the coefficient on total occupation-specific population growth is 1.15 (0.13).

²⁸ A similar conclusion is reached by Wright et al. (1997), although they do not

IV. Effects of Local Population Shares on Employment and Wages of Natives and Older Immigrants

This section turns to an analysis of the effects of changes in the skill composition of the local labor force on the labor market outcomes of different occupation groups. The investigation is conducted within the framework of the theoretical model in Section I, which specifies that the relative wages and employment rates of each group depend on the population shares of the groups. Although the population shares are computed using the entire adult population of each city, I fitted separate models for the outcomes of native men, native women, immigrant men, and immigrant women. Under the assumption that local labor markets are defined by occupation (rather than by nativity or gender), a shift in the share of the local population in a specific occupation should have the same effect on the employment and wages of all four gender-nativity subgroups. Thus, a comparison of the effects of shifting local population shares on the labor market outcomes of the four subgroups provides a test of the assumption of occupationally based labor markets.²⁹ As noted in Section I, a key concern in interpreting the effect of relative supplies on the structure of city-specific wages is that occupation-specific local demand shocks may be correlated with the relative supplies of labor in a city. Following the approach in the previous section, I use the supply-push component of recent immigrant inflows to each city as an instrumental variable for the population shares of the various occupation groups.

Table 6 presents estimates of the effect of occupation-specific local population shares on the employment rates of individuals who would be expected to work in that occupation in the absence of unusual local labor market competition. The format of the table is similar to that of table 4: thus each column presents results for a different demographic subgroup, and each row pertains to a different estimation method or sample. In addition to the log population share of the occupation group, the models include city and occupation dummies and a set of controls for the characteristics of the local population (e.g., the mean age and education of

distinguish among skill groups within cities. I conducted an analysis along the lines of table 4 using total adult city populations to see if total population growth is depressed by immigrant inflows (regardless of the skill composition of the inflows). The results (available on request) confirm the findings of Wright et al. (1997): total population growth of a city responds positively to new immigrant inflows.

²⁹ A similar test is suggested by Jaeger (1995), using changes for 50 large cities between 1980 and 1990. He concludes that immigrants and natives are nearly perfect substitutes within broad occupation groups.

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

	Natives		Pre-1985 Immigrants	
	Men	Women	Men	Women
Ordinary least squares estimation:				
A. 175 cities weighted	-.028 (.004)	-.045 (.005)	-.019 (.005)	-.023 (.007)
B. 175 cities unweighted	-.035 (.005)	-.047 (.005)	-.032 (.006)	-.020 (.008)
C. Top 50 cities weighted	-.022 (.008)	-.046 (.009)	-.007 (.006)	-.035 (.009)
Instrumental variables estimation (instrument is predicted immigrant inflow):				
D. 175 cities weighted	-.202 (.042)	-.081 (.018)	-.096 (.040)	-.146 (.036)
E. Top 50 cities weighted	-.185 (.056)	-.070 (.020)	-.041 (.027)	-.072 (.032)
F. Three least-educated occupations only	-.068 (.019)	-.032 (.014)	-.020 (.020)	-.045 (.036)
G. Laborers/low-skill services and professional/technical only	-.040 (.010)	-.060 (.010)	-.022 (.011)	-.038 (.013)

NOTE.—Entries are estimated regression coefficients of the log population share of a specific occupation group in a model for the employment rate of individuals in the occupation group. Models are fitted separately by gender and nativity: each model is estimated on a sample of six occupation groups in 175 cities, except as noted in rows F and G. All models include occupation group dummies, city dummies, mean age, mean education, percentage black, and percentage married; and (for immigrants only) mean years in the United States and fractions of immigrants from Western Europe, Asia, and Mexico for the gender/origin/skill group in the particular city in 1990. The employment rates for each city and occupation group are adjusted for the characteristics of individuals in the particular city and occupation using a first-stage regression model, as described in the text. Standard errors are in parentheses.

individuals in the specific occupation and demographic subgroup). The upper panel reports OLS estimates, while the lower panel reports IV estimates that use the predicted inflow rate of new immigrants as an instrument for the log population shares.

