

**The Labor Demand Curve *Is* Downward Sloping:  
Reexamining the Impact of Immigration on the Labor Market**

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### **Abstract**

This paper presents a new approach for estimating the labor market impact of immigration. The existing studies typically exploit the geographic clustering of immigrants and use differences across local labor markets to identify the impact. This approach has not been successful because it ignores the strong currents that tend to equalize economic conditions across regions. My analysis is based on the notion that increases in labor supply in a finely-detailed skill group should affect the earnings and employment opportunities of that group. I use a key insight of human capital theory to define the skill groups: a worker acquires skills both in school *and* on the job. The comparison of labor market outcomes across these skill groups suggests that immigration has indeed harmed the earnings and employment opportunities of competing native workers. An immigrant influx that increases the supply of workers in a particular schooling-experience group by 10 percent lowers the wage of natives in that group by 3 to 4 percent, and reduces weeks worked by 2 to 3 percent.

## **The Labor Demand Curve Is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market**

**George J. Borjas\***

“By keeping labor supply down, a restrictive immigration policy tends to keep wages high.”

Paul Samuelson, *Economics*, 1973.

“While the pool of officially unemployed and those otherwise willing to work may continue to shrink, as it has persistently over the past seven years, there is an effective limit to new hiring, unless immigration is uncapped. At some point in the continuous reduction in the number of available workers willing to take jobs, short of the repeal of the law of supply and demand, wage increases must rise above even impressive gains in productivity... In short, unless we are able to... continuously augment immigration quotas, overall demand for goods and services cannot chronically exceed the underlying growth rate of supply.”

Alan Greenspan, 2000.

### **I. Introduction**

Do immigrants harm or improve the employment opportunities of native workers? As the crystal clear conclusion by Paul Samuelson and the more long-winded statement by Alan Greenspan imply, the textbook model of a competitive labor market indicates that an immigrant influx should lower the wage of competing factors (e.g., of workers who have the same types of skills as the immigrants).<sup>1</sup>

Despite the intuitive appeal of these theoretical implications, and despite the large number of careful studies in the literature, few problems in labor economics have seemed more

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<sup>1</sup> The historical context of Samuelson’s assertion is interesting. Writing in 1973, just as the resurgence of large-scale immigration was beginning, Samuelson states: “After World War I, laws were passed severely limiting immigration. Only a trickle of immigrants has been admitted since then. This is a first example of interference with the free play of competition in the wage market. By keeping labor supply down, immigration policy tends to keep

resistant to a satisfactory empirical resolution in the past two decades. It has proved surprisingly difficult to demonstrate empirically that immigration has a sizable and significant adverse effect on competing workers. For example, a widely cited survey by Friedberg and Hunt (1995, p. 42) concludes that “the effect of immigration on the labor market outcomes of natives is small.” Similarly, the 1997 National Academy of Sciences report on the economic impact of immigration argues that “the weight of the empirical evidence suggests that the impact of immigration on the wages of competing native workers is small” (Smith and Edmonston, 1997, p. 220).<sup>2</sup> These conclusions are difficult to reconcile with the textbook model because the immigrant supply shock in recent decades has been very large, and most studies of labor demand (outside the immigration context) conclude that the labor demand curve is not perfectly elastic (Hamermesh, 1993).

This paper presents a new approach for thinking about and estimating the labor market impact of immigration. My reexamination suggests that those of us who have toiled long and hard trying to measure the wage and employment adjustments that take place as immigrants enter the labor market (including several earlier iterations of my own work) have been looking in all the wrong places, and have overlooked the most obvious place suggested by human capital theory. In particular, most studies exploit the geographic clustering of immigrants and use differences across local labor markets to identify the impact of immigration. This approach has been troublesome because it ignores the strong economic currents that tend to equalize economic conditions across cities and regions. In this paper, I argue that by paying closer attention to the characteristics that define a skill group—and, in particular, by using the insight from human

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wages high” (p. 573). Greenspan’s statement is contained in a speech entitled “The Revolution in Information Technology,” made at the Boston College Conference on the New Economy, March 6, 2000.

<sup>2</sup> Surveys of the literature by Borjas (1994) and LaLonde and Topel (1996) reach the same conclusion.

capital theory that both schooling *and* work experience are equally important determinants of a person's stock of acquired skills—one can make substantial progress in determining whether immigration influences the employment and earnings opportunities of native workers.

The empirical analysis uses data drawn from the 1960-1990 U.S. Decennial Censuses, as well as the 1998-2001 Current Population Surveys. It turns out that immigration—even within a particular schooling group, say high school graduates—is not balanced evenly across all experience cells in that group. Because of the large differences in the age distributions of immigrants and natives who are high school graduates, the immigrant influx will tend to affect some native workers more than others and the nature of the supply “imbalance” changes over time. This fact generates a great deal of variation—across schooling groups, experience cells, and over time—that helps to identify the impact of immigration on the labor market. Most importantly, the size of the native workforce in each of these skills groups is relatively exogenous and fixed, so that there is little potential for native flows to contaminate the comparison of outcomes across skill groups.

In contrast to the confusing array of results that now dominate the literature, the evidence strongly suggests that immigration has indeed harmed the earnings and employment opportunities of competing native workers. An immigrant influx that increases the size of a particular skill group by 10 percent lowers the wage of native workers in that group by about 3 to 4 percent and reduces weeks worked by 2 to 3 percent.

## **II. Measuring the Labor Market Impact of Immigration**

The laws of supply and demand have unambiguous implications for how immigration should affect labor market conditions. As Figure 1 shows, the shift in supply induced by

immigration (shifting the supply curve from  $S_0$  to  $S_1$ ) reduces the real wage of competing native workers from  $w_0$  to  $w_1$ .<sup>3</sup> As long as the supply curve is upward sloping, the immigrant supply shock will also reduce the quantity of labor supplied by the native workforce from  $N_0$  to  $N_1$ .

If one could observe a number of closed labor markets that immigrants penetrate randomly, one could then relate the change in the wage of workers in a particular skill group to the proportion of immigrants in the relevant population. The estimated correlations would then provide information on the impact of immigration. A negative correlation (i.e., native wages are lower in those markets penetrated by immigrants) would indicate that immigrants worsen the employment opportunities of competing native workers.

In the United States, immigrants cluster in a small number of geographic areas. In 1990, for example, 32.5 percent of the immigrant population lived in only three metropolitan areas (Los Angeles, New York, and Miami). In contrast, only 9.1 percent of the native population clustered in the three largest metropolitan areas housing natives (New York, Los Angeles, and Chicago). Practically all empirical studies in the literature, beginning with Grossman (1982), exploit this demographic feature to identify the labor market impact of immigration.<sup>4</sup> The typical study defines a metropolitan area as the labor market that is being penetrated by immigrants. The

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<sup>3</sup> In this simple framework, capital is held constant and the price of the output is the numeraire, so that immigration does not shift the demand (i.e., marginal product) curve. Altonji and Card (1991) present a more general model that allows immigration to affect prices in a two-good, two-factor economy, where one good is traded and the other good is a locally produced service, and the two factors of production are low-skill and high-skill labor. This more general approach, like the supply-demand framework in Figure 1, concludes that immigration lowers the real wage of competing workers; see also Johnson (1980).

