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# 6 Labor Market Adjustments to Increased Immigration

Robert J. LaLonde and Robert H. Topel

During the 1970s, immigration to the United States was higher than in any decade since the 1920s, raising the number of immigrants in the U.S. labor market by 45 percent. The flow of new immigrants has actually increased during the 1980s, and in many areas immigration is a major component of labor force growth. These facts are central to the current debate over immigration policy since it is widely believed that new immigrants have deleterious effects on the labor market opportunities of native Americans. For example, if the main costs of immigration are borne by less-skilled natives through reduced earnings and employment opportunities, the case for immigration controls and redistributive policies is strengthened. In contrast, if the labor market easily absorbs new immigrants without serious distributional effects, these policy options are less attractive.

Increased labor supply due to immigration enhances the welfare of the typical consumer, but it also creates adverse distributional effects among workers whose skills compete with those of immigrants. Yet it is difficult to argue that even the large flow of immigrants in the 1970s could have had a substantial

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effect on the U.S. labor market. New immigrants of all ages contributed only about 2.5 million extra persons to the labor force over this period, compared to the concomitant increase of twenty million among workers aged 32 or less that was caused by the baby boom and increased labor force participation by young women.<sup>3</sup> At this level of aggregation, immigration would have only a second-order effect on the labor market. However, nearly half of all new immigrants live in six metropolitan areas, so that the potential effects of increased immigration may be similarly concentrated in local labor markets. In fact, this feature of immigration is the focus of the current policy debate. Those who believe that immigration has important effects are concerned not with the earnings and employment of the typical worker, who probably gains, but instead with the prospects for certain groups who reside in specific areas, such as young blacks in Miami or native Hispanics in Los Angeles.

Our analysis exploits this geographic diversity to study the effect of immigration on local labor markets. In our view, the empirical issue is how increased immigration affects labor market opportunities for workers who are close substitutes for immigrants. Since theory offers little guidance about which groups these are, our strategy is to analyze the effect of immigration on labor market outcomes for workers who are a priori similar to new immigrants—other members of current and past immigrant cohorts of similar ethnicity. Substitution effects for these workers will generally dominate those for nonimmigrant labor, so estimates of these effects will serve as upper bounds for the effect of immigration on labor market outcomes for natives.<sup>4</sup> We also test these bounds by estimating corresponding substitution effects for young blacks and native Hispanics.

The empirical analysis uses earnings and employment data for immigrants and native-born workers from the 1970 and 1980 Censuses. To estimate the effect of immigration on labor market outcomes, we rely on three distinct sources of variation in the relative importance of immigrants in local labor markets: (i) the share of all immigrants within a locale; (ii) the share of new immigrants; and (iii) the changes in these immigrant shares between 1970 and 1980. The first source of variation, the immigrants' labor force shares, will generate corresponding differences in immigrant and nonimmigrant earnings if the geographic location of new immigration is exogenous and if nonimmigrant or other factor mobility does not fully arbitrage wage differences in market equilibrium. In other words, labor supply to a locale must be inelastic, at least in the short run. We find that earnings of both new and old immigrant cohorts are lower in areas where immigrants—especially new immigrants form a large or growing portion of the local labor force. This relation suggests important effects of immigration on earnings, although an alternative explanation is that less-skilled immigrants locate in areas where immigrants form a large share of the labor force.

The second, and more important, source of variation in immigration across areas is the labor force shares of different immigrant cohorts within locales.

Variations over time in the rate and location of immigration have generated substantial differences between locales in average arrival times of immigrants. We find that an increase in the relative share of an immigrant cohort within an area (e.g., immigrants who arrived between 1970 and 1974) causes a corresponding decline in the wages and earnings of members of that cohort. Our best estimate is that a doubling of new immigration to a locale would reduce new immigrant annual earnings by less than 3 percent. This modest earnings disadvantage for members of large immigrant cohorts dissipates with time in the United States. It appears that immigrants assimilate into the broader labor market as they accumulate skills that are appropriate to the U.S. labor market. Our evidence also indicates that new immigration reduces the earnings of earlier immigrant cohorts. Thus, "new" and "old" immigrants are substitutes. However, as theory predicts, these substitution effects on wages are found to be smaller for older immigrant cohorts, which is also consistent with the assimilation of immigrants. We regard these results as evidence for the existence of within-market substitution effects of immigration on wages.

In light of these results, it is not surprising that the effect of immigration on natives appears to be minor. For young (aged 16–34) blacks, we find a small negative effect of immigration on relative earnings. Our largest estimate is that a long-term doubling of immigration to an area may reduce the annual earnings of young blacks by about 4 percent, with much smaller effects on young Hispanics. Since market outcomes for young blacks and Hispanics are likely to be the most sensitive to changes in the supply of immigrants, we think this evidence weakens the case for serious distributional effects of immigration.

These conclusions are reinforced by estimates derived from the third source of variation: within-market changes in the labor force shares of immigrant workers generated by new immigration. Interarea mobility will arbitrage geographic wage differentials in the long run, but we view the accelerated pace of immigration during the 1970s as an exogenous increase in supply that in the short run will generate relative wage adjustments in areas of unusually heavy immigration. Thus, we expect a decline in the relative earnings of immigrants (and close substitutes) between 1970 and 1980, and we expect that this decline will be concentrated in areas with unusually heavy immigration as well as among more recent immigrant cohorts. We find evidence for these effects: our best estimate from this experiment is that a doubling of the number of recent immigrants within a locale would reduce their relative earnings by about 3 percent. The strong correspondence between these panel estimates and those generated from a single cross section increases our confidence in the results.

Our broad assessment of this evidence is that immigration flows do affect earnings and employment of immigrants and nonimmigrants. Members of large immigrant cohorts suffer slightly reduced earnings, especially on first arriving in the United States. But it appears that immigrants assimilate rapidly, and important effects on nonimmigrants are difficult to find. We conclude that

recent increases in the pace of immigration have been easily absorbed by the labor market so that distributional consequences are not a firm basis for policies that would further restrict immigration to the United States.

### 6.1 The Empirical Setting

The geographic distribution of immigrants, especially new immigrants, is central to our analysis. Table 6.1 illustrates the geographic concentration of both new and old immigrants, showing the arrival date of the stock of immigrants in six "gateway" metropolitan areas in 1970 and 1980. These areas account for about 40 percent of all immigrants in both years and nearly half (47 percent) of all recent immigrants (those arriving within ten years of the survey date). Reflecting the increased flow of immigration, the population

Table 6.1 Immigrants in the United States and Six Gateway Cities, 1970 and 1980

	United States	Chicago	Houston	Los Angeles	Miami	New York	San Francisco
Foreign born as							
% of population:							
1970	4.8	8.1	2.6	11.2	24.4	15.0	11.0
1980	6.2	10.5	7.6	22.3	35.6	21.3	15.7
Immigrants in SMSA							
as % of immigrants							
in U.S.:							
1970		5.8	.5	8.1	3.2	17.8	3.5
1980		5.3	1.6	11.8	4.1	13.8	3.6
Recent immigrants in							
SMSA as % of all rec	ent						
immigrants in U.S.:							
1970		5.5	.8	11.6	6.9	18.4	4.5
1980		5.6	2.6	17.1	3.7	13.6	3.9
Proportion of immi-							
grants in SMSA							
arriving in past:							
0-10 years:							
1970	29.3	37.9	41.7	42.0	63.9	30.4	38.2
1980	39.5	41.9	64.5	57.0	35.6	38.7	43.1
10-20 years:							
1970	18.1	22.8	19.9	21.8	10.7	16.0	20.1
1980	22.2	19.8	18.3	21.8	45.2	24.6	24.1

Sources: U.S. Census of Population, 1980, General Social and Economic Characteristics, United States Summary and State Summaries, table 99; and U.S. Census of Population, 1970, Characteristics of the Population, table 144. The six cities in the table accounted for 40 percent of all immigrants in the United States. Note that these statistics, which report the importance of immigrants in the total population and in different SMSAs, understate the importance of immigrants in the work force of these cities since a larger share of immigrants is in the labor force than is the case for the native population as a whole.

share of immigrants increased by 30 percent during the 1970s; by 1980, about 40 percent of all immigrants in the United States had arrived during the previous decade, up from 30 percent in 1970. This estimate is widely distributed across cities: in Los Angeles, more than half of all immigrants arrived during the 1970s, and the population share of immigrants doubled over the decade. Currently, immigrants account for nearly a quarter of the male labor force in the Los Angeles standard metropolitan statistical area (SMSA) and more than a third in Miami.

Table 6.2 offers a more detailed picture of the geographic distribution of immigrants and their importance as a source of labor force growth. The first two columns report the distributions of "new" and "old" male immigrants for SMSAs that account for at least 1 percent of all foreign-born persons in the work force. The remarkable correspondence between the flow distribution for new immigrants (col. 1) and the distribution of the stock that arrived before 1970 illustrates the importance of immigrant "enclaves": new immigrants go where previous ones went. Separate distributions for persons of European, Mexican, and Asian origin confirm the relation and show that enclaves are primarily ethnic in origin. Because of this factor, the geographic distribution of immigrants tends to replicate itself through time. Thus, there is little evidence of wide swings in the geographic distribution of immigrants over time, which partly justifies our assumption, exploited below, that the locational decisions of new immigrants are exogenous.

The last two columns of table 6.2 show the importance of immigration as a source of labor force growth in these areas. Though immigration is a minor factor in economy-wide labor force growth, it is the most important factor contributing to the growth of some markets. For example, in Los Angeles, immigration during the 1970s would in itself have caused a 31 percent increase in the local labor force, and new immigrants accounted for nearly two-thirds of the actual increase in the labor force during this period. Of course, these estimates would be even larger if the base population were restricted to those with skills that are similar to those of new immigrants.

Our econometric analysis will treat immigrants from different arrival cohorts as imperfect substitutes in production. This assumption will hold if either (i) immigrants "assimilate" with time in the United States in the sense of acquiring skills relevant to the American market or (ii) different arrival cohorts bring qualitatively different skills to the United States. Table 6.3 examines these possibilities, presenting differences between the mean log weekly wages of immigrants and white natives of the same age, by Census year. The table demonstrates three important facts. First, within a Census year, relative earnings profiles appear to reflect assimilation in the sense that earlier arrivals earn more (Chiswick 1978). Second, however, assimilation appears to be much less important if an arrival cohort is followed through time (Borjas 1985). For example, workers who were 25 to 34 years old in 1970 earned about 29 percent less than their native white counterparts, and by 1980

Table 6.2	New Immigrati	ation Flows a	tion Flows and Stocks (the distribution of new and old male immigrants)	ne distributi	on of new an	d old male ii	mmigrants)			
	All Imr	nigrants	Europeans	eans	Mexicans	cans	Asians	ans	1970–80 Immigra a Proportion o	0–80 Immigra a Proportion c
	Share of	Share of	Share of	Share of	Share of	Share of	Share of	Share of	Share of Share of Share of Share of Share of Share of 1970 Labor 1970-	1970-

	197080	pre-1970	1970-80	pre-1970	19/0-80	pre-19/0	19/0-80	pre-19/0	Force	Force Growth
Anaheim	3.4	2.4	1.4	2.3	6.9	4.3	3.0	4.4	23.3	14.1
Boston	1.8	2.3	4.6	3.5	:	-:	1.5	2.3	7.3	17.6
Chicago	8.3	7.7	8.8	9.0	11.9	10.3	7.8	6.2	10.5	27.5
Cleveland	9.	1.2	1.7	2.0	:	:	1.0	9	2.8	23.6
Dallas/Fort Worth	2.1	1.0	1.1	9.	4.3	2.8	1.6	œί	7.5	6.5
Detroit	4.1	3.1	3.2	4.9	-:	7.	1.5	1.8	4.0	8.8
Houston	4.4	2.0	1.4	οó	8.5	6.1	4.1	2.6	17.3	9.5
Jersey City	1.2	4.1	1.6	1.1	:	τ.	9.	4.	:	
Los Angeles	22.1	12.7	8.9	7.6	42.2	34.9	19.0	14.7	31.1	65.0
Miami	3.9	6.1	1.6	1.0	.2		'n	.2	38.0	37.7
New York	17.4	19.7	22.0	22.4	٠ċ	9.	16.3	14.9	5.7	-56.4
Newark	2.2	2.3	4.7	2.9	<b>-</b> .		1.6	1.5	10.8	22.4
Philadelphia	1.5	1.9	3.6	2.6	.2	Τ.	2.3	1.5	3.4	16.2
Seattle	۲.	1.2	1.1	1.7	.2	5.	1.7	1.8	6.9	8.1
San Diego	1.9	1.8	6.	1.4	3.6	5.6	1.6	1.5	18.9	14.7
San Francisco	4.1	4.7	2.3	3.6	2.3	4.1	10.2	16.1	15.9	30.4
San Jose	7. 8.	1.6	1.4	1.3	1.7	2.6	3.3	5.6	19.2	14.7
Washington, D.C.	2.2	1.6	3.0	4.1	:	.2	2.7	3.3	10.4	16.8

Table 6.3 Relative Weekly Wages of Male Immigrants by Place of Origin and Years Since Immigration, 1970 and 1980

		Years Since	e Immigration	
Place of Origin	0–5	6–10	11–15	16–20
All immigrants:				
25-34	292	119	075	0
35-44	<b>409</b>	244	095	055
1980:				
35-44	473	349	220	122
45-54	582	529	385	206
Europe:				
1970:				
25-34	133	.017	022	.085
35-44	229	090	008	.004
1980:				
35–44	144	210	032	<b>015</b>
45-54	356	259	214	050
Asia:				
1970:				
25–34	206	016	.061	486
35–44	400	152	.103	039
1980:				
35–44	472	065	.058	.036
45–54	549	360	288	.064
Mideast:				
1970:				
25–34	244	<b>040</b>	.147	.122
35–44	081	171	.123	209
1980:				
35–44	<b>274</b>	001	.087	.123
45–54	262	243	.009	.129
Mexico:				
1970:				
25–34	<b>-</b> .659	<b>411</b>	353	322
35–44	856	623	398	351
1980:				
35–44	983	764	582	399
45–54	927	930	605	669
Other Latin American:				
1970:				
25–34	436	196	<b>150</b>	083
35–44	559	354	332	034
1980:	-3-2			.001
35–44	609	492	446	193
45–54	895	740	535	355

Sources: Public Use Files from the 1970 and 1980 Censuses. For sample selection criteria, see the Appendix.