The city-specific employment rates for each demographic group are obtained from a 2-step procedure similar to the one used to derive the adjusted outflow rates used in table 4. Specifically, the dependent variables are estimated city dummies taken from a series of 24 weighted linear probability models for employment status, fitted by occupation and demographic subgroup to national samples of individuals and using as weights the predicted probabilities of working in the occupation in a standardized labor market.³⁰ These first-stage models include a rich set of

³⁰ Although eq. (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

individual-specific characteristics (see the appendix) that control for any observable differences in the characteristics of each subgroup in each city that might happen to be correlated with average employment rates and the relative population shares.

Rows A–C of table 6 report weighted and unweighted OLS estimates for the 175 major cities and for the subset of 50 largest cities. Consistent with the theoretical model, the estimated effects of an increase in population share are uniformly negative and are similar in magnitude across the four subgroups. The estimates are also similar across specifications. Although not reported in the table, estimates using actual employment rates, rather than regression-adjusted employment rates, are very close to the ones in table 6.

I also fitted a set of parallel models that used an augmented population share measure, based on formulas presented in Card (1997). Specifically, the observed occupation shares were adjusted for intercity differences in the population shares of six subgroups: native men, native women, pre-1985 immigrant men, pre-1985 immigrant women, post-1985 immigrant men, and post-1985 immigrant women. The adjusted shares were derived by weighting the counts of individuals in each demographic subgroup by their relative annual earnings (estimated nationally by occupation). Empirically, however, there is very limited intercity variation in the adjustment factors. Estimates from these specifications are, therefore, quite close to those shown in the table.

Rows D–F of table 6 present IV estimates that use the supply-push component of recent immigrant inflows as an instrument for the population shares. Although not shown in the table, the first-stage equations for the IV models show large and highly significant effects of predicted immigrant inflows on the log of the population share, with t -ratios over 5. The IV estimates are uniformly more negative than the corresponding OLS estimates (compare rows D and E to rows A and C, respectively), which suggests the presence of skill-group-specific local demand shocks that are correlated with local population shares. They are also a little more variable across the four demographic subgroups, but they are generally significantly different from zero.

The existence of a strong reduced-form correlation between the supply-push component of immigrant inflows and the employment-population rate of individuals in the same occupation group is illustrated in figure 4, using data for native men in the laborers and low-skilled services occupation group. Although there is substantial variability in average employment rates across cities, a negative relationship between employ-

effects on the log employment rate by multiplying by the inverse of the average employment rate (0.85 for men, 0.70 for women).

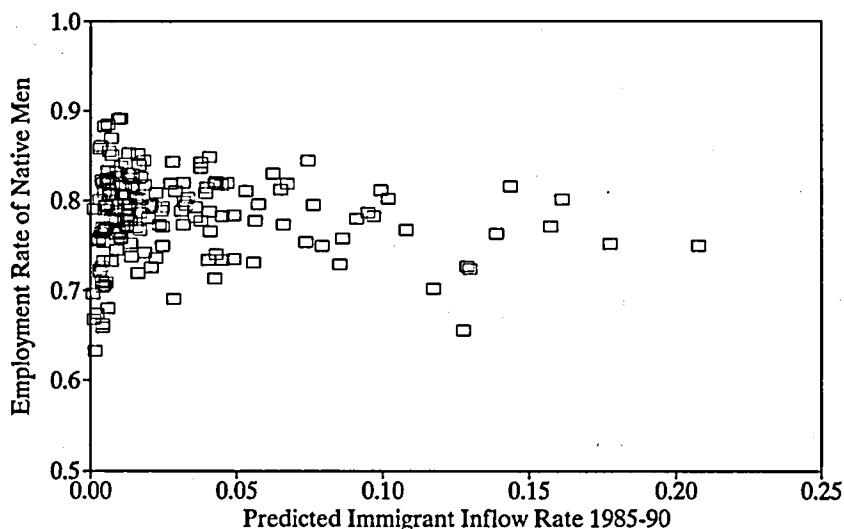


FIG. 4.—Predicted immigrant inflows and employment rate of native men in laborer and less-skilled service occupations.

ment and the supply-push component of immigrant inflows is clearly discernable.³¹ Thus, both simple evidence, such as the scatter in figure 4, and estimates from the structural models in table 6 point to an impact of immigrant inflows on employment outcomes.