<sup>4</sup> Representative studies of the spatial correlation approach include Altonji and Card (1991), Borjas (1987), LaLonde and Topel (1991), and Schoeni (1997). The approach has also been applied to other host countries by De New and Zimmerman (1994), Hunt (1992), and Pischke and Velling (1997). Friedberg (2001) presents a rare study that uses the supply shock in an occupation to identify the labor market impact of immigration in the Israeli labor market. Although the raw Israeli data suggest a substantial negative impact, correcting for the endogeneity of occupational choice leads to the usual result that immigration has little impact on the wage structure. Card (2001) uses data on occupation and metropolitan area to define skill groups and estimates a slight negative impact of supply increases within these skill groups on wages.

study then goes on to calculate a “spatial correlation” measuring the relation between the native wage in the locality and the relative number of immigrants in that locality. The best known spatial correlations are reported in Card’s (1990) influential study of the Mariel flow. Using CPS data, Card compared labor market conditions in Miami and in other cities before and after the *Marielitos* increased Miami’s workforce by 7 percent. Card’s difference-in-differences estimate of the spatial correlation indicated that this sudden and unexpected immigrant influx did not have a discernable effect on employment and wages in Miami’s labor market.

Recent studies have raised two questions about the validity of interpreting weak spatial correlations as evidence that immigration has no labor market impact.<sup>5</sup> First, immigrants may not be randomly distributed across labor markets. If immigrants tend to endogenously cluster in cities with thriving economies, there would be a spurious positive correlation between immigration and local outcomes.<sup>6</sup> Any possible adverse impact of immigration on local wages could well be swamped by this spurious correlation.

Second, natives may respond to the immigrant supply shock in a local labor market by moving their labor or capital to other cities.<sup>7</sup> Suppose, for example, that some cities in California receive a large influx of low-skill immigrants, and that the relative wage for low-skill labor falls in those cities. Employers who hire low-skill workers will want to relocate to those cities.

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<sup>5</sup> Even abstracting from the conceptual problems discussed below, it is doubtful that this consensus should have been reached. Most of the estimates that led to the “zero impact” consensus were drawn from studies that used 1970 and 1980 Census data. It turns out that the sign and magnitude of the spatial correlations would have been different if the calculations had used data for other decades; see Borjas, Freeman, and Katz (1997) and Schoeni (1997).

<sup>6</sup> Borjas (2001) presents evidence indicating that newly arrived immigrants belonging to a particular schooling group tend to settle in those regions of the country that offer the highest return to their skills. Because of the absence of valid instruments, however, the use of instrumental variables to correct for this endogeneity problem often leads to a “blowing up” of the spatial correlations; see Altonji and Card (1991) and Schoeni (1997).

Similarly, laborers living in Michigan who were thinking about moving to California may now decide to remain where they are or move elsewhere, and some Californians may find it worthwhile to incur the cost of leaving the state to search for better opportunities. In an important sense, the internal migration of capital and labor accomplishes what the immigrant flow, with its tendency to cluster in a small number of localities, could not—a “spreading out” of the additional workers over the entire nation, rather than in just a limited number of localities. A comparison of the economic opportunities facing native workers in different cities would show little or no difference because, in the end, immigration affected *every* city, not just the ones that actually received immigrants.<sup>8</sup>

Because of the strong likelihood that the local labor market adjusts to immigration—through the internal migration of jobs or workers—some recent studies have suggested changing the unit of analysis to the *national* level (Borjas, Freeman, and Katz, 1992, 1997). If the aggregate technology of the host country can be described by a linear homogeneous CES production function with two inputs, low-skill and high-skill labor, the relative wage of the two groups will then depend linearly on their relative quantities. Note that by restricting the analysis to two skill groups, the “factor proportions approach” precludes the estimation of the impact of immigration—there are only two data points at any given point in time, giving relative wages and relative employment for the two skill groups. As a result, the typical empirical application of this

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<sup>7</sup> Saiz (2003) revisits Card’s Mariel analysis and documents yet another way through which the market can adjust. In particular, the Mariel flow seemed to have a significant impact on rental prices in Miami’s housing market.

<sup>8</sup> Recent work by Borjas, Freeman, and Katz (1997) and Card (2001) provide the first attempts to jointly analyze labor market outcomes and native migration decisions. These two studies, however, reach very different conclusions. Card reports a slight positive correlation between the 1985-90 rate of growth in native population and the immigrant supply shock by metropolitan area, while Borjas, Freeman, and Katz report a negative correlation between native net migration in 1970-90 and immigration by state—once one standardizes for the pre-existing migration trends in the states; see also Filer (1992), Frey (1995), and Wright, Ellis, and Reibel (1997).

approach compares the host country's actual supplies of workers in particular skill groups to those it would have had in the absence of immigration, and then uses outside information on labor demand elasticities to simulate the wage consequences of immigration. During the 1980s and 1990s, the immigrant flow to the United States was relatively less skilled. As a result, the Borjas-Freeman-Katz (1997) simulation implies that for reasonable elasticity estimates, nearly half of the 11 percentage point decline in the relative wage of high school dropouts between 1979 and 1995 may be attributable to the immigration of low-skill workers.

### **A New Approach**

Despite all of the confusion in the literature, the available evidence teaches two important lessons: the study of the geographic dispersion in the economic opportunities facing native workers is unlikely to be a fruitful way for attempting to measure the economic impact of immigration; the local labor market can adjust in far too many ways to provide a reasonable analogue to the "closed market" economy that underlies the textbook supply-and-demand framework. Similarly, the factor proportions approach is ultimately unsatisfactory. It departs from the valuable tradition of decades of empirical research in labor economics that attempts to estimate the impact of a particular shock on the labor market by directly observing how the shock affects some workers and not others. The factor proportions approach does not estimate the impact of immigration on the labor market; rather, it simulates the impact. For a given elasticity of substitution, the approach mechanically predicts the relative wage consequences of a supply shock.

Ideally, one would want to estimate how immigration alters the earnings and employment opportunities of a particular skill group. As noted above, however, by aggregating workers into groups based on educational attainment, there is just too little variation to estimate how supply

shocks affect relative wages. Even if one classifies workers into the four typical schooling groups (i.e., high school dropouts, high school graduates, workers with some college, and college graduates), each decennial Census would still only provide four wage and employment observations at the national level.

The human capital literature has always emphasized that schooling is not the only—and perhaps not even the most important—determinant of a worker’s skills. The seminal work of Becker (1975) and Mincer (1974) places equal emphasis on the skills acquired both before and after a person enters the labor market. In other words, a skill group should be defined in terms of both schooling and labor market experience.

To see how this insight can provide a productive approach to the empirical analysis of the labor market impact of immigration, consider the following example. It is well known that recent immigration has increased the relative supply of high school dropouts substantially. But the labor market implications of this supply shock would clearly depend on how the distribution of work experience in the immigrant population contrasts with that of native workers. After all, one particular set of native high school dropouts would likely be affected if all of the new low-skill immigrants were very young, and a very different set would be affected if all of the low-skill immigrants were near retirement age. It is unlikely that workers with very different levels of work experience are highly substitutable—even if they have the same educational attainment.<sup>9</sup>

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<sup>9</sup> In fact, the evidence indicates that immigrant and native men who belong to the same schooling-experience group tend to do the same kinds of jobs. Let  $p_c$  be the share of native workers in a particular schooling-experience group who work in (three-digit) occupation  $c$ , and let  $q_c$  denote the respective statistic for immigrants. In the 1990 Census, the correlation between  $p_c$  and  $q_c$  is strongest (within a schooling category) when comparing the occupational sorting of workers who belong to the same experience group. For example, the correlation between  $p_c$  and  $q_c$  for college graduates with 30-40 years of experience is .87. In contrast, the correlation between the occupational sorting of native college graduates with 30-40 years of experience and immigrant college graduates with 0-10 years of experience is .63. Similarly, the correlation between the occupational sorting of native and immigrant high school dropouts with 30-40 years of experience is .73. But this correlation falls to .56 when comparing the sorting of native high school dropouts with 30-40 years of experience with that of immigrant high school dropouts with 0-10 years of experience.