Note: Estimates are differences between mean log weekly earnings of immigrants and of white natives in the indicated age category.

they still earned 22 percent less. This estimate of relative assimilation is much smaller than what either cross section would imply, and it means that the average skills of successive arrival cohorts may have declined through time. The third point is that relative immigrant wages declined during the 1970s. This holds in virtually all age categories in the table. Again, one possibility is declining immigrant quality, but another is simple price adjustments in response to market forces, driven perhaps by the increased supply of new immigrants.

Do wages respond to immigration flows? Table 6.4 reports relative weekly wages in 119 SMSAs for various immigrant groups in 1970 and 1980. The estimates are tabulated by the proportion of the local labor force in 1980 that is accounted for by immigrants who arrived during the previous decade. "Top third" in the table refers to the set of SMSAs with the largest immigration rates, which account for one-third of all immigration over the decade. "Middle third" refers to the next most immigrant-intensive SMSAs, which account for another third of total immigration, and so on. Relative weekly wages are calculated as the difference between the mean log wages of immigrants and of white males of the same age, within each SMSA. The data show that relative immigrant wages were dramatically lower in labor markets where new immigration flows were largest. For example, row 6 of the table shows that weekly wages of recent immigrants (those who arrived in the last ten years) fell by over 20 percent relative to white natives in cities with the highest immigration rates. The comparable estimate in cities with the lowest immigration rates is only 7.5 percent. One explanation for this pattern is that wages adjust to increases in supply, at least in the short run. An alternative explanation with much different implications is that less-skilled immigrants locate in immigrant enclaves, so that large immigrant populations are less skilled, on average. Our econometric approach seeks to isolate the first of these effects.

### 6.2 Theoretical Framework

In what follows, we view immigration flows as exogenous shifts in the supply of labor to geographically defined labor markets. So long as immigrants form labor aggregates that substitute imperfectly for others in local production, these supply shifts will have their largest effect on immigrant earnings, with declining effects on other input aggregates as substitution possibilities decline. Thus, for example, an increase in new immigration to a locale will reduce the relative earnings of new immigrants and to a lesser extent the earnings of others for whom immigrants are substitutes. The empirical issue is the magnitude of these effects.<sup>5</sup>

If immigrants have important effects on other market participants, it must be via the substitution effects just mentioned. An a priori restriction that we find reasonable is that the best substitute for the representative immigrant is another immigrant. At the other extreme, the representative native may be a

	ed by shares or 1.	THE THE PERSON OF THE PERSON O	
	Top Third	Middle Third	Bottom Third
1. Immigrants arriving after			
1970, in 1980	642	491	284
25–34	500	395	244
35–44	640	537	<b>-</b> .257
45-54	<b>765</b>	<b>-</b> .662	419
2. All immigrants in 1980	<b>-</b> .422	297	078
3. Pre-1970 immigrants in 1980	210	159	046
4. All immigrants in 1970	278	<b>-</b> .184	036
5. Immigrants arriving after			
1960, in 1970	<b>438</b>	352	208
6. Change in relative wages of			
recent immigrants (1-5)	204	139	075
7. Change in relative wages of			
all immigrants (2-4)	144	113	042

Table 6.4 Relative Weekly Wages of Male Immigrants and White Natives in SMSAs Ranked by Shares of Immigrants in Work Forces

Sources: Public Use Files from the 1970 and 1980 Censuses. For sample selection criteria, see the Appendix.

Note: Estimates in the table are differences between geometric mean wages for immigrants and white males within each SMSA. SMSAs are ranked by the share of the male labor force accounted for by immigrants who arrived between 1970 and 1980. "Top third" refers to SMSAs with the largest immigration rates that together account for one-third of all post-1970 immigrants. "Middle third" refers to those SMSAs with the next largest rates of immigration that together account for another third of all new immigrants. Finally, the column labeled "bottom third" refers to SMSAs with the lowest rates of immigration that together account for the remaining one-third of new immigrants.

very poor substitute for new immigrants, who enter the United States with skills (e.g., language and institutional knowledge) that typically are less valued in the American market. Yet over time the immigrants assimilate. In our analysis, this assimilation entails greater ease of substitution between an immigrant cohort and native workers as their time in the United States accumulates. Thus, substitution between old and new immigrant cohorts is also imperfect. We further expect these intercohort substitution effects to dominate those between new immigrants and (most) native workers. The following model formalizes these ideas and serves to guide the subsequent empirical work.

We assume the existence of a large number of geographically distinct labor markets. Immigrant and nonimmigrant labor are combined in a concave local production function represented by

(1) 
$$Y_{c} = F[\theta_{c}g(M_{c1}, \ldots, M_{ck}), \alpha_{c}h(N_{c1}, \ldots, N_{cL})].$$

In equation (1),  $Y_c$  refers to total output produced in locale c (empirically an SMSA), and  $M_{cj}$  is total human capital supplied by labor aggregate j in locale c. In our discussion, we assume that the labor aggregates in  $g(\cdot)$  include immigrant arrival cohorts  $(j = 1, \ldots, k - 1)$  plus nonimmigrant labor  $(j = 1, \ldots, k - 1)$ 

k) as inputs, though empirical implementation requires further judgments about substitution possibilities. Thus, some natives who are thought to be close substitutes for immigrants—young Hispanics or blacks, for example—can be included as separate factors. Another possibility is to allow immigrant groups of different ethnicities to form separate inputs in the production function. The (weak) separability assumption in equation (1) is maintained throughout. Given our specification of  $g(\cdot)$ ,  $h(\cdot)$  contains capital and other resources that are incidental to the analysis. The parameters  $\theta_c$  and  $\alpha_c$  are locale-specific factor-neutral shifters of the effective quantities of labor and other factors. For example, these shifters may represent forces that shift the local demand for labor. Given varying sizes of cities to which the model may be applied, a plausible assumption about  $g(\cdot)$  is that it has constant returns, so that doubling all labor quantities leaves relative wages unchanged within any locale.

Assume for the moment that each member of arrival cohort j supplies one unit of relevant human capital. Then the marginal product (wage) of group j workers at locale c is

$$(2) W_{ci} = F_1(\cdot)\theta_c g_i(M_{c1}, \ldots, M_{ck}),$$

where subscripts to functions denote partial derivatives with respect to the indicated argument. The separability assumption in equation (1) implies that other inputs enter the marginal product of labor only through  $F_1(\cdot)$ . Thus, shifts in  $\theta_c$ ,  $\alpha_c$ , or other nonlabor components leave *relative* wages for labor inputs unchanged. Given (2), the log wage of group j workers in locale c is

(3) 
$$w_{ci} = \ln [F_1(\cdot)\theta_c] + \ln g_i(M_{c1}, \ldots, M_{ck}).$$

The first term on the right-hand side of equation (3) is an area-specific term and is independent of j; it is fixed for all labor inputs within a locale. Equation (3) is the basis for our empirical analysis.

The first step toward an empirical specification of (3) is to replace  $\ln [F_1(\cdot)\theta_c]$  with an area-specific fixed effect,  $\beta_c$  and to expand  $\ln g_j(M_{c_1}, \ldots, M_{c_k})$  to first order in logs:

(4) 
$$W_{ci} = \beta_c + \sum_i \gamma_{ii} \ln M_{ci}.$$

In (4), the parameters  $\gamma_{ji}$  ( $i=1,2,\ldots,k$ ) are "elasticities of complementarity" ( $\partial \ln W_{cj}/\partial \ln M_{ci}$ ) that satisfy  $\Sigma_i \gamma_{ji} = 0$  if there are constant returns. Aside from this homogeneity condition, the only restriction implied by theory is  $\gamma_{jj} < 0$ —an increase in the supply of group j workers reduces their wage. However, if j indexes cohorts by their time in the United States, we expect  $\gamma_{ij} < 0$  (for  $i \neq j$ ) with effects that dissipate as |j-i| increases. In the language of demand theory, adjacent immigrant cohorts should be q-substitutes (see Hamermesh 1986). In other words, recent immigrants offer the greatest substitution possibilities for new immigrants, so the  $\gamma_{ij}$  will trace out an assimilation profile of wage adjustments. Complementarity is also a possibility

 $(\gamma_{ij} > 0)$ . For example, a large enclave of past immigrants may improve market opportunities for new immigrants, especially when language and cultural ties are important. These restrictions are tested below.

To complete the empirical specification, we drop the assumption that each individual contributes a single unit of human capital to the stock  $M_j$ . We assume that an individual's stock of human capital, m, depends on his characteristics, X, so that, for person l in cohort j and city c,  $m_{cjl} = \exp\{X_{cjl}\delta + \beta_j + \beta_0 + \epsilon_{cjl}\}$ . The cohort effects  $\beta_j$  allow for both assimilation (earlier cohorts have acquired skills relevant to the U.S. market) and differences in the quality of immigrants over time. Similarly, the "origin effects"  $\beta_0$  control for differences in average immigrant characteristics between broadly defined places of origin. With this assumption, the log wage of individual l is

(5) 
$$w_{cjl} = \beta_c + \beta_j + \beta_0 + X_{cjl} \delta + \sum_i \gamma_{ji} \ln M_{ci} + \varepsilon_{cjl}.$$

Three points about (5) are noteworthy. First, the appearance of locale effects  $(\beta_c)$  in (5) implies that the  $\gamma_{ii}$ 's capture shifts in the relative earnings of different immigrant groups within a locale that are induced by changes in the relative shares of immigrants. More precisely, with fixed city effects, the estimable substitution parameters are  $\gamma_{ji} - \gamma_{ki}$ ,  $j = 1, \ldots, k - 1$ . Since k refers to native workers as an aggregate, our maintained assumption is that  $\gamma_{ki} = 0$ ; changes in the stocks of immigrants do not affect the wages of the typical native worker, so relative wage adjustments capture the effects of interest. 10 For example,  $\gamma_{11} < 0$  implies that, in a locale where the market share of new immigrants is large, wages of new immigrants will be low relative to the earnings of other workers in that area. Thus, our analysis examines the effect of immigration on rotations of the assimilation profile of immigrant wages within locales. Sample selection due to unobservable differences across areas in immigrant "quality" will not affect our results. For the same reason, controlling for locale effects implies that our results are not affected by differences in demand conditions, local amenities, or the cost of living across markets, so long as these conditions have factor-neutral effects on the wages of separate labor categories within a locale. Therefore, demand-induced shifts in immigration to a locale are not an issue unless they have differential effects on certain immigrant cohorts.