The assumption of a CES technology implies that the relative employment rate of each occupation group depends only on its own population share. One way to test this assumption is to reestimate the model on a subset of occupations. For example, the IV estimates in row F are based on outcomes for the three least-educated occupation groups. The point estimates of the population share coefficient are somewhat smaller than in the corresponding estimates that pool all six occupation groups, potentially indicating a higher elasticity of substitution within these three groups than across all groups. (Recall that the coefficient of the log population share in eq. [4'] is $d_2 = -\epsilon/(\epsilon + \sigma)$, which will be smaller in absolute value, the larger the elasticity of substitution, σ .) It is interesting, however, that estimates from a specification that pools only the lowest and the highest occupation groups (shown in row G) are also smaller in absolute value than the estimates that pool all six occupation groups.

Taken as a whole, the estimates in table 6 point to a modest effect of

³¹ A simple weighted regression of the adjusted native male employment rate on the predicted immigrant inflow rate has a coefficient of -0.29 , with a standard error of 0.10 .

relative population shares on local employment rates. In terms of the theoretical model, the OLS estimates in row A imply that the coefficient d_2 from equation 4' is in the range of -0.03 to -0.06 , whereas the IV estimates in row F point to a larger estimate: one in the range of -0.1 to -0.2 .³² The IV estimates suggest that a rise in the local population share of the lowest occupation group from 20% to 24% (equivalent to the difference between St. Louis and New York) would be expected to reduce the employment-population rate for individuals in this occupation by 0.02 to 0.04. Translated into an impact of new immigrant inflows, a 0.10 inflow rate of new immigrants in the lowest occupation group (comparable to the rate for Oakland, California, or Bergen County, New Jersey, between 1985 and 1990) would be expected to increase the log population share of the group by 0.10 and to depress the employment rate of natives and earlier immigrants in the occupation group by about 0.01–0.02. A massive 0.20 immigrant inflow rate—comparable with the impact of the Mariel boatlift—would be expected to have about twice as big an effect.³³

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 analyses 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. In particular, if higher-wage individuals in a given occupation are more likely to remain employed in the face of declining demand conditions, the coefficient estimates in table 7 will be biased toward zero. I return to this issue below.

The OLS estimates in rows A–C of table 7 show systematically negative effects of higher local population shares on the relative wages of different occupation groups. The estimates are roughly comparable in magnitude with the corresponding estimates in table 6, which suggests that the elasticity of labor supply (or, more precisely, employment participation) is around one. In comparison with the relatively stable OLS estimates, the IV estimates in rows D–G are more variable across specifications and between the four demographic groups. If unobserved occupation-specific local demand shocks are positively correlated with local population shares, one would expect the IV estimates in row D or row E to be systematically more negative than the corresponding OLS estimates

³² Recall that the theoretical model is written in terms of the log employment rate, so the coefficients in table 6 have to be divided by the average employment rate to calculate the implied estimate of d_2 .

³³ In my 1990 paper, I estimated that the boatlift increased the Miami labor force by 7%. Assuming that three-quarters of the Marielitos were in laborer and less-skilled service occupations, the boatlift would have increased the relative population share of these occupations by about 25%.

Table 7
Effects of Skill Group Population Share on Mean Log Wages of Natives and Earlier Immigrants

	Natives		Pre-1985 Immigrants	
	Men	Women	Men	Women
Ordinary least squares estimation:				
A. 175 cities weighted	-.025 (.005)	-.058 (.005)	-.051 (.010)	-.041 (.010)
B. 175 cities unweighted	-.010 (.006)	-.051 (.004)	-.037 (.013)	-.022 (.012)
C. Top 50 cities weighted	-.054 (.009)	-.058 (.007)	-.059 (.013)	-.064 (.012)
Instrumental variables estimation (instrument is predicted immigrant inflow):				
D. 175 cities weighted	-.099 (.033)	.063 (.020)	.037 (.073)	-.251 (.055)
E. Top 50 cities weighted	-.039 (.038)	.050 (.023)	-.022 (.055)	-.116 (.042)
F. Three least-educated occupations only	-.041 (.020)	.020 (.012)	-.018 (.036)	-.213 (.054)
G. Laborers/low-skill services and professional/technical only	-.031 (.012)	-.056 (.008)	-.057 (.022)	-.048 (.019)