The empirical analysis presented below uses this insight to define skill groups in terms of both educational attainment and work experience. It turns out that the immigrant supply shock—even within a particular schooling category—is not balanced evenly across all experience groups. In other words, immigration tends to affect some experience groups far more than it affects others, and the nature of the supply “imbalance” changes over time. As a result, the definition of skill groups in terms of education-experience cells provides a great deal more independent (and exogenous!) variation in the immigrant supply shock. This additional variation helps to identify how immigration alters the economic opportunities facing particular groups of native workers.

Of course, the key underlying assumption of this empirical approach is that there is a single national labor market for particular skill groups, so that one can only observe one wage-employment outcome for each group at a point in time. In effect, the approach proposed in this paper builds on the key insights provided by the factor proportions approach, but attempts to estimate how the labor market adjusts to the supply shock, rather than simulate the impact.

### **III. Data and Evidence**

The empirical analysis uses data drawn from the 1960, 1970, 1980, and 1990 Public Use Microdata Samples (PUMS) of the Decennial Census, and the 1999, 2000, and 2001 Annual Demographic Supplement of the Current Population Surveys (CPS). I will pool all three of the CPS surveys and refer to these pooled data as the “2000” cross-section. In the 1960 and 1970 Censuses, the data extracts form a 1 percent random sample of the population. In 1980 and 1990, the immigrant extracts form a 5 percent random sample, and the native extracts form a 1 percent random sample. The analysis is restricted to men who participate in the civilian labor force and

are not enrolled in school. Finally, a person is defined to be an immigrant if he was born abroad and is either a non-citizen or a naturalized citizen; all other persons are classified as natives.

As noted above, the classification of workers into particular skill groups will use both educational attainment and work experience. In particular, I classify the men in the various cross-sections into four distinct education groups: persons who are high school dropouts (i.e., they have less than 12 years of completed schooling), high school graduates (they have exactly 12 years of schooling), persons who have some college (they have between 13 and 15 years of schooling), and college graduates (they have at least 16 years of schooling).

The classification of workers into experience groups is bound to be imprecise because the Census does not provide any measure of labor market experience or of the age at which a worker first enters the labor market. As an approximation, I will initially define work experience as the number of years that have elapsed since the person completed school. This approximation of work experience is reasonably accurate for most native men, but would surely contain serious measurement errors if the calculations were also conducted for women, particularly in the earlier cross-sections when the female labor force participation rate was much lower.

Equally important, this measure of experience is also likely to mis-measure “effective” experience in the sample of immigrants—i.e., the number of years of work experience that are valued by an American employer. After all, a variable which roughly approximates “Age – Education – 6” does not differentiate between experience acquired in the source country and experience acquired in the United States. I address this problem in detail in the next section where I will construct a measure of “effective experience” for the immigrant population.

However, it is easier to illustrate and understand the nature of the empirical exercise by focusing

on the simpler case where experience is simply time elapsed since the person entered the labor market, regardless of where that experience was acquired.

For all men, therefore, I assume that the typical high school dropout enters the labor market at age 17; the typical high school graduate enters at age 19; the typical person with some college enters at age 21; and the typical college graduate enters at age 23. I experimented with minor variations in these definitions of the entry age, and the results were quantitatively very similar to those reported below. Let  $A_T$  be the assumed entry age for a particular schooling group. The measure of work experience is then given by  $(\text{Age} - A_T)$ . The analysis is restricted to persons who have between 1 and 40 years of labor market experience.

Consider a group of workers who have educational attainment  $i$  ( $i = 1, \dots, 4$ ), experience level  $j$  ( $j = 1, \dots, 40$ ), and are observed in calendar year  $t$ . The  $(i, j, t)$  cell defines a skill group at a point in time. The measure of the immigrant supply shock for this skill group is defined by:

$$(1) \quad m_{ijt} = \frac{M_{ijt}}{(M_{ijt} + N_{ijt})},$$

where  $M_{ijt}$  gives the number of immigrants in cell  $(i, j, t)$ , and  $N_{ijt}$  gives the corresponding number of natives. The variable  $m_{ijt}$  measures the foreign-born share of the labor force in a particular skill group.

It is instructive to begin the empirical analysis by illustrating the supply shocks experienced by the different skill groups between 1960 and 2000. Perhaps the most interesting finding in Figure 2 is that there is a great deal of dispersion in these supply shocks even within schooling categories. For example, it is well known that immigration has greatly increased the supply of high school dropouts in the U.S. labor market in recent decades. What is less well

known, however, is that this supply shift did not affect equally all experience groups within the dropout population. Moreover, the imbalance in the supply shock changes over time. For example, immigrants made up half of all high school dropouts with 10 to 20 years of experience in 2000, but only 20 to 30 percent of those with less than 5 years of experience. In 1960, however, the immigration of high school dropouts increased the supply of the most experienced workers the most. Similarly, the immigrant supply shock for college graduates in 1980 was reasonably well balanced across all experience groups, generally increasing the supply by around 10 percent. But the supply shock for college graduates in 1960 was larger for the most experienced groups, while in 2000 it was largest for the groups with 5 to 15 years of experience.

The data, therefore, clearly show that immigration does not have a balanced impact on the supply of workers, either within education groups or within experience groups, and that the nature of the imbalance changes over time. This is the source of the exogenous variation that will be exploited throughout much of the empirical analysis presented below.

Not surprisingly, there are also huge differences in the labor market outcomes experienced by the various skill groups, with the relative outcomes changing dramatically between 1960 and 2000. Figure 3 illustrates the experience profiles of log weekly earnings for the various schooling groups. The weekly earnings data used throughout this paper are drawn from the sample of workers who reported positive annual earnings and weeks worked in the year prior to the survey, and who are employed in the wage and salary sector. Further, the weekly wage is deflated by using the CPI-U series.

Figure 3 clearly illustrates that the shape of the experience-earnings profile changed in fundamental ways over the period. In view of the huge changes in the returns to skills that occurred in the 1980s, many of these changes should not be surprising (see Katz and Murphy,

1992; and Murphy and Welch, 1992). Consider, for instance, the experience-earnings profiles of high school dropouts. These profiles dropped over time—so that real wages for high school dropouts were falling over the period—and became flatter. In contrast, the experience-earnings profiles of college graduates became somewhat steeper over time.

### Basic Regressions

Let  $y_{ijt}$  denote the mean value of a particular labor market outcome for *native* men who have education level  $i$ , experience level  $j$ , and are observed in calendar year  $t$ . Much of the empirical analysis conducted in this paper stacks these data across all skill groups and all calendar years and estimates the regression model:

$$(2) \quad y_{ijt} = \theta m_{ijt} + s_i + v_j + \pi_t + (s_i \times v_j) + (s_i \times \pi_t) + (v_j \times \pi_t) + \varepsilon_{ijt},$$

where  $s_i$  is a vector of fixed effects indicating the group's educational attainment;  $v_j$  is a vector of fixed effects indicating the group's work experience; and  $\pi_t$  is a vector of fixed effects indicating the calendar year of the observation. The linear terms of the fixed effects included in equation (2) control for differences in labor market outcomes across schooling groups, experience groups, and over time. The regression model, however, also includes a full set of interactions among these three vectors. The interactions  $(s_i \times v_j)$  control for the fact that the experience profile for a particular labor market outcome probably differs across schooling groups. Similarly, the interactions  $(s_i \times \pi_t)$  and  $(v_j \times \pi_t)$  control for the possibility that the impact of education and experience on labor market outcomes changed over time. The specification in (2), therefore, fully

controls for the facts that experience-earnings profiles are steeper for more educated workers, and that the returns to schooling and experience increased substantially in the 1980s and 1990s.