A second noteworthy point about equation (5) is that, while the estimated area effects,  $\beta_c$ , subsume wage adjustments for each locale, it is still true that an increase in the total supply of immigrants will normally reduce immigrant earnings relative to those of nonimmigrants. These relative wage adjustments can be evaluated from (5). Because the cross-substitution effects  $\gamma_{ji}$  (for  $j \neq i$ ) typically will be nonzero, an increase in the supply of all immigrants may have a larger negative effect on immigrant earnings than would be implied by own substitution effects  $(\gamma_{ij})$  alone.<sup>11</sup>

Finally, equation (5) controls for cohort (time of arrival) effects directly, so that differences in immigrant quality over time do not influence the estimates

of  $\gamma_{ji}$ . For example, if recent immigrant cohorts are less skilled than their predecessors, a model like (5) that did not control for time in the United States might attribute the entire decline of relative earnings among recent immigrant cohorts to the increased relative supply of new immigrants. Model (5) is not subject to this bias as long as within-cohort average quality is neutral with respect to locale. Similar arguments apply to the presence of place of origin effects,  $\beta_0$ .

### 6.2.1 Relative Wage Adjustments within Areas

Despite these controls, model (5) arguably is inappropriate since mobility of either natives or other factors may arbitrage geographic wage differentials in the long run. Differences in immigrant shares can persist in equilibrium, but, if factors are mobile, these differences have no implications for wage differentials. This argument is less persuasive when applied to short-run adjustments to *changes* in the flow of immigrants. Our evidence in section 6.1 documented the large increase in the flow of immigrants during the 1970s and showed that the direction of this flow was mainly toward existing immigrant enclaves. We assume that these facts represent an exogenous increase in the supply of immigrants to these areas and that the effects of this supply shift on wages cannot be arbitraged in the short run by mobility of other factors. This suggests a comparison of within-area wage *changes* between the 1970 and the 1980 Censuses in response to changes in the stock of immigrants. More formally, we effectively difference (5) within areas by including city by cohort effects in the model:<sup>12</sup>

(6) 
$$w_{cjlt} = \beta_{cj} + \beta_{0t} + X_{cjlt} \delta + \sum_{i=1}^{k} \gamma_{ji} \ln M_{cit} + \nu_{cjlt},$$

where t indexes Census year (1970, 1980). In equation (6), differences in immigrant earnings across areas are subsumed in the  $\beta_{cj}$ 's, which vary by area and entry cohort (but not by year). In this model, parameters  $\gamma_{ij}$  are identified from within-area *changes* in relative immigrant shares over time. For example,  $\gamma_{11} < 0$  implies that areas experiencing an increase in the share of new immigrants over the decade will also show declining wages of new immigrants relative to other workers in those locales.

# **6.3** Empirical Results: The Effects of Immigration on Wages and Earnings

#### 6.3.1 Results from the 1980 Census

In this section, we report parameter estimates for versions of models (5) and (6). The basic sample consists of 26,681 immigrants derived from the 1% Sample of the 1980 Census. Immigrant arrival cohorts in these data are de-

fined by date of arrival in the United States as recorded by the Census. The six identifiable cohorts are immigrants with zero to five, six to ten, eleven to fifteen, sixteen to twenty, twenty-one to thirty, and more than thirty years in the United States. All our results are for men between the ages of 16 and 64 who were labor force participants (employed or unemployed) at the time of the Census survey (roughly, April 1980) and who had positive earnings during the previous calendar year. These men resided in 119 SMSAs (listed in the Appendix). Details of selection criteria, variable definitions, and summary statistics are also appended. The dependent variable in all the models estimated below is the natural logarithm of the average weekly wage (annual earnings divided by weeks worked) for each individual.<sup>13</sup>

Judgments about which labor aggregates to include in the model determine the base group against which relative earnings adjustments of immigrants are measured. We have tried several aggregation schemes, with very similar results, of which two are noteworthy. First, when the base group is defined to be natives as an aggregate, the estimable substitution matrix  $\Gamma = [\gamma_{ii}]$  has forty-two independent elements. Using this model, the substitution effects that we estimate are quite small. Further, we were unable to reject (either jointly or individually) the hypothesis that  $\gamma_{6i} = 0$ ,  $i = 1, \ldots, 6$ , in this case, which indicates that the wages of immigrants with more than thirty years in the United States are fully assimilated insofar as substitution effects are concerned. This suggests a second aggregation scheme that restricts attention to immigrants only and where the normalizing group is immigrants with more than thirty years in the United States. In this case,  $\Gamma$  contains thirty independent elements. This sample produced slightly larger estimates of the effect of immigration on relative wages. Since our main finding is that these effects are small in all relevant cases, we report only the results using the second approach.14

Column 1 of table 6.5 reports the estimated diagonal elements of  $\Gamma = [\gamma_{ji}]$  from a completely unrestricted model. Taken literally, these "own" effects imply that a 10 percent increase in the flow of new immigrants to an area would reduce new immigrant weekly wages by about 1 percent  $(-.098 \times .1)$  relative to immigrants in the United States for more than thirty years. This estimate is not very precise, and, in the unrestricted models of columns 1–3, it is the only effect that is larger than its standard error. Off-diagonal terms in  $\Gamma$  (not reported) are also imprecisely estimated. In part, this imprecision reflects a vain effort to estimate the thirty free parameters of  $\Gamma$  from immigrant shares in only 119 SMSAs. The problem is colinearity. One way to impose further structure and summarize the overall effect of immigration on wages is to estimate the effect of a proportional increase in the size of all immigrant groups. Since  $d \ln w = \Gamma d \ln M$ , the estimated effect on each cohort is simply the row sum from the substitution matrix,  $\Gamma$ . Estimates of these effects for the unrestricted models of columns 1–3 of table 6.5 are shown in table 6.6. In general, these estimates imply that immigration reduces wages, especially among

Table 6.5 The Effects of Immigration on the Wages of Immigrants (dependent variable is log average weekly earnings of males in 1979)

		tricted Vers		Res	tricted Vers Constrain	ion: Cross I ned to Zero	Effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own effects: $\gamma_{ii}$ :							
Years in the U.S.:							
0–5	098	<b>-</b> .099	<b>-</b> .099	045	047	045	045
	(.043)	(.044)	(.044)	(.014)	(.015)	(.015)	(.015)
6–10	052	064	072	045	051	047	050
	(.053)	(.054)	(.055)	(.014)	(.014)	(.014)	(.014)
11–15	001	001	.006	031	036	033	037
	(.048)	(.049)	(.049)	(.014)	(.014)	(.015)	(.015)
16-20	.018	.017	.031	002	002	.003	005
	(.045)	(.046)	(.046)	(.015)	(.015)	(.015)	(.015)
21-30	.050	.061	.064	.020	.015	.021	.014
	(.065)	(.066)	(.066)	(.020)	(.021)	(.021)	(.021)
Arrival cohort effects: Years in the U.S.:							
0–5	519	567	579	376	412	414	443
	(.106)	(.107)	(.108)	(.050)	(.051)	(.051)	(.051)
6–10	292	375	375	267	316	312	347
	(.107)	(.108)	(.109)	(.049)	(.050)	(.050)	(.050)
11–15	294	346	333	164	201	186	231
	(.109)	(.111)	(.112)	(.052)	(.053)	(.053)	(.053)
16-20	180	216	189	006	019	003	041
	(.118)	(.119)	(.120)	(.058)	(.059)	(.059)	(.059)
21-30	.013	032	012	.076	.042	.065	.039
	(.105)	(.107)	(.108)	(.071)	(.072)	(.073)	(.072)
Regression includes:							
Cross effects: years in U.S. interacted with other city co- hort shares	yes	yes	yes	no	no	no	no
Occupation controls	yes	no	no	yes	no	no	no
Industry controls	yes	yes	no	yes	yes	no	yes
Place of origin con- trols	yes	yes	yes	yes	yes	yes	no

Note: Regressions control for years of schooling, potential experience and experience squared, race, the presence of children, two marital status dummy variables, and a dummy variable for a disability that limits a person's work. There are nine occupation controls, eighteen industry controls, and six place of origin controls: Europe, Canada, Australia, and New Zealand; Asia; the Middle East; Mexico; other Latin America; and other immigrants. Standard errors are in parentheses. The cross-substitution estimates associated with columns 1–3 are not reported in the table.

more recent arrivals: a sustained increase in immigration of the indicated magnitude would reduce the wage of new arrivals by about 9 percent, with smaller but still substantial effects on the wages of earlier cohorts. <sup>16</sup> Only the earliest arrivals (twenty-one to thirty years) are insulated from relative wage adjustments.

Table 6.6 Estimated Effects on Log Weekly Wages of a Proportional Increase  $(d \ln M_i = 1)$  in All Immigrant Cohorts, Unrestricted Substitution Effects, 1980

		Yes	ars Since Immigrat	tion	
Model	0-5	6–10	11–15	16–20	21–30
1	091	046	054	040	.006
	(.028)	(.029)	(.030)	(.032)	(.028)
2	096	059	065	046	.0
	(.029)	(.029)	(.030)	(.032)	(.029)
3	098	057	060	039	.004
	(.029)	(.030)	(.031)	(.033)	(.029)

Note: Calculated from estimated substitution matrix for the unrestricted models in columns 1-3 of table 6.5. For each immigrant group, the estimated effect of a proportional increase in all immigrants in a local labor market is the sum of coefficients in the corresponding row of the substitution matrix. For other controls in each model, see table 6.5. Standard errors are in parentheses.

Columns 4–7 of table 6.5 report more parsimonious specifications that constrain the off-diagonal terms of  $\Gamma$  to zero. In these specifications, arrival cohorts are assumed to be independent inputs in local production, so there are no intercohort crowding effects on wages. In these models, a larger own labor force share for an immigrant cohort tends to reduce wages for that cohort but has no effect on other cohorts. These own-substitution effects also tend to die out as time in the United States accumulates. Thus, there appears to be significant crowding among recent arrivals, but the effects of own cohort size dissipate over time.

The parsimony of the specification in columns 4–7 of table 6.5 was purchased with a substantial loss of generality: cross-cohort substitution was assumed away. We next reintroduce these substitution effects with additional structure. We hypothesize that, for each immigrant cohort, cross effects are smaller than own effects ( $\gamma_{ij} < \gamma_{ji}$  for  $i \neq j$ ) and that these substitution effects dissipate as [i-j] increases. That is, members of adjacent arrival cohorts are better substitutes than are members of distant ones. Under this hypothesis, in each row of  $\Gamma$  the largest negative element is along the diagonal, while other effects should be smaller moving away from the diagonal in either direction. To test this hypothesis, we allow

(7) 
$$\gamma_{ji} = \gamma_{jj} + \lambda_j |i-j|, j=1, 2, ..., 5.$$

If adjacent cohorts are imperfect substitutes, then we expect  $\gamma_{jj} < 0$  and  $\lambda_j > 0$ , with  $|\lambda_j| < |\gamma_{jj}|$ . The linear restrictions (7) reduce the number of estimated substitution parameters from thirty to ten while retaining substantial flexibility. In fact, the restrictions imposed in equation (7) cannot be rejected—either individually or jointly—in any form of the model that we have estimated. Estimates based on (7) are shown in table 6.7 for various combinations of other controls.

Table 6.7 The Effects of Immigration on Wages, Linear Restrictions on Intercohort Substitution (dependent variable: log average weekly earnings in 1979)

	(1)	(2)	(3)	(4)	(5)
Own Cross Effects:					
Years in the U.S.:					
0-5 years:					
Own effect $(\gamma_{11})$	032	035	032	030	033
	(.011)	(.012)	(.012)	(.012)	(.012)
Cross effect $(\lambda_1)$	.011	.012	.011	.010	.011
-	(.005)	(.005)	(.005)	(.005)	(.005)
6–10 years:					
Own effect $(\gamma_{22})$	037	038	036	036	037
	(.012)	(.012)	(.012)	(.012)	(.012)
Cross effect $(\lambda_2)$	.018	.017	.016	.016	.017
	(.007)	(.007)	(.007)	(.007)	(.007)
11-15 years:					
Own effect $(\gamma_{33})$	<b>-</b> .010	013	009	012	015
	(.015)	(.015)	(.016)	(.016)	(.015)
Cross effect $(\lambda_3)$	.003	.004	.002	.003	.005
	(.011)	(.011)	(.01)	(.011)	(.011)
16–20 years:					
Own effect $(\gamma_{44})$	.015	.015	.01	.013	.011
	(.019)	(.019)	(.02)	(.019)	(.019)
Cross effect $(\lambda_4)$	011	012	<b>–</b> .01	010	<b>–</b> .010
	(.012)	(.012)	(.01)	(.013)	(.012)
21-30 years:					
Own effect $(\gamma_{55})$	.027	.028	.03	.027	.026
	(.014)	(.015)	(.01)	(.015)	(.015)
Cross effect $(\lambda_5)$	013	<b>–</b> .011	013	013	<b>-</b> .013
	(.007)	(.007)	(.007)	(.007)	(.007)
Regression includes:					
Occupation controls	yes	no	no	no	no
Industry controls	yes	yes	no	no	yes
Place of origin controls	yes	yes	yes	no	no
Arrival cohort controls	yes	yes	yes	yes	yes

*Note:* See note to table 6.5. The own effects  $(\gamma_{ij})$  for each cohort j are unrestricted. The cross-substitution effects are restricted to follow  $\gamma_{ji} = \gamma_{jj} + \lambda_j |i - j|$ , where i indexes the time of arrival of cohort i relative to cohort j.