NOTE.—Entries are estimated regression coefficients of the log population share of a specific occupation group in a model for the hourly wage of individuals in the occupation group. Models are fitted separately by gender and nativity: each model is estimated on a sample of six occupation groups in 175 cities, except as noted in rows F and G. All models include occupation group dummies, city dummies, mean age, mean education, percentage black, and percentage married; and (for immigrants only) mean years in the United States and fractions of immigrants from Western Europe, Asia, and Mexico for the gender/origin/skill group in the particular city in 1990. The mean wages for each city and occupation group are adjusted for the characteristics of individuals in the particular city and occupation using a first-stage regression model, as described in the text. Standard errors are in parentheses.

in row A or row 3. This pattern is true for native men and immigrant women, but not for the other two subgroups. The IV estimates for the subset of the three least-educated occupations (row F) are a little more stable across demographic groups, while those based on wages for the lowest and highest occupation groups (row G) are quite similar across subgroups.

An issue in the interpretation of the estimates in table 7 is selectivity bias. One way to assess the potential magnitude of any such bias is to posit a specific model for the employment outcomes of individuals within each occupation group. Following Gronau (1974), suppose that individual wages (i.e., the wages that individuals could receive if they worked) are distributed within occupation/city cells according to

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

where w_{jc} is the mean wage for individuals in occupation j and city c , and

ξ_{ijc} is normally distributed with mean 0 and standard deviation $\sigma(\xi)$. Suppose that individual i 's employment outcome is determined by the sign of a latent index, $H_{ijc} = d_{jc} + \alpha\xi_{ijc} + v_{ijc}$ where v_{ijc} is another normally distributed error. In this case, the mean of observed wages for workers in city c and occupation j is related to the unconditional mean by

$$E(\log w_{ijc} | H_{ijc} \geq 0) = \log w_{jc} + E(\xi_{ijc} | H_{ijc} \geq 0) = \log w_{jc} + \rho\sigma(\xi)\lambda(\pi_{jc}),$$

where ρ is the correlation coefficient between ξ_{ijc} and the composite error $\alpha\xi_{ijc} + v_{ijc}$, π_{jc} is the employment rate of group j in city c , and $\lambda(\pi) = \phi(\Phi^{-1}(\pi))/\pi$ is the inverse Mill's ratio function. The selectivity bias component in the mean of observed wages is $\rho\sigma(\xi)\lambda(\pi_{jc})$, which is positive and decreasing in π if $\rho > 0$. Since the function $\lambda(\pi)$ is approximately linear over most of its range, the assumption of joint normality of the error components implies that the selectivity bias component is approximately a linear function of the employment rate of the group. Indeed, for $0.4 < \pi < 0.9$, $\lambda(\pi) \approx 1.5 - 1.5\pi$. Assuming that $\sigma(\xi)$ is approximately equal to 0.5, the selectivity bias in the mean observed wages of occupation j in city c is

$$\text{Bias}_{jc} \approx 0.75\rho - 0.75\rho\pi_{jc}.$$

To illustrate the implications of this formula, note that the estimates in table 6 suggest that the employment rate of a skill group is negatively related to the log population share of the group with a coefficient of (roughly) -0.15 . Using this estimate, the implied selectivity bias in a regression of observed mean log wages on log population shares is approximately 0.11ρ . Since ρ cannot exceed one, an upper bound on the selectivity bias is 0.11 , and a more reasonable bound might be 0.05 (assuming $\rho < 0.5$).

Given that most 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 larger bound for immigrant women. This range of estimates can be combined with evidence on the range for the coefficient d_2 from table 6 to construct estimates of the theoretical parameters underlying equations (3') and (4')—the participation elasticity ε and the substitution elasticity σ . Assuming that $-0.15 \leq d_1 \leq -0.05$ and $-0.20 \leq d_2 \leq -0.10$, the data point to an estimate of $\varepsilon = d_2/d_1$ that is on the order of one. This is somewhat above estimates based on comparisons of the aggregate changes in wage and employment rates of different demographic groups over the 1980s (e.g., Juhn 1992; Card, Kramarz, and Lemieux 1999), but given the range of uncertainty in

the estimates of d_1 , it is hard to draw strong inferences. The implied estimate of the substitution elasticity, $\sigma = -(1 + d_2)/d_1$, is large—at least 5, and probably more like 10, using the midpoint of the estimates. This magnitude is consistent with the observation that relative wages are not much different in cities that have substantially different relative population shares of different occupation groups.³⁴ In terms of implications for immigrant inflows, an estimate of $d_1 = -0.15$ implies that an inflow rate of 10% for one occupation group (which raises the log population share of the group by about 0.1) would reduce relative wages for the occupation by 1.5%. An inflow of 20%—equivalent to the highest rates seen in the data between 1985 and 1990—would be expected to lower relative wages by 3%.