The regression analysis will use several dependent variables, including the log of annual earnings, the log of weekly earnings, the log of weeks worked (defined in the subsample of persons who worked), and the probability that the person worked at some point in the past calendar year. All regressions are weighted by the sample size used to calculate the mean outcome  $y_{ijt}$  for skill group  $(i, j, t)$ .

Table 1 presents the basic estimates of the regression model. Consider initially the results obtained when the dependent variable is the log of weekly earnings of native workers (see row 2). The third column of the table reports the coefficient estimated from the full specification of the regression model, the specification that includes all of the interactions among the fixed effects. The estimate of the adjustment coefficient  $\theta$  is  $-.481$ , with a standard error of  $.090$ .

It is easier to interpret the results by converting this coefficient into a factor price elasticity that gives the percent change in wages associated with a percent change in labor supply. Let  $z_{ijt} = M_{ijt}/N_{ijt}$ , or the percentage increase in the labor supply of skill group  $(i, j, t)$  attributable to immigration. The factor price elasticity can then be defined as:<sup>10</sup>

$$(3) \quad \frac{\partial \log w_{ijt}}{\partial z_{ijt}} = \theta \frac{1}{(1 + z_{ijt})^2}.$$

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<sup>10</sup> The generic regression model in equation (2) could just as easily have been specified with  $z$  as a regressor (rather than  $m$ ). I opted for the specification with the immigrant share because the variable  $m$  varies greatly over time (due to the increase in the size of the immigrant population), and would lead to less stable results if the relation between the dependent variable  $y$  and  $m$  is nonlinear. Note that  $\log z \approx (M - N)/(.5(M + N)) = 2(2m - 1)$ . In other words, the immigrant share effectively “logs” the percentage increase in labor supply due to immigration, stabilizing the variation in the size of the immigrant population across schooling-experience cells and over time.

By 2000, immigrants had increased the number of men in the labor force by 16 percent. Equation (3) implies that the factor price elasticity—evaluated at the mean value of the immigrant supply increase—can be obtained by multiplying the coefficient  $\theta$  by approximately .75. The third column of Table 1 then implies that the factor price elasticity for weekly earnings is  $-.36$  (or  $-.481 \times .75$ ). Put differently, a 10 percent supply shock (i.e., an immigrant flow that increases the number of workers in the skill group by 10 percentage points) would reduce weekly earnings by 3.6 percentage points.<sup>11</sup>

The other rows of Table 1 show that immigration has an even stronger impact on the log of annual earnings. In the most complete specification reported in column 3, a 10 percent supply shock reduces annual earnings by 6.0 percentage points, suggesting that immigration causes a substantial reduction in the labor supply of male workers. In fact, as the third row shows, a 10 percent immigrant supply shock reduces weeks worked by 2.4 percent.<sup>12</sup> The separate estimates

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<sup>11</sup> It is worth noting that this estimate of the factor price elasticities is roughly similar to those that have been estimated in the labor demand literature (in studies that have nothing to do with immigration). Hamermesh's (1993) encyclopedic survey suggests that a 10 percent increase in the supply of workers lowers wages by around 3 percent. Because the spatial correlations between labor market outcomes and immigrant penetrations reported in the literature are unstable and are usually statistically insignificant, it is more difficult to contrast the estimated coefficients in Table 1 with "consensus" estimates from that literature. For example, the Altonji and Card (1991, Table 7) OLS estimate of the elasticity of log weekly wages of low-skill natives with respect to the immigrant share in the locality is  $-.26$  (with a standard error of  $.23$ ), while the elasticity for log weeks worked is  $+.23$  ( $.13$ ).

<sup>12</sup> I estimated alternative specifications of the model to assess the sensitivity of the results to specification changes. For example, the coefficients reported in Table 1 use only the sample of men for calculating both the mean outcomes in the left-hand-side of the regression, as well as the immigrant supply shock on the right-hand-side. The estimated coefficients would be stronger if the immigrant supply shock were calculated using all persons in the labor force, including women. In particular, the coefficient  $\theta$  (in the full interaction model) would be  $-.921$  ( $.127$ ) for log annual earnings,  $-.597$  ( $.094$ ) for log weekly earnings,  $-.324$  ( $.077$ ) for log weeks worked, and  $-.237$  ( $.027$ ) for the probability of working during the year. Similarly, the regressions reported in Table 1 are weighted by the sample size of the skill cell. The estimated coefficient  $\theta$  (in the full interaction model) for the unweighted regressions would be  $-.847$  ( $.104$ ) for log annual earnings,  $-.577$  ( $.075$ ) for log weekly earnings,  $-.270$  ( $.059$ ) for log weeks worked, and  $-.225$  ( $.027$ ) for the work probability. Finally, an increase in the immigrant supply shock variable can capture both an increase in immigration as well as a decline in the number of native workers in that skill group. The results are similar when the regression also includes the log of native workers in the skill group as a regressor. The adjustment coefficients (in the full interaction model) would then be  $-.956$  ( $.125$ ) for log annual earnings,  $-.411$  ( $.094$ ) for log weekly earnings,  $-.545$  ( $.068$ ) for log weeks worked, and  $-.172$  ( $.026$ ) for the work probability. In short, the findings reported in Table 1 are not sensitive to major specification changes.

of the impact of immigration on weekly earnings and on weeks worked can be used to estimate the labor supply elasticity. The supply-demand framework illustrated in Figure 1 implies that the labor supply elasticity is given by the ratio of the percentage change in the labor supply of native workers to the change in weekly earnings. The point estimates in the full interaction specification, therefore, imply that the labor supply elasticity for native men is .67.<sup>13</sup>

Before proceeding to a more refined analysis of the data, it is worth noting that the evidence summarized in Table 1 does not suffer from one of the key flaws of the spatial correlations approach—the inability of that approach to generate parameter estimates that are reasonably stable over time. The summaries of parameter estimates in the spatial correlation framework provided by Schoeni (1997) and Borjas, Freeman, and Katz (1997) indicate that the estimated correlations often have wild sign switches across adjoining decades. In the Borjas-Freeman-Katz analysis, for example, there is a negative correlation between immigration and wages in the 1960s, but the coefficient becomes positive (and numerically larger) in the 1970s, and turns negative and modest in the 1980s.

The coefficients reported in Table 1 were obtained by pooling all skill groups across all survey years. It turns out that the results would be roughly similar even if they only used each set of two adjacent cross-sections, so that the regression models would be effectively differencing the data over a decade. Table 2 reports the coefficients estimated for each decade using the full interaction model. Within each decade, the immigrant supply shock has a negative impact on log weekly earnings, and the effect is often significant. The adjustment coefficient  $\beta$  ranges only

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<sup>13</sup> This estimate is higher than the ones reported by Juhn, Murphy, and Topel (1991). They use both geographic and time series variation in weeks worked to estimate the determinants of labor supply, and conclude that the labor supply elasticity is in the range of .1 to .4, with the elasticity being higher in low-skill populations.

from -.21 to -.45. The evidence, therefore, suggests a stability in the estimated impact of immigration that is absent from the estimates provided by the spatial correlations approach.

### **Substitutability among Adjacent Experience Cells**

The regression coefficients reported in Tables 1 and 2 define a skill group in terms of educational attainment and a particular level of experience (i.e., one year, two years, and so on). As noted in Welch's (1979) classic study of the impact of cohort size on the earnings of baby boomers, workers in adjacent experience cells are more likely to influence each other's labor market opportunities than workers in cells that are further apart.<sup>14</sup> In other words, the earnings of native college graduates with 15 years of experience will likely be affected by the entry of immigrants who have "around" 15 years of experience, but will be much less sensitive to the entry of foreign-born college graduates who are in their early 20s or who are nearing retirement age.