The key finding in table 6.7 is that own effects of cohort size  $(\gamma_{jj})$  are negative and significant for recent arrivals, while cross-cohort substitution effects die out with the difference in time of entry to the United States  $(\lambda > 0)$ . Especially for recent arrivals, we find that adjacent cohorts are q-substitutes. <sup>17</sup> Both the own and the cross effects of cohort size tend to diminish with years since entry. We take this finding as evidence of assimilation: the effect on

wages of a large cohort is diluted as immigrants melt into the broader market of native workers. To pursue this point, we add additional structure to (7) by assuming that

(8) 
$$\gamma_{jj} = \gamma + \mu(j-1), \\ \lambda_j = \lambda + \phi(j-1).$$

Together, restrictions (7) and (8) express the form of the substitution matrix in terms of just four parameters. If assimilation means increasing substitution between past immigrants and the labor market as a whole, as time in the United States accumulates, we expect  $\gamma < 0$ ,  $\mu > 0$ ,  $\lambda > 0$ , and  $\phi < 0$ . Furthermore, the parameters should also satisfy  $|\phi| < |\gamma|$  and  $|\lambda| < |\gamma|$  if there is (imperfect) substitution among immigrant cohorts.

Estimates of this parameterization of the substitution matrix are shown in table 6.8 for three illustrative sets of other controls. Other specifications differ trivially from these. All parameters are of the anticipated signs and relative magnitudes, and they are significantly different from zero by conventional standards. The reported F-statistics in the table test the four-parameter structure given by (8) against the unrestricted, thirty-parameter model of  $\Gamma$ . Remarkably in a sample of this size, the restrictions are never rejected. Thus, (8) offers a good summary of the data. The estimates imply that an increase of roughly 170 percent ( $d \ln M = 1$ ) in the stock of new immigrants would reduce the relative weekly wages of new immigrants by about 3 percent ( $\gamma < 0$ ). The immediate effect on earlier immigrant cohorts of this increase would be smaller ( $\lambda > 0$ ). As time in the United States accumulates for an arrival cohort, the earnings disadvantage caused by being a member of a large cohort evaporates ( $\mu > 0$ ), as do the cross effects of cohort size on adjacent

Table 6.8 The Effects of Immigration on Wages: Linear Restrictions on Own and Intercohort Substitution (dependent variable: log average weekly earnings in 1979)

		Par	ameter		F-Statistic
Model	γ	λ	μ	ф	for Restrictions
1	029	.010	.010	004	.970
	(.007)	(.003)	(.003)	(.002)	
2	033	.011	.011	004	.955
	(800.)	(.003)	(.004)	(.002)	
3	030	.010	.011	004	1.169
	(.008)	(.003)	(.004)	(.002)	

Note: Model 1 controls include cohort, origin, occupation, and industry effects in addition to the demographic controls listed in table 6.5. Model 2 drops occupation from the set of controls, and model 3 drops industry and occupation. The reported F-statistics test the restricted four-parameter model relative to the completely unrestricted model with thirty parameters. Dependent variable is log weekly wages; standard errors are in parentheses. For definitions of parameters, see the text.

arrivals ( $\phi < 0$ ).<sup>19</sup> All these estimates are consistent with immigrant crowding in local markets, tempered by assimilation and imperfect substitution.

### 6.3.2 Annual Earnings versus Wages: Do Quantities Matter?

The analysis to this point has focused only on market clearing price adjustments with inelastic labor supply. However, if immigration also causes quantity adjustments in terms of unemployment, hours, or weeks worked, then annual earnings may be a more appropriate measure of welfare. A detailed analysis of adjustments on each of these margins is beyond the scope of this paper (see Altonji and Card, in this volume). Yet quantity and price adjustments are likely to be correlated, so the effects of immigration on annual earnings may be larger than on wages. The estimates in tables 6.5–6.8 would then underestimate the distributive effects of immigration. To explore this possibility, table 6.9 reproduces the estimates in tables 6.6 and 6.8 when log annual earnings in 1979 instead of log average weekly earnings is used as the dependent variable.

The estimates from the unrestricted model of the effect of a proportional increase in all immigrant groups, in part A of the table, are slightly larger than the corresponding estimates in table 6.6 (the most recent arrival cohort is an exception). For the specification in row 2 of table 6.9, part A, the effects on earnings exceed those on wages, on average, by about a third, though the standard errors are large enough that equality of effects cannot be rejected. Thus, it appears that the main distributive effects of immigration operate through price flexibility rather than through adjustments in unemployment or participation. This conclusion is reinforced by a comparison of the estimates in part B with those of table 6.8, which report restricted estimates of substitution parameters. The estimates for wages and annual earnings differ only trivially. On this evidence, we conclude that the main actor in market adjustments to immigration must be wage flexibility. Adjustments in unemployment or participation are negligible.

## 6.3.3 The Effects of Immigration on Young Native Blacks and Hispanics

To this point, we have treated all nonimmigrants as a single aggregate, while focusing on substitution possibilities among immigrants. For these groups, the effect of immigration on measures of welfare are quite small. Even so, some groups of native Americans may be more sensitive to the crowding effects of immigration than others, and for them the implied redistributive effects are of some concern. Here, we focus on two identifiable groups who may face the most important crowding effects of immigration: young (aged 16–34) blacks and Hispanics.

We treat young blacks and Hispanics as separate inputs that interact with immigrants in local production (see eq. [1] above). The unrestricted matrix of estimated substitution effects now contains fifty-six parameters, and it is not very informative. As above, we may calculate the effect of a scale ( $d \ln M_i$ )

Table 6.9

A. Effects on Log Annual Earnings of a Proportional Increase ( $d \ln M_i = 1$ ) in All Immigrant Cohorts, Unrestricted Substitution Effects (dependent variable: log annual earnings in 1979)

		Ye	ears Since Immigra	ation	
Model	0-5	6–10	11–15	16–20	21-30
1	089	064	077	066	008
	(.032)	(.032)	(.034)	(.036)	(.032)
2	093	079	085	<b>071</b>	<b>-</b> .014
	(.033)	(.033)	(.034)	(.037)	(.033)
3	<b>091</b>	074	078	062	008
	(.033)	(.033)	(.034)	(.037)	(.033)

B. The Effects of Immigration on Earnings: Linear Restrictions on Own and Intercohort Substitution (dependent variable: log annual earnings)

		Par	ameter		E Candida
Model	γ	λ	μ	φ	F-Statistic for Restrictions
1	026	.008	.009	003	.721
	(800.)	(.004)	(.004)	(.002)	
2	030	.009	.011	004	.756
	(.009)	(.004)	(.004)	(.002)	
3	028	.009	.011	004	.822
	(.009)	(.004)	(.004)	(.002)	

Note: See notes to tables 6.6 and 6.8. Standard errors are in parentheses.

1) increase in all immigrant cohorts on the wages or earnings of blacks and Hispanics. These estimated effects are shown in part A of table 6.10 for two specifications of the model.<sup>20</sup> Overall, there is only weak evidence that immigration reduces the wages and earnings of these natives. The largest estimates that we obtained are shown in row 1: the point estimate of the effect of a 170 percent increase in the size of all immigrant cohorts on black wages is only 2.4 percent, though the estimate is smaller than its standard error. The corresponding estimate for Hispanics is less than 1 percent. Surprisingly, in light of our previous results, the effects on earnings are slightly larger than on wages. Thus, there is some evidence of reinforcing adjustments on time worked, especially among young blacks. Again, however, these effects are not precisely estimated.

An alternative strategy for examining these effects is to impose the restrictions given by (7) and (8) on the matrix of intercohort substitution terms among immigrants, while leaving own and cross effects for blacks and Hispanics as free parameters. To impose some structure, we allow black and Hispanic wages to be affected separately by immigrant cohorts that arrived before and after 1965. The hypothesis is that crowding effects of immigration are

Table 6.10 The Effects of Immigration on Wages and Earnings of Young Blacks and Hispanics

A. The Effects of a Proportional	Increase in All Immigrant	Cohorts (unrestricted models)
----------------------------------	---------------------------	-------------------------------

		Effect On:						
Model	Black Wages	Black Earnings	Hispanic Wages	Hispanic Earnings				
1	024	059	009	015				
	(.030)	(.035)	(.032)	(.037)				
2	020	046	008	012				
	(.030)	(.036)	(.032)	(.038)				

B. Estimated Cross Effects of Immigrants on Blacks and Hispanics (linear restrictions imposed)

	Effect on Blacks of an Increase in:			Effect on Hispanics of an Increase in:			
Model	Native Blacks	Post-1965 Immigrants	Pre-1965 Immigrants	Native Hispanics	Post-1965 Immigrants	Pre-1965 Immigrants	
Earnings:							
1	042	006	005	014	.015	025	
	(.018)	(800.)	(.012)	(.018)	(.010)	(.015)	
2	028	006	008	008	.018	030	
	(.018)	(.007)	(.012)	(.017)	(.010)	(.015)	
Wages:							
1	042	010	.008	020	.007	013	
	(.015)	(.006)	(.010)	(.015)	(.010)	(.013)	
2	031	009	.005	014	.010	016	
	(.015)	(.006)	(.010)	(.015)	(.009)	(.013)	

Note: Part A parameter estimates refer to the effect of a unit change in log employment of all immigrant cohorts ( $d \ln M_i = 1$  for all i) on log wages or earnings of blacks and Hispanics. Part B estimates represent the effect of a unit change in log employment of the indicated group. Model 1 contains all demographic controls listed in table 6.8. Model 2 adds industry and occupation controls. Standard errors are in parentheses. Part B models constrain intercohort substitution matrix for immigrants to follow eqq. (7) and (8). Black and Hispanic effects are free parameters.

concentrated on these demographic groups and that recent immigration is the most important factor.

We report (in pt. B of table 6.10) the own effects for both blacks and Hispanics as well as estimated cross effects with immigrants. In each case, we find crowding effects of blacks and Hispanics on their own wages; increases in the labor force shares of these groups reduce their wages, though only the estimate for blacks is significant. We also find that recent immigrants are substitutes for young blacks, though the effect is small (-.01 is the largest estimate we obtained) and imprecisely estimated. It is substantially smaller than the own effect on black wages (-.042). The estimates for Hispanics are more mixed. Finally, for neither group do we find important differences between the wage and the earnings estimates, suggesting that employment and hours adjustments are also minor concerns. Overall, these estimates do not suggest to

us that immigration is a prime factor affecting labor market outcomes for these young natives.

### 6.3.4 Results from the 1970 Census

According to Census data, immigration to the United States in the 1970s was roughly double its level in the 1960s. Because this sharp increase in the flow of new immigrants was highly geographically concentrated (see sec. 6.1), it is plausible that short-run labor market adjustments would generate a stronger relation between immigration and relative wages in the 1980 Census than in the 1970 Census. We examine this point in table 6.11, which summarizes estimates of the substitution effects from the 1970 Census. Because the story is not much different in these data, we report only the substitution effects of a proportional increase in all immigrant cohorts from the unrestricted model (eq. [5]) in part A of table 6.11 and the restricted form of intercohort substitution effects (eq. [8]) in part B.

A. Effects on Relative Log Weekly Wages of a Proportional Increase in All Immigrant Cohorts (unrestricted substitution effects, 1970)

		Years Since Immigration								
Model	0-5	6–10	11–15	16-20	21–30					
1	.012	024		017	.004					
	(.022)	(.024)	(.027)	(.028)	(.024)					
2	.008	025	003	024	.012					
	(.023)	(.024)	(.028)	(.029)	(.025)					
3	.009	028	006	017	.015					
	(.023)	(.024)	(.028)	(.029)	(.025)					

B. Estimated Substitution and Assimilation Parameters for Log Weekly Wages of Immigrants (linear restrictions imposed, 1970)

		Parameter				
Model	γ	λ	μ	ф	F-Statistic for Restrictions	
1	019	.008	.001	0005	.861	
	(.006)	(.003)	(.002)	(.001)		
2	- 020	.008	.001	0004	.834	
	(.007)	(.003)	(.002)	(.001)		
3	021	.008	.001	0004	.814	
	(.007)	(.003)	(.002)	(.001)		

Note: Part A calculated from estimated substitution matrix for unrestricted models analogous to those in columns 1-3 of table 6.5. These results are comparable to those in table 6.6. For other controls in each model, see table 6.5. Calculations are based on a sample of 17,158 immigrants in 119 large SMSAs from the 1970 Census. Standard errors in parentheses. For part B, see notes to table 6.8. Dependent variable is log weekly wages; standard errors are in parentheses. The results when the dependent variable is log annual earnings are similar.