It is worth noting that the findings in tables 6 and 7 are qualitatively and quantitatively similar to findings in an earlier version of this article (Card 1997) that used a different skill group classification system, based on 10 intervals of predicted wages rather than six predicted occupations. The use of the smaller number of occupation-based skill groups leads to somewhat stronger evidence that the relative wages of different groups are affected by their relative population shares, while the estimated impacts on relative employment are very similar under the two classification systems. In light of the uncertainty over how to define skill groups and how many skill groups to define, this comparability is reassuring.

V. Summary and Conclusions

The findings in this article point to three substantive conclusions. First, inflows of new immigrants to individual cities 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, cities that received large inflows of new immigrants generally experienced large 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. Ordinary least squares estimates of the effect of an increase in the relative population share of an occupation group suggest that a 10% increase in population share is associated with up to a 0.5-percentage-point reduction in the employment rate of the group. Instrumental variables estimates using the supply-push component of recent immigrant inflows are two to three times bigger. The larger IV estimates are consistent with the existence of skill-group specific local demand shocks that are positively correlated with relative population shares of different groups. Such demand shocks may be attributable to exogenous factors, or they could potentially represent an endogenous

³⁴ Jaeger (1995) also obtains relatively large elasticities of substitution.

adaptation of local industry structure to the local supplies of different skill groups, as predicted by multisector trade models. Taken together, these first two findings imply that, in the short run at least, inflows of new immigrants in the 1985–90 period reduced the relative employment rates of natives and earlier immigrants in laborer and low-skilled service occupations by up to 1 percentage point, and by up to 3 percentage points in very high-immigrant cities like Los Angeles or Miami.

A third and more tentative finding is that shifts in relative population shares are associated with changes in relative wages. On balance, the estimates suggest that the elasticity of relative wages with respect to relative population shares is comparable with, or slightly smaller than, the elasticity of relative employment. While OLS estimates of the relative wage effects are fairly stable, the IV estimates vary across demographic subgroups, and they are also somewhat sensitive to specification choices. Moreover, the measured wage effects are potentially biased by selective labor force participation behavior. Despite these sources of uncertainty, it seems likely that immigrant inflows over the late 1980s reduced the relative wages of laborers and less-skilled service workers in high immigrant cities by no more than 3%. The effects in other cities, and for other occupation groups that were less affected by new immigrant arrivals, were probably much smaller.

In the context of the simple theoretical model developed in this article, the estimation results suggest that the elasticity of substitution between different skill categories is relatively high. Given this high degree of substitutability, shifts in the relative supply of different occupations do not affect the relative wage structure very much. This is true even in the short run in response to supply-push immigrant inflows over the preceding 5 years. Shifts in the relative supply of the different skill groups may, of course, affect the overall level of wages in a city, but a complete examination of this possibility is beyond the scope of this article.³⁵

In comparing the findings of this article with the results in the existing literature, it is worth noting that most earlier studies make no distinction among different subgroups of immigrants: rather, native wage and employment outcomes are correlated with levels or changes in the overall fraction of immigrants in different local labor markets. The analysis here, on the other hand, assumes that local labor markets are occupation-specific, and it focuses on the effect of immigrant inflows on the relative supplies of different occupation groups in different cities. Even with these distinctions, the measured effects of immigrant inflows on the native wage

³⁵ It should be noted that in the cross-section of major cities studied here, average wages are significantly higher in cities with high overall immigrant inflow rates (see table A1). This is consistent with the existing literature, e.g., with Schoeni (1996).

structure are small. The results in this article are, therefore, consistent with most of the existing literature on immigration and native wages. They are also consistent with the results of Lalonde and Topel (1991), who find relatively modest effects of immigrant inflows on immigrant relative wages.