This argument suggests that one should define the immigrant supply shock in terms of how immigration increased the labor supply of a set of adjacent cells. In particular, the size of the supply shock encountered by a native worker with  $j$  years of work experience is the relative number of immigrants in the population of workers who have "roughly"  $j$  years of experience. In effect, the variable measuring the immigrant supply shock should be defined as a type of moving average across experience cells within a schooling group. The operational difficulty, of course, is the choice of the subset of experience cells over which workers in a particular schooling group

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<sup>14</sup> Welch (1979) assumes that the wage of a worker with  $j$  years of experience is affected by the supply of workers who have between  $j-2$  and  $j+2$  years of experience, with the size of the group in each of these experience years receiving a different weight when calculating the total effective supply that affects the worker. In particular, Welch uses a vector of weights equal to (.33, .33, .67, 1.0, .67, .33). It is worth noting that Welch's elasticity estimates of the persistent impact of cohort size on own-group wages is around -.2.

are relatively substitutable. Suppose that workers in  $k$  adjacent cells around point  $j$  are similar (with  $k$  odd). The relevant supply shock facing a worker in group  $(i, j, t)$  is then given by:

$$(4) \quad \bar{m}_{ijt} = \frac{\sum_{\ell=-(k-1)/2}^{\ell=(k-1)/2} M_{i,j+\ell,t}}{\sum_{\ell=-(k-1)/2}^{\ell=(k-1)/2} (M_{i,j+\ell,t} + N_{i,j+\ell,t})},$$

so that the immigrant supply shock is roughly given by a  $k$ -year moving average of the immigrant share series illustrated in Figure 2.<sup>15</sup>

The top panel of Table 3 reports the adjustment coefficients obtained by using a five-year moving average. The coefficient  $\theta$  for log weekly earnings in the full interaction model is -.629 (with a standard error of .103), implying a factor price elasticity of -.47. This elasticity is somewhat higher than the one obtained in Table 1, which uses the single-year definition of an experience cell. In short, the specification of an experience group as a moving average of a set of neighboring cells actually leads to numerically stronger estimates of the adverse labor market impact of immigration.

An alternative way of dealing with the problem is simply to group workers into more broadly defined experience brackets. In particular, I classified workers into one of eight experience brackets defined by 1 to 5 years of experience, 5 to 10 years, 11 to 15 years, 16 to 20 years, 21 to 25 years, 26 to 30 years, 31 to 35 years, and 36 to 40 years. The bottom panel of Table 3 reports the regression coefficients estimated from this grouping. Although the

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<sup>15</sup> The moving average is calculated over all available data, even at the truncated endpoints of the time series of experience. As a result, there are no missing values for the immigrant supply shock. As an example, if  $k = 5$ , the supply shock for a worker with 2 years of experience would use the data available for experience years 1, 2, 3, and 4. It is worth noting that the results are quite similar if I use alternative lengths for the moving average, such as 9 years.

adjustment coefficients have higher standard errors, the estimated elasticities are quite similar to those reported earlier.<sup>16</sup> For example, the coefficient  $\theta$  in the full interaction specification of the regression is  $-.579 (.165)$ , so that a 10 percent increase in supply due to immigration reduces the weekly earnings of native workers by 4.3 percent.

In sum, the approach proposed in this paper—namely, defining skill groups in terms of both educational attainment and work experience—leads to results that differ strikingly from those found in the existing literature on the labor market impact of immigration. In particular, there is strong and consistent evidence that immigrants do indeed adversely affect the earnings and employment opportunities of competing native workers, and this effect is both numerically sizable and statistically significant.<sup>17</sup>

#### IV. Measuring Effective Experience

In the last section, labor market experience was defined as the time elapsed since entry into the labor market for both immigrants and natives, regardless of whether the experience was

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<sup>16</sup> The grouping of workers into a relatively small number of experience brackets also addresses a technical problem with the calculation of the standard errors in the moving average regressions. Since labor market impacts spill over across adjoining experience cells, it is unclear how many independent observations the data actually contain.

<sup>17</sup> I also estimated the basic regression model in Table 3 separately within schooling groups and within experience groups. The within-schooling group coefficients (and standard errors) were: high school dropouts,  $-.971 (.170)$ ; high school graduates,  $-2.091 (.525)$ ; workers with some college,  $-.897 (.499)$ ; and college graduates,  $.644 (.405)$ . Note, however, that these regressions cannot control for the changing shape of the experience-earnings profile over the period, so that the coefficient of the immigrant supply shock variable may be measuring a spurious correlation between immigration and factors that changed the wage structure within particular schooling groups. It is of interest that the estimate of  $\theta$  is marginally positive only for college graduates, the group that probably experienced the largest change in the wage structure in recent decades. The within-experience group coefficients were: 1-5 years,  $.148 (.956)$ ; 6-10 years,  $-.234 (.416)$ ; 11-15 years,  $-.306 (.339)$ ; 16-20 years,  $-.405 (.285)$ ; 21-25 years,  $-.409 (.280)$ ; 26-30 years,  $-.465 (.285)$ ; 31-35 years,  $-.305 (.266)$ ; and 36-40 years,  $.066 (.260)$ . Despite the fact that these within-experience regressions have only 20 observations (4 schooling groups in five cross-sections), the point estimate of  $\beta$  for all the groups between 5 and 35 years of experience (i.e., after the entry period and before the retirement period) is roughly similar to that obtained in the aggregate model, though with larger standard errors.

acquired in the source country or the United States. In effect, the analysis equated labor market exposure with the labor market experience valuable to American employers.

Beginning with Chiswick (1978), the labor economics literature has paid a great deal of attention to estimating the differential value that American employers attach to experience acquired abroad and experience acquired in the United States.<sup>18</sup> These studies typically find that an American employer attaches a lower value to a year of source-country experience than to a year of experience acquired by a native worker *and* that the employer attaches a higher value to a year of U.S. experience acquired by an immigrant than to a year of experience acquired by a native worker. The usual explanation for this type of evidence relies on the argument that experience acquired in the source country is partly specific to that country, and cannot be easily transferred to the U.S. labor market. Once in the United States, immigrants tend to invest heavily in human capital, and this helps explain why a year of U.S. experience acquired by the foreign-born has a higher return than a year of work experience acquired by a native worker.

These findings suggest that the analysis should use the “effective experience” of an immigrant worker before assigning that worker to a particular schooling-experience cell, where effective experience measures the number of years of work exposure that are actually valued by American employers. Let  $A$  denote age,  $A_m$  the age of entry into the United States, and  $A_T$  the age of entry into the labor market. The number of years of effective experience that immigrants offer to American employers can then be defined by:

$$(5) \quad X = \begin{cases} \alpha(A_M - A_T) + \beta(A - A_m), & \text{if } A_m > A_T \\ \gamma(A - A_m), & \text{if } A_m \leq A_T \end{cases}$$

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<sup>18</sup> See also Borjas (1985), Friedberg (1992), LaLonde and Topel (1992), and Lubotsky (2001).

where  $\alpha$  is the weight that translates a year of source country experience acquired by immigrants who migrated as adults (i.e.,  $A_m > A_T$ ) into the equivalent value of work experience acquired by a native worker;  $\beta$  is the weight that rescales the value of a year of U.S. experience acquired by these adult immigrants; and  $\gamma$  is the weight that rescales the experience acquired by immigrants who migrated as children (i.e.,  $A_m \leq A_T$ ) into the equivalent value of experience acquired by native workers.<sup>19</sup>