The estimates in part A should be compared to the corresponding estimates for 1980 in table 6.6. Whereas the 1980 estimates implied sharply lower earnings among new immigrants, the corresponding estimates for 1970 are negligible. For earlier arrivals, the estimates are negative though generally smaller than in 1980, and none are significant by conventional standards. These points are also apparent in part B; while all the substitution relations take the anticipated sign, only  $\gamma$  is significant. The key point is that all these effects are substantially smaller than in the 1980 data (see table 6.8).

The relation between the estimates generated by the 1970 and 1980 cross sections raises an important issue. Did the *increased* immigration of the 1970s generate the substantial crowding effects that seem to show up in the 1980 cross section? To answer this question, we create a pseudo-panel from the combined 1970 and 1980 Census files and analyze within-market changes in immigration, wages, and earnings.

# 6.3.5 Panel Estimates: Relative Wage Adjustments within SMSAs, 1970-80

The preceding econometric results rely on cross-sectional differences in labor force shares to generate price adjustments. Since labor is mobile in the long run, the existence of these wage differentials appears inconsistent with spatial equilibrium, so our interpretation of these results may be suspect. In light of this problem, we estimate equation (6), which pools the data from the 1970 and 1980 Censuses. We add to the model six hundred fixed effects that control for entry cohort (time in the United States) within each SMSA. Thus, the variation used to estimate substitution effects occurs over time and within SMSA-cohort cells. In effect, we ask whether areas that experienced unusually rapid immigration over the decade also experienced falling relative wages and earnings of recent immigrants and whether there were spillover effects of these changes on other groups.<sup>21</sup>

Results are summarized in tables 6.12 and 6.13. In table 6.12, we report models for the determination of log weekly wages and annual earnings that constrain intercohort substitution effects to follow (7). Each row of the substitution matrix is summarized by two parameters: an "own" effect of increasing cohort size on members of the cohort and a cross-cohort substitution effect that allows each cohort to have the largest effects on adjacent arrival cohorts. As above, we expect the former effect to be negative and the latter to be positive.

The results are surprisingly similar to the cross-sectional estimates (see table 6.7), though standard errors are somewhat larger. In four of five cases, the point estimate of the own effect of cohort size is negative, with smaller effects on adjacent cohorts. Differences between the estimates for log weekly wages and annual earnings are small, which indicates again that the main effects of immigration are on wages rather than employment (weeks worked). Furthermore, the estimates show a tendency to "die out" as time in the United

Table 6.12 Wages Changes within Locales: The Effect of Immigration on Changes in Wages and Earnings within SMSAs, Linear Restrictions on Intercohort Substitution, 1970–80

	Dependent Variable						
Cohomt Varia	Log We	ekly Wage	Log Earnings				
Cohort: Years Since Immigration	(1)	(2)	(3)	(4)			
0–5:				_			
Own effect	039	034	049	045			
	(.014)	(.014)	(.016)	(.015)			
Cross effects	.018	.016	.021	.020			
	(.006)	(.006)	(.006)	(.006)			
6–10:							
Own effect	041	036	065	061			
	(.014)	(.014)	(.015)	(.015)			
Cross effects	.020	.018	.036	.020			
	(.008)	(.008)	(.009)	(.006)			
11–15:							
Own effect	007	009	002	003			
	(.013)	(.013)	(.014)	(.014)			
Cross effects	.006	.007	.002	.003			
	(.009)	(.009)	(.010)	(.010)			
16–20:							
Own effect	.032	.027	.047	.042			
	(.018)	(.018)	(.021)	(.021)			
Cross effects	011	008	019	015			
	(.011)	(.011)	(.013)	(.012)			
21–30:							
Own effect	010	<b>–</b> .010	006	005			
	(.015)	(.014)	(.016)	(.016)			
Cross effects	.003	.001	.002	.001			
	(.006)	(.006)	(.007)	(.007)			
Origin effects	yes	yes	yes	yes			
Cohort × SMSA effects	yes	yes	yes	yes			
Industry effects	no	yes	no	yes			
Occupation effects	no	no	no	no			
$R^2$	.258	.272	.243	.257			

*Note:* For other regressors, see note to table 6.5. The models include a dummy variable for 1980. Standard errors are in parentheses.

States accumulates: effects of within-city changes in shares are stronger for more recent arrivals.

In light of the last point, table 6.13 shows estimates for the most parsimonious specification, which restricts substitution terms to follow (8). These "panel" estimates should be compared to the cross-sectional results reported

Table 6.13 Wage Changes within Locales: The Effect of Immigration on Changes in Log Wages and Earnings within SMSAs: Linear Restrictions on Own and Cross-Substitution Effects, 1970–80

	Log Weekly Wage		Log E	Earnings
	(1)	(2)	(3)	(4)
γ	023	020	029	027
	(.009)	(.009)	(.014)	(.010)
λ	.013	.012	.016	.015
	(.004)	(.004)	(.004)	(.004)
μ	.003	.003	.005	.005
•	(.002)	(.002)	(.002)	(.002)
ф	002	002	002	002
,	(.001)	(.001)	(.001)	(.001)
Origin effects	yes	yes	yes	yes
Cohort × SMSA effects	yes	yes	yes	yes
Industry effects	no	yes	no	yes
Occupation effects	no	no	no	no
$R^2$	.257	.272	.243	.256

*Note*: See note to table 6.8. Standard errors are in parentheses. N = 44,004.

in tables 6.8 and part B of table 6.9. In light of our previously stated concerns, we are surprised that the panel and cross-sectional results are almost identical. All parameters are of the anticipated signs, with relative magnitudes that accord with theory. Our point estimates imply that a rough tripling  $(d \ln M = 1)$  of the rate of new immigration to an area would reduce the relative wages and earnings of new immigrants by 2–3 percent. Again, this crowding effect of membership in a large cohort dies out as U.S. experience accumulates, which indicates assimilation. Effects of new immigration on previous immigrants are smaller than the direct effects, which is indicative of imperfect substitution.

### 6.4 Conclusion

This paper has examined the effect of immigration on the labor market. Our basic finding is that increased immigration reduces the wages and earnings of immigrants and their close substitutes, though in our view the effects are not large. For immigrants themselves, a sustained doubling of the rate of new immigration may reduce relative earnings of new immigrants by about 3 percent, but even this effect tends to die out over time as immigrants assimilate to the American market. Labor market effects on nonimmigrants appear to be quantitatively unimportant: the wages and earnings of young blacks and Hispanics are not very sensitive to immigration. In short, our estimates imply that immigrants are rather easily absorbed into the American labor market. There

is little here to indicate that the redistributive effects of immigration should be a major policy concern.

These conclusions are tempered by at least two points. First, our analysis has relied heavily on differences in wages across geographic areas. These differentials are difficult to rationalize as an element of a long-run equilibrium of the labor market. We argued that the upsurge of immigration in the 1970s was a change in labor supply that generated short-run wage adjustments among areas, and comparison of time-series and cross-sectional results tended to support this assumption. Second, our analysis mainly treated immigrants as a homogeneous group, and so we ignored the effect that specific immigrant groups may have. For example, in light of our results, it is plausible that illegal immigration from Mexico affects mainly young Hispanics. These points deserve attention, but we defer them to later research.

# Data Appendix

# Selection and Construction of Variables

The data used in this study were drawn from the 1970 and the 1980 U.S. Census of Population and Housing, Public Use Samples (see U.S. Bureau of the Census 1973, 1983). The samples include males sixteen to sixty-four years old, who were not attending school, who were currently in the labor force at the time of the Census, who had worked for pay during 1979, who were not institutionalized, and who were living in SMSAs identified on both the 1970 and the 1980 Public Use Samples. For 1980, we used the 1%-B Public Use Sample. For 1970, we used the 1%-5% questionnaire—County Group Public Use Sample.

### **SMSA Definitions**

During the 1970s, the Office of Management and Budget changed the definitions of many SMSAs based on population and commuting patterns in the 1970 Census. These changes are published in "Standard Metropolitan Statistical Areas" (Office of Management and Budget 1976). We used this information to make the SMSA definitions in the 1980 and 1970 samples as comparable as possible. In principle, there are two ways to make these adjustments: (i) the SMSA definitions in the 1980 sample can be adjusted so that they conform to the 1970 definitions (see Altonji and Card, in this volume); (ii) the SMSA definitions in the 1970 sample can be adjusted so that they conform to those in 1980. Neither Public Use Sample provides enough information so that a user can redefine the SMSA definitions to make the two years exactly comparable. However, for most SMSAs, the changes do not add or

subtract many persons from the sample. The first procedure (i) is a little more precise, although it leads to a smaller sample size, while the second procedure (ii) is less precise but leads to a larger sample size. We tried both procedures and found that the results were robust to either method. All the results reported in the paper are based on the second procedure, where we redefined the 1970 SMSA definitions to make them comparable to the 1980 definitions.

Adjusting the SMSA definitions is difficult because the Public Use Samples do not provide enough information on a household's county group. Therefore, a user often does not know for sure whether some households are in a particular SMSA after a county (or a portion of a county) has been either added or subtracted between two Census years. In many cases, we drew a random sample of persons from a particular county (or group of counties if this was the finest level of identification) that corresponded to the share of persons in the area that was actually added or subtracted from the SMSA definition. This task is particularly difficult in New England and eastern Virginia. In a few cases, it was simpler and more precise to use the 1970 SMSA definitions as opposed to the 1980 definitions as the standard. This poses no problems for the analysis as the important thing is to have comparable SMSA definitions for the two years.

Table 6A.1 presents a list of the 119 SMSAs used in the analysis, along with the shares of all immigrants and recent immigrants in both 1970 and 1980 and the 1980 shares of young (16 to 34 years old) blacks and Hispanics in each SMSA's employed labor force. Note that the share of employed young blacks seems small in large SMSAs. This fact, however, is due to the concentration of blacks in the central cities. For example, in Chicago, blacks are concentrated in the city, whereas there are fewer blacks in heavily populated suburban Cook, Lake, and DuPage counties. In southern SMSAs, a much larger share of the outlying population is black.

#### Variable Definitions

We used two measures of earnings as dependent variables, weekly wages and annual earnings. Annual earnings is the sum of wage and salary income and self-employment income. We excluded persons who reported that their self-employment earnings where negative. Weekly wages are defined as annual earnings divided by weeks worked in 1969 and 1979.