The conclusion that immigrant inflows affect native employment rates is new. However, the implied effects for natives as a whole 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. Between 1985 and 1990, however, 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. The results in this article suggest that these massive expansions may have significantly reduced employment rates for younger and less-educated natives in these cities.

Appendix

Data Appendix

A. Basic Sample Criteria

I begin with a 25% random sample of all native-born individuals ages 16–68 in the 5% public use samples of the 1990 census, and 100% 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 five) is greater than one in 1990. Years of education are assigned to the education codes used in the 1990 census following Park (1996). The minimum age restriction eliminates about 4.5% of natives and 4% 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 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 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 PUMAs straddle the boundary of one or more MSAs, and in these mixed PUMAs, 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% 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 MSAs. The computer code for this assignment is available on request. A small fraction of immigrants who are coded as having arrived in the United States between 1985 and 1990 report data on their place of residence in 1985. For simplicity, however, I assume these individuals lived outside of the United States in 1985, and I ignore them in constructing 1985 population counts for individual MSAs.

D. Models Used to Determine Occupation Groups

Separate multinomial logit models were fitted for native-born and immigrant men and women, using the samples of individuals living in the largest 175 cities with valid wages in 1990, as described above. The native models included a linear education term; a quartic in potential experience; indicators for black, Asian, or Aboriginal race; indicators for marital status, disability status, and veteran status; interactions of education with the race indicators and linear and quadratic experience; interactions of the race indicators with marital status and veteran status; and indicators for the 30 largest cities and cities in California, Texas, Florida, or the northeast region. 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 a linear education term; a quartic in potential experience; a quadratic function of years in the United States fully interacted with education; a dummy for having moved to the United States before age 6; 17 origin dummies; and interactions of years of education with indicators for three main origin groups (immigrants from Mexico, Canada/Australia/Europe; and Asia); dummies for black and Asian race, being married, and reporting a disability; and indicators for the 30 largest cities and cities in California, Texas, Florida, or the northeast region. 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.

Predicted probabilities of working in each occupation were formed for each individual, using the estimated coefficients from the appropriate model and assuming residence outside the 30 largest cities, or California, Texas, Florida, or the northeast region.

E. Models Used to Construct Adjusted Outmigration 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 12 models are fitted for the six different occupation groups by nativity. The models for each occupation are fitted by weighted least squares, using as weights the predicted probabilities of working in the occupation. For each occupation-nativity group, I fitted 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 30; and the interaction of gender and 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 30, and gender \times age under 30; 16 dummies for country of origin; interactions of the country-of-origin dummies with years since arrival in the United States, and with years since arrival squared.

F. Models Used to Construct Adjusted Employment and Wage Rates

The employment rates and wage rates used as dependent variables in tables 6 and 7 are city dummies estimated from separate sets of models fit by occupation group and gender-nativity to samples of individuals who lived in one of the 175 largest cities in 1990. The models used to construct the employment rates are linear probability models for the event of reporting positive earnings and hours in 1989, while the models used to construct the average wages are models for the log of average hourly wages in 1989. The models for each occupation are fitted by weighted least squares, using as weights the probabilities of working in that occupation. For native men and women, the other covariates included in the models were years of education and an indicator for holding a college degree; a cubic function of experience; an indicator for being married; and interactions of race indicator with education, experience, and the marital status indicator. For immigrant men and women, the other covariates included years of education and an indicator for holding a college degree; a cubic function of experience; an indicator for marital status; 16 dummies for country of origin; interactions of the country-of-origin dummies with years since arrival in the United States, and with years since arrival squared; and interactions of education with years in the United States and indicators for three main origin groups (immigrants from Mexico, Canada/Australia/Europe, and Asia).

Table A1
Population, Immigrant Fraction, and Occupational Distributions in 30
Largest Cities