If the values of the parameters  $\alpha$ ,  $\beta$ , and  $\gamma$  were known, one could use the definitions in equation (5) to compute the effective experience of each immigrant in the data, and use this measure of effective experience to classify the immigrants into the relevant education-experience skill groups. In fact, the parameters  $\alpha$ ,  $\beta$ , and  $\gamma$  can be estimated by using the standard model of immigrant assimilation, a model that also accounts for any existing differences in immigrant “quality” across cohorts (Borjas, 1985). To illustrate, suppose we pool data for native and immigrant workers in two separate cross-sections of data (such as the 1980 and 1990 Censuses). A generic regression model that can identify all of the relevant parameters is given by:

$$(6) \quad \log w = s\phi + \varphi_C I^C + \varphi_D I^D + \lambda_N N(A - A_T) + \lambda_C I^C(A - A_T) \\ + \lambda_{D0} I^D(A_m - A_T) + \lambda_{D1} I^D(A - A_m) + \delta Y + \rho\pi + \varepsilon,$$

where  $w$  gives the weekly wage of a worker observed in a particular cross-section;  $s$  is a vector of dummy variables indicating the worker’s educational attainment;  $I^C$  is a dummy variable set to unity if the immigrant migrated to the United States as a child (i.e., prior to the age of entry into

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<sup>19</sup> The adjustment coefficients estimated in the previous section assume that  $\alpha = \beta = \gamma = 1.0$ .

the labor market);  $I^D$  is a dummy variable set to unity if the immigrant entered the country as an adult (i.e., past the age of entry into the labor market);  $N$  is a dummy variable indicating if the worker is native-born ( $N = 1 - I^C - I^D$ );  $A$  gives the worker's age at the time of the survey;  $A_m$  gives the worker's age at the time he entered the United States;  $A_T$  gives the worker's age at the time he entered the labor market;  $Y$  gives the calendar year in which an immigrant worker arrived in the United States (set to zero for native workers); and  $\pi$  is a dummy variable indicating if the observation is drawn from the 1990 Census (and zero if it is drawn from the 1980 Census). The key parameters in this type of regression model are the ones that estimate the aging effects (the vector of  $\lambda$  coefficients), the cohort effect ( $\delta$ ), and the period effect ( $\rho$ ). It is well known that these parameters are not separately identified unless some restriction is imposed on the data. Equation (6) imposes the standard assumption that the period effect is the same for immigrant and native workers.

The coefficient  $\lambda_N$  gives the market value of a year of experience acquired by a native worker;  $\lambda_C$  gives the market value of a year of experience acquired in the United States by an immigrant who arrived at a young age;  $\lambda_{D0}$  gives the market value of a year of source country experience acquired by an adult immigrant; and  $\lambda_{D1}$  gives the U.S. market value of a year of U.S. experience acquired by that immigrant. By taking the appropriate ratios of these coefficients, one can define the weights that define an immigrant's effective experience. In particular, the weights can be calculated as:

$$(7) \quad \alpha = \frac{\lambda_{D0}}{\lambda_N}, \quad \beta = \frac{\lambda_{D1}}{\lambda_N}, \quad \gamma = \frac{\lambda_C}{\lambda_N}.$$

For example, the “true” value of a year of experience acquired in the source country by an adult immigrant is given by the market value that American employers attach to that year of experience relative to the value that American employers attach to a year of experience acquired by a native worker.

Although the generic regression model in equation (6) is pedagogically useful, it ignores the curvature of the experience-earnings profile, and also ignores the possibility that the coefficients of educational attainment differ among the various groups (i.e., natives, adult immigrants, and immigrants who migrated at a young age). Further, it is preferable to define the calendar year of an immigrant’s arrival in terms of a vector of dummy variables indicating the year of arrival, rather than as a linear time trend.<sup>20</sup> I estimated this more general model using the pooled 1980 and 1990 data. Table 4 reports the relevant coefficients from the relevant experience variables included in this regression.

It is worth noting that the experience coefficients for natives and for immigrants who migrated at a young age have almost identical numerical values, so that a marginal year of U.S. work experience is valued at the same rate by employers.<sup>21</sup> This implies that the weight  $\gamma$  is estimated to be 1.0.

In contrast, the value of an additional year of source country experience for adult immigrants (evaluated at the mean years of source country experience) is .008, while the value of an additional year of U.S. experience for these immigrants is .028. The relevant baseline for these marginal rates is the value of an additional year of experience for native workers who have

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<sup>20</sup> The dummy variables in this vector indicate if the immigrant arrived between 1985-1989, 1980-1984, 1975-1979, 1970-1974, 1965-1969, 1960-1964, 1950-1959, and before 1950. The estimated regression model interacts this vector with the variable indicating if the immigrant arrived as an adult or as a child.

<sup>21</sup> Because the regression has over 1 million observations, the tiny numerical difference is statistically significant.

20.9 years of experience (the sum of the 10.4 years of source country and 10.5 years of U.S. experience). This marginal value is .017. By using the definitions in equation (7), the estimated values of the experience weights for the sample of immigrants who migrated as adults are  $\alpha = .5$  and  $\beta = 1.6$ .

I used these weights to calculate the effective experience of each immigrant in the various samples, and then regrouped the workers into the various schooling-experience skill groups using the computed measure of effective experience.<sup>22</sup> The immigrant's year of arrival is not reported in the 1960 Census, so that the calculations of effective experience for immigrant workers (as well as the regressions reported below) are restricted to the data drawn from the 1970 through 2000 cross-sections.

Before proceeding to the discussion of the estimated effects, it is instructive to see how the classification of workers into skill groups according to effective experience changes the pattern of the immigrant supply shocks for the various schooling groups. As a comparison of Figures 2 and 4 indicates, the pattern of supply shocks is roughly similar for high school dropouts, but differs for the more educated groups.<sup>23</sup>

Table 5 reports the estimates of the adjustment coefficient  $\theta$  when using effective experience to classify immigrants into the various schooling-experience skill groups. The estimated effects are roughly similar to those reported in the previous section. For example, the coefficients reported in the last column of Table 5 imply that a 10 percent immigrant supply

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<sup>22</sup> Neither the Census nor the CPS report the exact year in which immigrants entered the United States, but instead report the year of entry within particular brackets (e.g., 1980-84). To avoid the non-linearities that would arise if I measured effective experience by assigning each worker the midpoint year in his bracket (such as 1982.5), I instead used a uniform distribution to randomly assign workers in each bracket to each of the calendar years in that bracket.

<sup>23</sup> The correlation between effective experience and the number of years elapsed since entry into the labor market is .91 among immigrant workers in the 1990 Census.

shock lowers the weekly wage by 2.3 percent and reduces weeks worked by 3.9 percent. Both of these effects are statistically significant.

## **V. The Impact of Immigration on Immigrants**

Although the studies that estimate spatial correlations have usually failed to uncover a sizable impact of immigration on the earnings of native workers, they have inexplicably documented that new immigrants tend to lower the earnings and employment opportunities of earlier immigrants (Altonji and Card, 1991; Borjas, 1987; LaLonde and Topel, 1991). Therefore, it is of interest to examine if the current approach also finds a strong degree of substitutability within the immigrant population.

The top panel of Table 6 reports the adjustment coefficients  $\theta$  obtained in the immigrant sample using the measure of experience that simply counts time elapsed since entry into the labor market. The coefficients in the first two columns of the table are roughly similar to those reported in the previous section for native workers. For example, the adjustment coefficient for log weekly earnings when the regression does not include any interactions among the fixed effects is  $-.609$ , as compared to  $-.374$  for native workers (see the comparable regression reported in the bottom panel of Table 3). However, the adjustment coefficients, although still negative, typically become statistically insignificant when the full set of interactions is introduced, particularly the vectors that interact the period effect with either educational attainment or experience.