Two potential problems with these earnings data are that (i) earnings are reported up to a maximum of \$50,000 in 1970 and \$75,000 in 1980 and (ii) in 1970 weeks worked is reported in discrete intervals. For practical purposes, the "top coding" problem seems to be minor. In 1980, 1.2 percent of the immigrants, .1 percent of the young black males, .1 percent of the young Hispanic males, and 1.2 percent of all other native workers had either wage or salary income or self-employment income that was greater than \$75,000. In 1970, .6 immigrants had wage or salary income or self-employment income that was greater than \$50,000. To resolve the problem in the weeks worked data for 1970, we inputted weeks worked for each person based on the mean

Table 6A.1 Share of Immigrants and Young Native Blacks and Hispanics in Large SMSAs

	Proportion of Employed Male Labor Force						
		igrants in 1970		igrants in 1980			
		Recent		Recent	Natives	16–34 Years	
SMSA	All	Arrivals	All	Arrivals	Blacks	Hispanics	
AKRON,OH	.045	.013	.030	.003	.031	.002	
ALBANY-SCHEN-TROY,NY	.046	.010	.040	.012	.012	.003	
ALBUQUERQUE, NM	.027	.012	.043	.021	.005	.183	
ALLENTOWN-BETH-							
EASTON, PA-NJ	.034	.005	.036	.010	.008	.012	
ANAHEIM-SANTA							
ANA-GRDN GVE,CA	.082	.033	.161	.096	.007	.036	
APPLETON-OSHKOSH, WI	.023	.007	.022	.009	.000	.000	
ATLANTA,GA	.009	.004	.025	.011	.102	.002	
AUGUSTA,GA-SC	.006	.002	.017	.006	.126	.006	
AUSTIN,TX	.021	.005	.036	.014	.041	.078	
BAKERSFIELD,CA	.066	.018	.097	.047	.016	.073	
BALTIMORE, MD	.034	.010	.033	.012	.089	.002	
,	.008	.003	.033	.006			
BATON ROUGE, LA	.008	.003	.016	.000	.123	.003	
BEAUMONT-PT ARTHUR-	014	001	022	012	077	0.0	
ORANGE,TX	.014	.001	.023	.013	.077	.012	
BINGHAMPTON, NY-PA	.041	.013	.034	.012	.001	.001	
BIRMINGHAM, AL	.003	.002	.010	.003	.099	.002	
BOSTON, MA	.089	.029	.095	.037	.016	.005	
BRIDGEPORT,CT	.100	.033	.086	.026	.020	.036	
BUFFALO, NY	.059	.011	.064	.017	.023	.005	
CANTON,OH	.023	.006	.018	.004	.020	.003	
CHARLESTON,SC	.014	.002	.015	.004	.122	.007	
CHARLOTTE, NC	.015	.007	.022	.010	.092	.001	
CHATTANOOGA,TN	.004	.001	.010	.007	.056	.001	
CHICAGO,IL	.096	.034	.132	.067	.060	.019	
CINCINNATI,OH-KY-IN	.018	.005	.024	.007	.049	.002	
CLEVELAND, OH	.067	.017	.059	.018	.055	.007	
COLUMBIA, SC	.003	.000	.014	.006	.143	.006	
COLUMBUS,OH	.012	.003	.021	.009	.047	.002	
CORPUS CHRISTI,TX	.031	.006	.063	.026	.013	.228	
DALLAS-FORT WORTH,TX	.020	.006	.054	.035	.058	.029	
DAVENPT-ROCK IS-	.020	.000	.054	.033	.030	.029	
MOLINE, IA-IL	.019	.004	.027	.012	.019	.014	
	.014	.004	.027	.004	.035		
DAYTON,OH	.014	.008	.018 .046	.020	.033	.001	
DENVER,CO	.030	.013				.040	
DES MOINES, IA			.027	.020	.021	.004	
DETROIT,MI	.074	.016	.065	.017	.068	.005	
DULUTH-SUPERIOR, MI-WI	.033	.002	.023	.005	.000	.000	
EL PASO,TX	.196	.049	.233	.127	.006	.209	
ERIE,PA	.025	.005	.017	.005	.019	.002	
FLINT,MI	.045	.017	.014	.004	.061	.010	

Table 6A.1(continued)