	Adult Population	Percentage of Immigrants		Relative Population Shares of Six Major Occupation Groups						Relative Level and Dispersion of Wages	
		All	Recent	I	II	III	IV	V	VI	Level	SD
All major cities	102,108	13.9	3.0	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Los Angeles, CA	5,638	41.1	10.6	1.17	1.12	.92	.93	.84	.88	1.05	1.04
New York, NY	4,425	38.1	8.1	1.18	.96	.97	.90	.91	1.00	1.16	1.02
Chicago, IL	3,309	17.5	3.4	1.03	.97	.97	.96	1.00	1.06	1.08	.98
Philadelphia, PA	2,606	7.3	1.2	.98	.97	1.01	1.01	1.02	1.03	1.09	.96
Washington, DC	2,559	16.0	4.4	.92	.80	.92	.91	1.13	1.40	1.19	.97
Detroit, MI	2,247	6.4	.8	1.04	1.01	1.03	1.02	.98	.92	1.06	1.01
Houston, TX	1,886	17.3	3.3	1.06	1.05	.96	.95	.95	.98	.97	1.05
Nassau-Suffolk, NY	1,784	13.8	2.0	.83	.87	1.01	1.06	1.17	1.20	1.26	1.02
Boston, MA	1,746	14.8	3.9	.84	.82	.95	1.02	1.16	1.34	1.18	.95
Atlanta, GA	1,704	5.6	1.4	1.01	.97	.99	.95	1.01	1.07	1.01	.97
Anaheim, CA	1,668	29.6	8.5	.94	.99	.95	1.02	1.05	1.08	1.15	1.03
Dallas, TX	1,659	11.6	2.6	.96	.98	.98	.99	1.04	1.07	.99	1.01
San Diego, CA	1,578	22.0	5.2	.96	1.00	.99	1.00	1.00	1.04	.98	1.02
Baltimore, MD	1,501	5.2	.8	1.04	.99	.98	.96	.99	1.03	1.06	.95
Riverside, CA	1,439	19.4	4.5	1.05	1.14	1.03	1.01	.90	.80	1.02	.99
Oakland, CA	1,365	21.1	4.6	.93	.88	.96	.98	1.10	1.22	1.19	.98
Tampa, FL	1,322	9.5	1.5	.97	1.02	1.07	1.05	1.01	.90	.86	.96
Newark, NJ	1,305	18.5	3.6	1.00	.92	.98	.97	1.05	1.11	1.20	.99
St Louis, MO	1,302	2.7	.5	.99	.99	1.02	1.01	1.02	1.00	.98	.98
Phoenix, AZ	1,291	9.5	2.2	.90	.98	1.02	1.06	1.08	1.03	.94	.99
Pittsburgh, PA	1,235	2.4	.4	.94	1.02	1.07	1.06	1.01	.93	.92	1.01
Seattle, WA	1,217	10.1	2.1	.81	.86	1.00	1.07	1.20	1.22	1.07	.95
Minneapolis, MN	1,211	3.9	.9	.84	.93	1.03	1.08	1.14	1.10	1.03	.95
Miami, FL	1,201	57.6	11.1	1.30	1.10	.96	.83	.80	.82	.87	1.01
Cleveland, OH	1,075	6.3	.8	1.02	.99	1.03	1.00	.99	.97	.98	.96
San Jose, CA	1,041	28.7	7.1	.91	.92	.93	1.00	1.09	1.22	1.21	.99
San Francisco, CA	1,025	32.1	7.2	.90	.82	.89	.96	1.16	1.37	1.20	1.01
Denver, CO	1,007	6.7	1.2	.82	.89	1.01	1.05	1.18	1.18	.99	.98
Sacramento, CA	927	12.6	2.5	.89	.94	1.02	1.04	1.10	1.10	1.04	.95
Fort Worth, TX	902	8.2	1.6	.96	1.04	1.01	1.02	1.02	.96	.93	1.00
Correlation with:											
Fraction immigrant	...	1.00	.98	.46	.07	-.66	-.62	-.32	.04	.41	.48
Fraction recent immigrant98	1.00	.42	.06	-.70	-.60	-.30	.07	.42	.49

NOTE.—Adult population is thousands of people ages 16–68 with 2 or more years of potential experience. Relative population shares of the six occupation groups are the fraction of adults in the city in each of six occupation groups, divided by the national average fractions of adults in the same occupation. Occupation groups are I, laborers, farm workers, and low-skilled service workers; II, operatives and craft workers; III, clerical workers; IV, sales workers; V, managers; and VI, professional and technical workers. Relative level of wages is 1 plus the difference in mean log wages between the city and the national mean. Relative standard deviation of wages is the ratio of the standard deviation of log wages in the city to the standard deviation nationally. Correlations in the bottom two rows are weighted correlations over all 175 major cities between immigrant fractions and the variables represented by the column headings.

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