Part of the problem may be that the experience-earnings profiles for immigrants in any given cross-section confound an aging effect and a cohort effect. In other words, the wage differential at a point in time between “young” and “old” immigrants measures both the effect of

aging that takes place over the life cycle, as well as the possibility that the immigrants with less experience (who probably arrived more recently) have inherently fewer skills. By ignoring the fact that there is likely to be systematic variation in labor market outcomes within and across immigrant cohorts, the fixed effect interactions may not be appropriately controlling for the dynamics of wage evolution in the immigrant population.

In fact, the adjustment coefficients for annual and weekly earnings are negative and statistically significant when the regression adjusts for the immigrant worker's calendar year of arrival. The middle panel of Table 6, for example, shows the adjustment coefficients obtained when the regression uses only the sample of immigrant workers who have been in the United States fewer than 10 years in each of the cross-sections.<sup>24</sup> The estimated adjustment coefficient in the full interaction model is  $-.441$  (with a standard error of  $.221$ ) for annual earnings, and  $-.367$  ( $.189$ ) for weekly earnings. The implied factor price elasticities evaluated at the mean immigrant supply shock are  $-.33$  and  $-.28$ , respectively. The evidence reported in Table 6, therefore, suggests that immigrants have relatively similar impacts both on themselves and on natives. In short, immigration worsens employment opportunities for all competing workers.

## **VI. Measuring Effective Skills**

The calculation of "effective experience" in the previous sections raises a more general question about the overall comparability of the skills of immigrants and natives. After all, it seems likely that the U.S. labor market differentiates the value of human capital embodied in immigrants and natives along many dimensions other than experience. For example, the value

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<sup>24</sup> The analysis of the labor market outcomes of recently arrived immigrants uses only the data drawn from the 1970 through 2000 cross-sections because the 1960 Census does not report the year of immigration.

that firms attach to schooling or to particular types of occupational training will probably differ between immigrants and natives, and will also vary among immigrants belonging to different national origin groups. It is of interest, therefore, to devise a simple way of categorizing all of the differences in “effective skills” that exist between immigrants and natives within a schooling category. The most straightforward way to create groups of workers who have roughly the same number of efficiency units (as valued by U.S. firms) is to classify workers according to their placement in the wage distribution. Workers who fall in the same general location of the wage distribution (within a schooling group) have roughly the same number of efficiency units since employers attach the same value to the *entire* package of skills embodied in these workers.

To conduct this classification of workers into skill groups, I restrict the analysis in this section to workers who have valid wage data. For each of the four schooling groups, I sliced the weekly wage distribution of *native* workers into 25 quantiles. By construction, four percent of native workers in each schooling group fall into each of the quantiles. I then calculated how many of the immigrant workers in each schooling group and in each cross-section fall into each of the 25 quantiles. The immigrant supply shock can then be defined by:

$$(8) \quad \hat{m}_{ikt} = \frac{M_{ikt}}{(M_{ikt} + N_{ikt})},$$

where  $M_{ikt}$  and  $N_{ikt}$  give the number of foreign-born and native-born workers in schooling group  $i$ , quantile  $k$  ( $k = 1, \dots, 25$ ), at time  $t$ .

Figure 4 illustrates the trends in this measure of the immigrant supply shock between 1960 and 2000. As with the measure of the supply shock based on education and experience, it is evident that immigration is not balanced evenly across the various quantiles of the (within-

schooling) wage distribution. In 2000, around 50 percent of the high school dropouts who placed between the 5<sup>th</sup> to 10<sup>th</sup> quantile of the wage distribution were foreign-born, as compared to only about 20 to 30 percent for high school dropouts in the upper quantiles. In contrast, in 1980 roughly around 5 percent of the high school graduates in each of the quantiles of the respective wage distribution were foreign-born.

To calculate the impact of immigration, I aggregated the data within schooling-quantile-year cells and estimated the regression model:

$$(9) \quad y_{ikt} = \beta \hat{m}_{ikt} + s_i + q_k + \pi_t + (q_k \times s_i) + (s_i \times \pi_t) + (q_k \times \pi_t) + \varepsilon_{ikt},$$

where  $q_k$  is a vector of fixed effects indicating the quantile of the cell. Note that the interaction of the various fixed effects in equation (9) control for the dramatic changes in the wage structure that occurred in the 1960-2000 period. In particular, the interactions between the quantile and period fixed effects control for the likelihood that wages evolved differently for different quantiles of the (within-schooling) wage distribution.<sup>25</sup>

Table 7 reports the estimated adjustment coefficients from regressions that use the full interaction specification shown in equation (9). Despite the very different methodological approach employed in this section to define the skill groups, the estimated adjustment coefficients  $\theta$  are remarkably similar to those estimated in the earlier sections of the paper, at

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<sup>25</sup> Note that the classification of workers into skill groups conducted in this section does not use any demographic variables other than the worker's schooling and wage. The exercise could be redone (although in a much less useful way) by using only information on the worker's placement in the wage distribution. A skill cell would then consist of a particular quantile at a particular point in time, and one could pool all these cells over all time periods to estimate the impact of immigration. It is well known, however, that real wages fell dramatically for the bottom quantiles of the distribution. One could net this out by including an interaction between the cell's quantile and the time period, but this would essentially create a separate dummy variable for each observation. As a

least for native workers. In particular, the estimated adjustment coefficients for native workers are  $-.906$  (with a standard error of  $.188$ ) for annual earnings and  $-.457$  ( $.133$ ) for weekly earnings. Evaluated at the mean value of the immigrant supply shock, these coefficients imply that the factor price elasticity for native workers is  $-.68$  for annual earnings and  $-.34$  for weekly earnings.<sup>26</sup> The adjustment coefficients estimated in the sample of all immigrants display more variability, but are statistically significant. The coefficient is  $-.461$  ( $.187$ ) for annual earnings and  $-.814$  ( $.120$ ) for weekly earnings, implying factor price elasticities of  $-.35$  and  $-.61$ , respectively. Therefore, the evidence strongly suggests that the clustering of immigrants into particular segments of the wage distribution significantly worsened the wage outcomes of both natives and immigrants who shared those regions of the wage distribution with the new workers.

## VII. Summary

The concern over the adverse labor market impact of immigration has always played a central role in the immigration debate in the United States. Despite the policy importance of this issue, no empirical studies attempted to document the existence of these labor market effects prior to 1980. Since then, however, many studies claim to measure how immigrants alter labor market opportunities for native workers. This research effort, based mainly on comparisons of native economic status across cities or regions, has not been entirely successful. The weak cross-

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result, the variable measuring the immigrant supply shock (which would be larger for the lower quantiles) would be measuring a spurious negative correlation associated with the changes in the wage structure.

<sup>26</sup> I did not estimate the impact of immigration on the probability that the person worked in the past year because the analysis was restricted to persons with valid wage data. One could classify non-workers into the various quantiles of the wage distribution by using a first-stage regression that predicts earnings for workers based on their educational attainment, experience, immigration status, and state of residence. The wages predicted from this regression can then be used to classify non-workers into the various skill groups. This approach would presumably provide a more complete measure of the supply shock attributable to immigration. It turns out that this approach—at least in the sample of men—would lead to results that are quite similar to those reported in the text.

city correlations typically estimated in these studies, although often construed as showing that immigrants do not harm native economic opportunities, are difficult to interpret. In fact, economic theory implies that the more that firms and workers adjust to the immigrant supply shock, the smaller these cross-city correlations will be—regardless of the “true” impact of immigration on the national economy.