FTLAUDERDALE— HOLLYWOOD,FL 1.053 .026 .084 .034 .044 .013  FRESNO,CA .080 .019 .137 .069 .015 .099  GARY-HAMMOND—BAST CHICAGO,IN .062 .012 .055 .016 .071 .026  GRAND RAPIDS,MI .032 .004 .031 .007 .026 .007  GREENSBORO—WSTN-SLM— HIGH PT,NC .005 .001 .016 .007 .077 .002  GREENVILLE,SC .016 .005 .019 .007 .055 .001  HARRISBURG,PA .019 .001 .019 .011 .026 .005  HARRISBURG,PA .005 .001 .005 .008 .009 .004  HOUSTON,TX .032 .014 .107 .074 .075 .043  HUNTINGTON— ASHLAND,WV—K—OH .007 .002 .012 .003 .009 .004  INDIANAPOLIS,IN .013 .003 .013 .004 .051 .002  JACKSON,MS .006 .002 .015 .006 .164 .001  JACKSON,MILE,FL .020 .006 .019 .005 .074 .007  JERSEY CITY,NJ .193 .128 .294 .153 .037 .059  JERSEY CITY, ND—KA .016 .006 .022 .009 .044 .008  KNOXVILLE,TN .005 .000 .018 .007 .017 .002  LAN CASTER,PA .011 .003 .023 .010 .003 .012  LAN SHER,PA .011 .003 .023 .010 .003 .012  LAN SHER,PA .011 .003 .023 .000 .025 .009 .019 .012  LAN SHER,PA .011 .003 .023 .000 .025 .009 .019 .012  LAN SHER,PA .011 .003 .023 .000 .025 .009 .019 .012  LAN SHER,PA .011 .003 .023 .000 .025 .009 .019 .012  LAN SHER,PA .011 .003 .023 .000 .025 .009 .019 .012  LAN SHER,PA .011 .003 .023 .000 .025 .009 .019 .012  LAN SHER,PA .011 .003 .023 .000 .025 .009 .019 .012  LAN SHER,PA .011 .003 .023 .000 .025 .009 .019 .012  LAN SHER,PA .011 .003 .003 .003 .005 .026 .020  LOS ANGELES—LONG  BEACH,CA .135 .067 .266 .202 .044 .055  LOUISVILLE,KY—IN .008 .001 .008 .004 .041 .000  MADISON,WI .038 .014 .033 .011 .006 .006  MADISON,WI .038 .014 .033 .011 .006 .006  MADISON,WI .038 .014 .038 .007 .011 .009 .004  MOBILE,AL .011 .000 .008 .003 .120 .006  NEW HAUFL,TT .009 .004 .009 .004 .004 .001  NEW HAUFL,CT .092 .029 .072 .020 .043 .008  NEW HAUFL,CT .099 .001 .00		Proportion of Employed Male Labor Force							
Recent			-		-				
HOLLYWOOD,FL   .053   .026   .084   .034   .044   .013     FRESNO,CA   .080   .019   .137   .069   .015   .099     GARY-HAMMOND-EAST   .062   .012   .055   .016   .071   .026     GRAND RAPIDS,MI   .032   .004   .031   .007   .026   .007     GRENSBORO-WSTIN-SLM-HIGH FT,NC   .005   .001   .016   .007   .077   .002     GREENVILLE,SC   .016   .005   .019   .007   .055   .001     HARRISBURG,PA   .019   .001   .019   .011   .026   .005     HARRISBURG,PA   .032   .014   .107   .074   .075   .043     HOUSTON,TX   .032   .014   .107   .074   .075   .043     HUNTINOTON-ASHLAND,WV-KY-OH   .007   .002   .012   .003   .009   .004     INDIANAPOLIS,IN   .013   .003   .013   .004   .051   .002     JACKSON,MS   .006   .002   .015   .006   .164   .001     JACKSONVILLE,FL   .020   .006   .019   .005   .074   .007     JOHNSTOWN,PA   .009   .000   .009   .004   .004   .002     KANOXVILLE,TN   .005   .000   .018   .007   .017   .002     LANCASTER,PA   .011   .003   .023   .010   .004   .002     LANCASTER,PA   .011   .003   .023   .010   .007   .017   .002     LAN SHGA,NV   .005   .000   .018   .007   .017   .002     LAN SHGA,NV   .040   .020   .085   .036   .046   .024     LITTLE ROCK-N LITTLE   .027   .005   .003   .009   .004   .004   .002     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027   .005   .033   .005   .026   .020     LOS ANGELES-LONG   .026   .027	SMSA	All		All			16-34 Years  Hispanics		
FRESNO,CA	FTLAUDERDALE-								
FRESNO,CA	HOLLYWOOD,FL	.053	.026	.084	.034	.044	.013		
CARY—HAMMOND—EAST   CHICAGO, IN	•		.019		.069				
GRAND RAPIDS,MI	GARY-HAMMOND-EAST								
GRAND RAPIDS,MI	CHICAGO, IN	.062	.012	.055	.016	.071	.026		
REENSBORO-WSTN-SLM-  HIGH PT,NC	GRAND RAPIDS,MI		.004						
Greenville, sc   .016   .005   .019   .007   .055   .001     Harrisburg, pa   .019   .001   .019   .011   .026   .005     Harrisdror, ct   .114   .040   .095   .028   .020   .014     Houston, tx   .032   .014   .107   .074   .075   .043     Huntington-	GREENSBORO-WSTN-SLM-								
Greenville,sc   .016   .005   .019   .007   .055   .001     Harrisburg,pa   .019   .001   .019   .011   .026   .005     Harrisdror,ct   .114   .040   .095   .028   .020   .014     Houston,tx   .032   .014   .107   .074   .075   .043     Huntington-	HIGH PT,NC	.005	.001	.016	.007	.077	.002		
HARRISBURG,PA									
HARTFORD,CT									
HOUSTON,TX	HARTFORD,CT		.040						
HUNTINGTON- ASHLAND,WV-KY-OH									
Indianapolis,in   .013   .003   .013   .004   .051   .002   Jackson,ms   .006   .002   .015   .006   .164   .001   Jacksonville,fl   .020   .006   .019   .005   .074   .007   Jersey City,nj   .193   .128   .294   .153   .037   .059   Johnstown,pa   .009   .000   .009   .004   .004   .002   .008   .004   .008   .008   .007   .017   .002   .008   .007   .008   .007   .017   .002   .008   .00									
Indianapolis,in   .013   .003   .013   .004   .051   .002   Jackson,ms   .006   .002   .015   .006   .164   .001   Jacksonville,fl   .020   .006   .019   .005   .074   .007   Jersey City,nj   .193   .128   .294   .153   .037   .059   Johnstown,pa   .009   .000   .009   .004   .004   .002   .008   .004   .008   .008   .007   .017   .002   .008   .007   .008   .007   .017   .002   .008   .00	ASHLAND, WV-KY-OH	.007	.002	.012	.003	.009	.004		
Jackson,ms   .006   .002   .015   .006   .164   .001     Jacksonville,fl   .020   .006   .019   .005   .074   .007     Jersey City,nj   .193   .128   .294   .153   .037   .059     Johnstown,pa   .009   .000   .009   .004   .004   .002     Kansas City,mo—ka   .016   .006   .022   .009   .044   .008     Knoxville,tn   .005   .000   .018   .007   .017   .002     Lancaster,pa   .011   .003   .023   .010   .003   .012     Lansing,mi   .023   .000   .025   .009   .019   .012     Las vegas,nv   .040   .020   .085   .036   .046   .024     Little rock—n Little     .007   .005   .003   .005   .026   .020     Los angeles—long   .008   .001   .004   .102   .003     Lorain—elyria,oh   .027   .005   .033   .005   .026   .020     Los angeles—long   .008   .001   .008   .004   .041   .000     Madison,wi   .038   .014   .033   .011   .006   .006     Memphis,tn—ar   .013   .004   .010   .003   .168   .001     Miami,fl   .264   .249   .420   .230   .062   .025     Milwaukee,wi   .039   .006   .039   .009   .034   .010     Mnpls—st Paul,mn   .027   .008   .027   .011   .009   .004     Mobile,al   .011   .000   .008   .003   .120   .006     NSHVL—Davidson,tn   .006   .003   .013   .006   .060   .001     New Haven,ct   .092   .029   .072   .020   .043   .008     New Orleans,la   .032   .016   .044   .020   .113   .013     New York,ny   .158   .065   .205   .010   .003   .030   .008     Newark,nj   .098   .036   .137   .064   .059   .015     Nwptnws—hampton,va   .010   .002   .024   .007   .110   .003     Nfolk—ptsmth,va   .009   .001   .023   .009   .134   .005	INDIANAPOLIS,IN								
Jacksonville, FL   .020   .006   .019   .005   .074   .007     Jersey City, nj   .193   .128   .294   .153   .037   .059     Johnstown, pa   .009   .000   .009   .004   .004   .002     Kansas City, mo—ka   .016   .006   .022   .009   .044   .008     Knoxville, tn   .005   .000   .018   .007   .017   .002     Lancaster, pa   .011   .003   .023   .010   .003   .012     Lansing, mi   .023   .000   .025   .009   .019   .012     Las vegas, nv   .040   .020   .085   .036   .046   .024     Little rock, ar   .009   .002   .010   .004   .102   .003     Lorain—elyria, oh   .027   .005   .033   .005   .026   .020     Los angeles—long   Beach, ca   .135   .067   .266   .202   .044   .055     Louisville, ky—in   .008   .001   .008   .004   .041   .000     Madison, wi   .038   .014   .033   .011   .006   .006     Memphis, tn—ar   .013   .004   .010   .003   .168   .001     Miami, fl   .264   .249   .420   .230   .062   .025     Milwaukee, wi   .039   .006   .039   .009   .034   .010     Mobile, al   .011   .000   .008   .003   .120   .006     Nshyl—davidson, tn   .006   .003   .013   .006   .006   .006     Nshyl—davidson, tn   .006   .003   .013   .006   .006   .001     Nshyl—davidson, tn   .006   .003   .013   .006   .006   .001     New haven, ct   .092   .029   .072   .020   .043   .008     New ork, ny   .158   .065   .205   .101   .038   .032     Newark, nj   .098   .036   .137   .064   .059   .015     Nwptnws—hampton, va   .010   .002   .024   .007   .110   .003     Nfolk—ptsmth, va   .009   .001   .023   .009   .134   .005	,								
Jersey City,nj   1.193   1.128   2.94   1.153   1.037   1.059     Johnstown,pa   1.009   1.000   1.009   1.004   1.004   1.002     Kansas City,mo—ka   1.016   1.006   1.022   1.009   1.044   1.008     Knoxville,tn   1.005   1.000   1.018   1.007   1.017   1.002     Lancaster,pa   1.011   1.003   1.023   1.010   1.003   1.012     Lansing,mi   1.023   1.000   1.025   1.009   1.019   1.012     Las vegas,nv   1.040   1.020   1.085   1.036   1.046   1.024     Little rock—n Little   1.005   1.005   1.033   1.005   1.026   1.020     Lorain—elyria,oh   1.027   1.005   1.033   1.005   1.026   1.020     Los angeles—Long   1.35   1.067   1.266   1.202   1.044   1.000     Madison,wi   1.038   1.014   1.033   1.011   1.006   1.006     Memphis,tn—ar   1.013   1.004   1.010   1.003   1.68   1.001     Miami,fl   1.264   1.249   1.420   1.230   1.062   1.025     Milwaukee,wi   1.039   1.006   1.033   1.010   1.008   1.000     Mobile,al   1.011   1.000   1.008   1.009   1.034   1.010     Mnpls—st paul,mn   1.027   1.008   1.027   1.011   1.009   1.004     Mobile,al   1.011   1.000   1.008   1.003   1.20   1.006     New Haven,ct   1.092   1.029   1.072   1.020   1.043   1.008     New Orleans,la   1.032   1.016   1.044   1.020   1.13   1.013     New York,ny   1.158   1.065   1.205   1.011   1.038   1.032     Newark,nj   1.098   1.036   1.37   1.064   1.059   1.015     Nwptnws—hampton,va   1.009   1.001   1.023   1.009   1.34   1.005     Newark,pi   1.009   1.001   1.002   1.004   1.005   1.005   1.005     Newark,pi   1.009   1.001   1.002   1.004   1									
Johnstown,pa   .009   .000   .009   .004   .004   .002									
Kansas City, Mo-ka									
KNOXVILLE,TN   .005   .000   .018   .007   .017   .002     LANCASTER,PA   .011   .003   .023   .010   .003   .012     LANSING,MI   .023   .000   .025   .009   .019   .012     LAS VEGAS,NV   .040   .020   .085   .036   .046   .024     LITTLE ROCK-N LITTLE		.016				.044			
Lancaster,pa									
LANSING,MI									
LAS VEGAS,NV									
LITTLE ROCK,AR									
ROCK,AR         .009         .002         .010         .004         .102         .003           LORAIN-ELYRIA,OH         .027         .005         .033         .005         .026         .020           LOS ANGELES-LONG         BEACH,CA         .135         .067         .266         .202         .044         .055           LOUISVILLE,KY-IN         .008         .001         .008         .004         .041         .000           MADISON,WI         .038         .014         .033         .011         .006         .006           MEMPHIS,TN-AR         .013         .004         .010         .003         .168         .001           MIAMI,FL         .264         .249         .420         .230         .062         .025           MILWAUKEE,WI         .039         .006         .039         .009         .034         .010           MOBILE,AL         .011         .000         .008         .003         .120         .006           NSHVL-DAVIDSON,TN         .006         .003         .013         .006         .060         .001           NEW HAVEN,CT         .092         .029         .072         .020         .043         .008									
LORAIN-ELYRIA,OH         .027         .005         .033         .005         .026         .020           LOS ANGELES-LONG         .135         .067         .266         .202         .044         .055           BEACH,CA         .135         .067         .266         .202         .044         .055           LOUISVILLE,KY-IN         .008         .001         .008         .004         .041         .000           MADISON,WI         .038         .014         .033         .011         .006         .006           MEMPHIS,TN-AR         .013         .004         .010         .003         .168         .001           MIAMI,FL         .264         .249         .420         .230         .062         .025           MILWAUKEE,WI         .039         .006         .039         .009         .034         .010           MNPLS-ST PAUL,MN         .027         .008         .027         .011         .009         .004           MOBILE,AL         .011         .000         .008         .003         .120         .006           NSHVL-DAVIDSON,TN         .006         .003         .013         .006         .060         .001           NEW HAVEN,CT		.009	.002	.010	.004	.102	.003		
Description									
BEACH,CA         .135         .067         .266         .202         .044         .055           LOUISVILLE,KY-IN         .008         .001         .008         .004         .041         .000           MADISON,WI         .038         .014         .033         .011         .006         .006           MEMPHIS,TN-AR         .013         .004         .010         .003         .168         .001           MIAMI,FL         .264         .249         .420         .230         .062         .025           MILWAUKEE,WI         .039         .006         .039         .009         .034         .010           MNPLS-ST PAUL,MN         .027         .008         .027         .011         .009         .004           MOBILE,AL         .011         .000         .008         .003         .120         .006           NSHVL-DAVIDSON,TN         .006         .003         .013         .006         .060         .001           NEW HAVEN,CT         .092         .029         .072         .020         .043         .008           NEW YORK,NY         .158         .065         .205         .101         .038         .032           NEWARK,NJ         .098<	LOS ANGELES-LONG								
LOUISVILLE,KY-IN         .008         .001         .008         .004         .041         .000           MADISON,WI         .038         .014         .033         .011         .006         .006           MEMPHIS,TN-AR         .013         .004         .010         .003         .168         .001           MIAMI,FL         .264         .249         .420         .230         .062         .025           MILWAUKEE,WI         .039         .006         .039         .009         .034         .010           MNPLS-ST PAUL,MN         .027         .008         .027         .011         .009         .004           MOBILE,AL         .011         .000         .008         .003         .120         .006           NSHVL-DAVIDSON,TN         .006         .003         .013         .006         .060         .001           NEW HAVEN,CT         .092         .029         .072         .020         .043         .008           NEW ORLEANS,LA         .032         .016         .044         .020         .113         .013           NEW ARK,NJ         .158         .065         .205         .101         .038         .032           NEWARK,NJ		.135	.067	.266	.202	.044	.055		
MADISON,WI         .038         .014         .033         .011         .006         .006           MEMPHIS,TN-AR         .013         .004         .010         .003         .168         .001           MIAMI,FL         .264         .249         .420         .230         .062         .025           MILWAUKEE,WI         .039         .006         .039         .009         .034         .010           MNPLS-ST PAUL,MN         .027         .008         .027         .011         .009         .004           MOBILE,AL         .011         .000         .008         .003         .120         .006           NSHVL-DAVIDSON,TN         .006         .003         .013         .006         .060         .001           NEW HAVEN,CT         .092         .029         .072         .020         .043         .008           NEW ORLEANS,LA         .032         .016         .044         .020         .113         .013           NEW APK,NY         .158         .065         .205         .101         .038         .032           NEWARK,NJ         .098         .036         .137         .064         .059         .015           NWPTNWS-HAMPTON,VA <t< td=""><td></td><td></td><td></td><td></td><td></td><td></td><td></td></t<>									
MEMPHIS, TN-AR         .013         .004         .010         .003         .168         .001           MIAMI, FL         .264         .249         .420         .230         .062         .025           MILWAUKEE, WI         .039         .006         .039         .009         .034         .010           MNPLS-ST PAUL, MN         .027         .008         .027         .011         .009         .004           MOBILE, AL         .011         .000         .008         .003         .120         .006           NSHVL-DAVIDSON, TN         .006         .003         .013         .006         .060         .001           NEW HAVEN, CT         .092         .029         .072         .020         .043         .008           NEW ORLEANS, LA         .032         .016         .044         .020         .113         .013           NEW YORK, NY         .158         .065         .205         .101         .038         .032           NEWARK, NJ         .098         .036         .137         .064         .059         .015           NWPTNWS-HAMPTON, VA         .010         .002         .024         .007         .110         .003           NFOLK-PTSMTH,									
MIAMI,FL         .264         .249         .420         .230         .062         .025           MILWAUKEE,WI         .039         .006         .039         .009         .034         .010           MNPLS—ST PAUL,MN         .027         .008         .027         .011         .009         .004           MOBILE,AL         .011         .000         .008         .003         .120         .006           NSHVL—DAVIDSON,TN         .006         .003         .013         .006         .060         .001           NEW HAVEN,CT         .092         .029         .072         .020         .043         .008           NEW ORLEANS,LA         .032         .016         .044         .020         .113         .013           NEW YORK,NY         .158         .065         .205         .101         .038         .032           NEWARK,NJ         .098         .036         .137         .064         .059         .015           NWPTNWS—HAMPTON,VA         .010         .002         .024         .007         .110         .003           NFOLK—PTSMTH,VA         .009         .001         .023         .009         .134         .005									
MILWAUKEE,WI         .039         .006         .039         .009         .034         .010           MNPLS-ST PAUL,MN         .027         .008         .027         .011         .009         .004           MOBILE,AL         .011         .000         .008         .003         .120         .006           NSHVL-DAVIDSON,TN         .006         .003         .013         .006         .060         .001           NEW HAVEN,CT         .092         .029         .072         .020         .043         .008           NEW ORLEANS,LA         .032         .016         .044         .020         .113         .013           NEW YORK,NY         .158         .065         .205         .101         .038         .032           NEWARK,NJ         .098         .036         .137         .064         .059         .015           NWPTNWS-HAMPTON,VA         .010         .002         .024         .007         .110         .003           NFOLK-PTSMTH,VA         .009         .001         .023         .009         .134         .005									
MNPLS-ST PAUL,MN         .027         .008         .027         .011         .009         .004           MOBILE,AL         .011         .000         .008         .003         .120         .006           NSHVL-DAVIDSON,TN         .006         .003         .013         .006         .060         .001           NEW HAVEN,CT         .092         .029         .072         .020         .043         .008           NEW ORLEANS,LA         .032         .016         .044         .020         .113         .013           NEW YORK,NY         .158         .065         .205         .101         .038         .032           NEWARK,NJ         .098         .036         .137         .064         .059         .015           NWPTNWS-HAMPTON,VA         .010         .002         .024         .007         .110         .003           NFOLK-PTSMTH,VA         .009         .001         .023         .009         .134         .005	,								
MOBILE,AL         .011         .000         .008         .003         .120         .006           NSHVL-DAVIDSON,TN         .006         .003         .013         .006         .060         .001           NEW HAVEN,CT         .092         .029         .072         .020         .043         .008           NEW ORLEANS,LA         .032         .016         .044         .020         .113         .013           NEW YORK,NY         .158         .065         .205         .101         .038         .032           NEWARK,NJ         .098         .036         .137         .064         .059         .015           NWPTNWS-HAMPTON,VA         .010         .002         .024         .007         .110         .003           NFOLK-PTSMTH,VA         .009         .001         .023         .009         .134         .005	·								
NSHVL—DAVIDSON,TN         .006         .003         .013         .006         .060         .001           NEW HAVEN,CT         .092         .029         .072         .020         .043         .008           NEW ORLEANS,LA         .032         .016         .044         .020         .113         .013           NEW YORK,NY         .158         .065         .205         .101         .038         .032           NEWARK,NJ         .098         .036         .137         .064         .059         .015           NWPTNWS-HAMPTON,VA         .010         .002         .024         .007         .110         .003           NFOLK-PTSMTH,VA         .009         .001         .023         .009         .134         .005	·								
NEW HAVEN,CT         .092         .029         .072         .020         .043         .008           NEW ORLEANS,LA         .032         .016         .044         .020         .113         .013           NEW YORK,NY         .158         .065         .205         .101         .038         .032           NEWARK,NJ         .098         .036         .137         .064         .059         .015           NWPTNWS-HAMPTON,VA         .010         .002         .024         .007         .110         .003           NFOLK-PTSMTH,VA         .009         .001         .023         .009         .134         .005	·								
NEW ORLEANS, LA         .032         .016         .044         .020         .113         .013           NEW YORK, NY         .158         .065         .205         .101         .038         .032           NEWARK, NJ         .098         .036         .137         .064         .059         .015           NWPTNWS-HAMPTON, VA         .010         .002         .024         .007         .110         .003           NFOLK-PTSMTH, VA         .009         .001         .023         .009         .134         .005	·								
NEW YORK,NY         .158         .065         .205         .101         .038         .032           NEWARK,NJ         .098         .036         .137         .064         .059         .015           NWPTNWS-HAMPTON,VA         .010         .002         .024         .007         .110         .003           NFOLK-PTSMTH,VA         .009         .001         .023         .009         .134         .005									
NEWARK,NJ       .098       .036       .137       .064       .059       .015         NWPTNWS-HAMPTON,VA       .010       .002       .024       .007       .110       .003         NFOLK-PTSMTH,VA       .009       .001       .023       .009       .134       .005									
NWPTNWS-HAMPTON, VA .010 .002 .024 .007 .110 .003 NFOLK-PTSMTH, VA .009 .001 .023 .009 .134 .005									
NFOLK-PTSMTH, VA .009 .001 .023 .009 .134 .005									
	· ·								
	OKLAHOMA CITY,OK	.009	.003	.023	.009	.043	.003		
ORLANDO,FL .032 .016 .044 .021 .042 .011	·								

Table 6A.1(continued)

	Proportion of Employed Male Labor Force						
		grants in		igrants in 1980			
SMSA	All	Recent Arrivals	All	Recent Arrivals	Natives Blacks	Hispanics	
OXNARD-VENTURA,CA	.105	.053	.161	.078	.011	.053	
PATERSON-CLIFTON-							
PASSAIC,NJ	.127	.046	.177	.084	.033	.044	
PEORIA,IL	.009	.001	.021	.012	.020	.000	
PHILADELPHIA, PA-NJ	.049	.011	.048	.018	.054	.008	
PHOENIX,AZ	.041	.010	.059	.025	.010	.055	
PITTSBURGH,PA	.036	.006	.025	.006	.022	.001	
PORTLAND, OR-WA	.038	.008	.048	.019	.011	.006	
PROVIDENCE, RI	.072	.025	.085	.041	.007	.002	
READING,PA	.026	.008	.027	.012	.006	.009	
RICHMOND, VA	.015	.005	.023	.007	.128	.007	
ROCHESTER, NY	.072	.027	.056	.014	.028	.005	
ROCKFORD,IL	.040	.006	.031	.009	.018	.006	
SACRAMENTO, CA	.064	.018	.068	.021	.020	.037	
ST LOUIS,MO-IL	.016	.004	.019	.006	.055	.003	
SALINAS-MONTEREY,CA	.121	.038	.204	.101	.010	.058	
SALT LAKE CITY,UT	.037	.008	.032	.005	.007	.027	
SAN ANTONIO,TX	.061	.014	.085	.036	.023	.200	
SAN DIEGO,CA	.079	.033	.138	.065	.021	.040	
SAN FRANCISCO—	.015	.000	.,,,,	.002	.021	.040	
OAKLAND,CA	.126	.054	.164	.076	.040	.032	
SAN JOSE,CA	.098	.044	.142	.076	.017	.063	
SANTA BARBARA,CA	.104	.042	.107	.038	.016	.072	
SEATTLE-EVERETT, WA	.066	.020	.065	.021	.015	.007	
SHREVEPORT, LA	.007	.003	.013	.001	.140	.007	
SPOKANE, WA	.045	.012	.042	.006	.007	.006	
SPRINGFIELD-CHCPEE-	.012	.012	.012	.000	.007	.000	
HLYKE,MA-CT	.069	.028	.058	.021	.010	.014	
STOCKTON, CA	.121	.041	.123	.064	.011	.066	
SYRACUSE, NY	.040	.012	.040	.007	.020	.001	
TACOMA, WA	.049	.011	.036	.015	.019	.010	
TAMPA-ST PETE,FL	.038	.012	.056	.016	.038	.017	
TOLEDO, OH-MI	.026	.005	.022	.007	.022	.009	
TRENTON,NJ	.076	.021	.078	.011	.040	.016	
TUCSON, AZ	.057	.016	.058	.016	.011	.088	
TULSA,OK	.008	.002	.011	.004	.030	.005	
UTICA-ROME,NY	.045	.011	.021	.002	.013	.000	
WASHINGTON, DC-MD-VA	.054	.024	.086	.045	.108	.006	
WEST PALM BEACH,FL	.066	.029	.090	.034	.049	.014	
WICHITA, KA	.012	.001	.026	.010	.030	.008	
WLMNGTN,DEL-NJ-MD	.012	.015	.033	.007	.052	.004	
WORCESTER, MA	.079	.021	.049	.007	.003	.004	
YORK,PA	.013	.000	.019	.012	.003	.007	
YNGSTWN-WRN,OH	.013	.003	.036	.006	.028	.001	
					.020	.003	

Table 6A.2 Coefficients from Wage Equation Reported in Table 6.5, Column 1 (dependent variable is log average weekly earnings)

	Coefficient	(Standard Error)
Education	.035	(.001)
Experience	.027	(.001)
Experience squared	0004	(.00003)
Married	.167	(.014)
Divorced	.112	(.020)
Children	.058	(.010)
Disability	141	(.025)
Black	<b>155</b>	(.024)
Hispanic	089	(.020)
Place of origin:		
Europe, USSR, Canada, New Zealand, Australia		
India, South and East Asia	130	(.015)
Pakistan, Mideast, North Africa	045	(.023)
Mexico	<b>-</b> .095	(.023)
Other Latin America and Caribbean	092	(.021)
All other areas	117	(.021)
Occupation:		
Professionals and technical workers		
Managers and administrators	.059	(.018)
Sales workers	069	(.023)
Clerical workers	337	(.023)
Services (nonhouse)	386	(.019)
Craft and repair	<b>-</b> .194	(.017)
Nontransportation operatives	323	(.019)
Transport operatives	<b>221</b>	(.026)
Laborers, handlers	333	(.023)
All others, including farm workers	360	(.045)
Industry:		
Agriculture		
Mining	.350	(.077)
Construction	.152	(.046)
Food, tobacco, textile, apparel, leather	.056	(.048)
Chemicals, petroleum products, rubber, and plastics	.145	(.050)
Paper, lumber, stone, glass, or clay products	.023	(.050)
Primary and fabricated metals	.185	(.048)
Electrical and nonelectrical machines	.151	(.047)
Transportation equipment	.247	(.049)
Other manufacturing	.100	(.051)
Transportation	.184	(.048)
Printing and publishing, communications, utility	.196	(.049)
Wholesale trade	.121	(.048)
Retail trade	077	(.045)
Finance, insurance, real estate	.075	(.048)
Business repair	.017	(.047)
Personal and entertainment	059	(.047)
Professional/government administration	.087	(.047)
Standard errors of regression	.684	, ,

*Note:* N = 26,844.

number of weeks worked for persons in the same interval in 1980. This procedure potentially affects only estimates where weekly wage, not annual earnings, was used as the dependent variable.

The Public Use Samples allow a user to identify whether a person is an immigrant and when he arrived in the United States. In 1980, immigrants are classified into six cohorts based on when they arrived in the United States: 1975–80, 1970–74, 1965–69, 1960–64, 1950–59, and before 1950. In 1970, immigrants are classified into ten cohorts based on when they arrived in the United States: 1965–70, 1960–64, 1955–59, 1950–54, 1945–49, 1935–44, 1924–34, 1915–24, before 1915, and a category for those who do not report when they arrived in the United States.

The Public Use Samples record in both Census years the highest year of schooling; age (which we used to construct potential experience as age minus schooling minus 6); marital status (which we use to construct dummy variables for those who are married and those who are separated, widowed, or divorced); whether there are children in the household; whether a person has a disability that limits his work (which is defined differently in 1970 than in 1980); race (which we use to construct our samples of young blacks and Hispanics); and, finally, place of origin, occupation, and industry. All these variables are used in the regressions reported in tables 6.6–6.10, unless the table indicates otherwise.

In table 6A.2, we present estimates of the coefficients that are not reported in table 6.5, column 1. The estimates of these coefficients in other tables are similar. These estimated coefficients are of some interest in themselves when comparing our findings to other research on the economic effects of immigration. Note that the returns to education and experience tend to be lower for immigrants than the returns that are estimated for natives, that the effects of marital status, children, and disability are consistent with other studies of the wages of natives, and that an individual's place of origin has an effect on earnings even after controlling for all other observable variables. Immigrants from Europe and the Mideast have the highest earnings, while immigrants from Asia have the lowest earnings. An immigrant's occupation and industry also had a significant effect on earnings.

# **Notes**

1. Several recent papers examine the changing skills of different immigrant cohorts (see Chiswick 1986; and Borjas 1985, 1987b). But the issues addressed in those papers are not new. Between 1900 and 1910, new immigrants accounted for 10 percent of the labor force, which sparked a similar policy debate at that time (see Douglas 1919). This debate culminated in the Immigration and Naturalization Act of 1923, which attempted to control the flow of immigrants through country-specific quotas. In 1965, amendments to the immigration laws changed the principal criteria used to control entry into the United States from the "national origin" quotas to a system based on

kinship with an American citizen or resident. The most recent legislation is the Immigration Reform Act of 1986, which attempts to regulate the flow of illegal aliens into the United States.

- 2. For a discussion of the potential distributional implications of immigration, see Johnson (1980) and Greenwood and McDowell (1986).
- 3. The estimate of 2.5 million assumes a labor force participation rate of .45 among all foreign-born persons in the 1980 Census who reported that they arrived in the United States between 1970 and 1979.
- 4. In this sense, our analysis is similar to earlier studies of the effect of the baby boom on wages, e.g., Welch (1979) and Bloom and Freeman (1987). These studies estimate the "own effect" of increased cohort size on earnings and employment of members of large cohorts.
- 5. Borjas (1987a) estimates a model of wage determination based on differences in demographic group labor force shares across geographic areas. He finds, as do we, that immigrant earnings are lowest in large immigrant enclaves.
- 6. Greater ease of substitution need not imply that immigrant wage *levels* converge to those of natives. The long-run stock of skills for the representative immigrant may remain below that of natives, so that immigrants earn less than natives, yet immigrant and native skills may substitute perfectly. In fact, in 1980 immigrants who arrived in the United States before 1950 earned more than natives.
- 7. Equilibrium among these markets is largely ignored in what follows, so we implicitly assume that mobility costs form a significant barrier to intermarket arbitrage in the short run. Topel (1986) contains an alternative approach that allows for migration among geographic markets.
- 8. Later in the paper, we examine the effect of a doubling of all immigrant cohorts on relative wages. Since native labor is being held constant for those calculations, the relative marginal products of immigrant labor can change.
- 9. Symmetry of cross-substitution effects is not implied; i.e.,  $\gamma_{ij} \neq \gamma_{ji}$ . Symmetry of signs is a restriction of the theory; i.e., sign  $(\gamma_{ji})$ , as is negative definiteness of the full matrix of substitution effects.
- 10. Symmetry of effects implies  $\partial W_{cj}/\partial M_{ci}=\partial W_{ci}/\partial M_{cj}$ , so  $\gamma_{ki}$  is proportional to  $\gamma_{ik}$ ,  $i=1,\ldots,k-1$ . Thus, under the assumption that  $\gamma_{kk}=0$ —an increase in the number of white natives at a locale has a negligible effect on wages—we may test  $\gamma_{ki}=0$  if symmetry is assumed. Our tests indicate  $\gamma_{ik}=0$  in all cases.
  - 11. This assumes that the matrix  $[\gamma_{ij}]$  is negative definite.
  - 12. Cohort refers to years in the United States.
- 13. Estimates for the determination of hourly wages differ trivially from those reported here.
  - 14. Estimates when natives are included in the data are available on request.
- 15. We remind the reader that our estimates measure relative wage adjustments, where the normalizing group is persons with more than thirty years in the United States.
- 16. This roughly corresponds to a tripling of the stock of immigrants. For example, a  $d \ln M = 1$  change in all immigrant quantities would roughly correspond to an SMSA whose shares of the six immigrant arrival cohorts relative to native workers increased from .033, .022, .022, .022, .011, .011, and .011 to .107, .067, .067, .034, .034, and .034, respectively. Multiply these estimates by .1 for the effect of a 10 percent change in the immigrant stock.
- 17. Though not reported separately, corresponding estimates for hourly wages show larger effects than for weekly wages. The implication is that adjustments in hours worked plays a minor and unsystematic role: all the effects reported here are due to price adjustments. We reach a similar conclusion with regard to weeks worked below.
- 18. We also computed F-statistics to test the four-parameter structure against the ten-parameter structure given by (7). These additional restrictions are also not rejected.

- 19. For comparison with the unrestricted estimates in table 6.6, these parameters imply that a proportional increase in the size of all immigrant cohorts would reduce the earnings of the most recent immigrants by 6.5 percent. This effect dies out by 1 percentage point for each prior entry cohort; e.g., -.055 for those with six to ten years in the United States.
- 20. Effects on immigrants themselves are nearly identical to those reported in table 6.6.
- 21. Many SMSAs in our sample experienced a significant increase in the share of new immigrants in their work forces during the 1970s. Miami and Jersey City are exceptions. Although the flow of new immigration into these cities was substantial during the 1970s, this influx represented the continuation of a trend begun the decade before.

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