This paper introduces a new approach for estimating the labor market impact of immigration. The analysis is based on the intuitively appealing notion that increases in labor supply in a finely-detailed skill group should affect the earnings and employment opportunities of that skill group. Earlier studies have typically defined skill groups solely in terms of educational attainment, so that there usually were few data points at the national level that could be used to measure the labor market impact of immigration. The crucial insight used in this paper follows directly from one of the main lessons of human capital theory: a worker acquires skills both in school *and* on the job.

Defining skill groups in terms of educational attainment and work experience introduces a great deal of exogenous variation in the data. In some years, the influx of immigrant with a particular level of schooling mainly affects younger workers, in other years it mainly affects older workers, and in still other years it mainly affects workers in the middle range of the distribution of work experience. The analysis presented in this paper uses the assumption that different experience groups form different skill classes to identify the impact of immigration on the labor market opportunities of native workers. In contrast to the existing literature, the evidence consistently indicates that immigration lowers the wage and reduces the labor supply of competing native workers, as suggested by the simplest textbook model of a competitive labor market.

The estimates of the factor price elasticity cluster between  $-.3$  and  $-.4$ . These estimates, combined with the very large immigrant influx in recent decades, imply that immigration has substantially worsened the labor market opportunities faced by many native workers. By 2000, immigrants had increased the size of the male labor force by 16 percent. The estimated factor price elasticities imply that this immigrant flow reduced the wage of the typical male native worker by 5 percent. The wage impact differs dramatically across education groups. Immigrants increased the supply of native high school dropouts by 55 percent, reducing the weekly earnings of this group by around 20 percent. In contrast, immigrants increased the supply of native high school graduates by 12 percent and that of native workers with some college by only 9 percent, leading to a wage reduction for these groups of 4 and 3 percent, respectively. Finally, immigrants increased the supply of native college graduates by 16 percent, reducing their weekly earnings by 5 percent.

Although the approach presented in this paper provides a fruitful direction for empirical research in this area, a number of important questions remain unanswered. For example, my analysis focused solely on estimating the own-group factor price elasticities. It is likely that the immigration of workers in a particular skill group (e.g., high school dropouts) alters the opportunities of workers in other skill groups (e.g., college graduates). Perhaps the skill-based approach introduced here can also provide a productive avenue for measuring the cross-effects.

Further, in contrast to the studies based on regional differences, the comparison of workers across narrowly defined skill classifications reveals a sizable adverse effect of immigration on native employment opportunities. But we still do not fully understand why the spatial correlation approach fails to find these effects. I suspect that we can learn a great deal more about the labor market impact of immigration by documenting the many adjustments that

take place, by workers and firms, both inside and outside the labor market, as immigration alters economic opportunities in many sectors of the U.S. economy.

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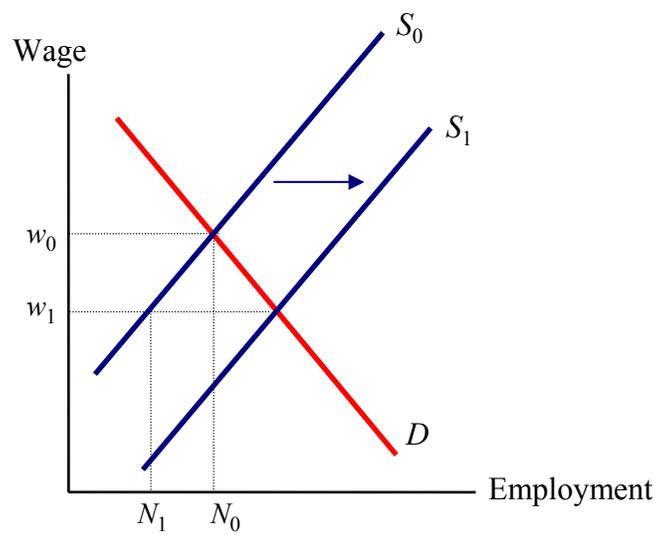
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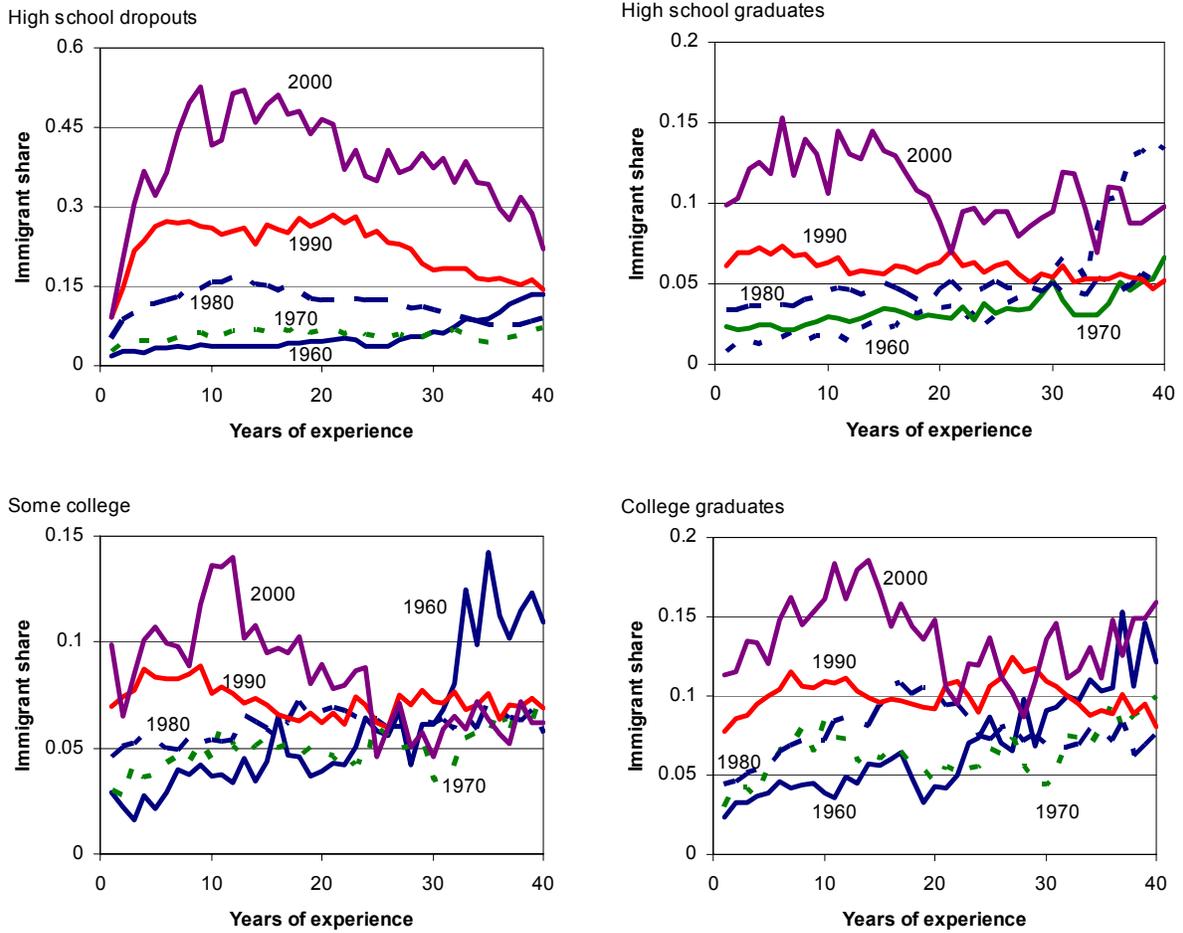
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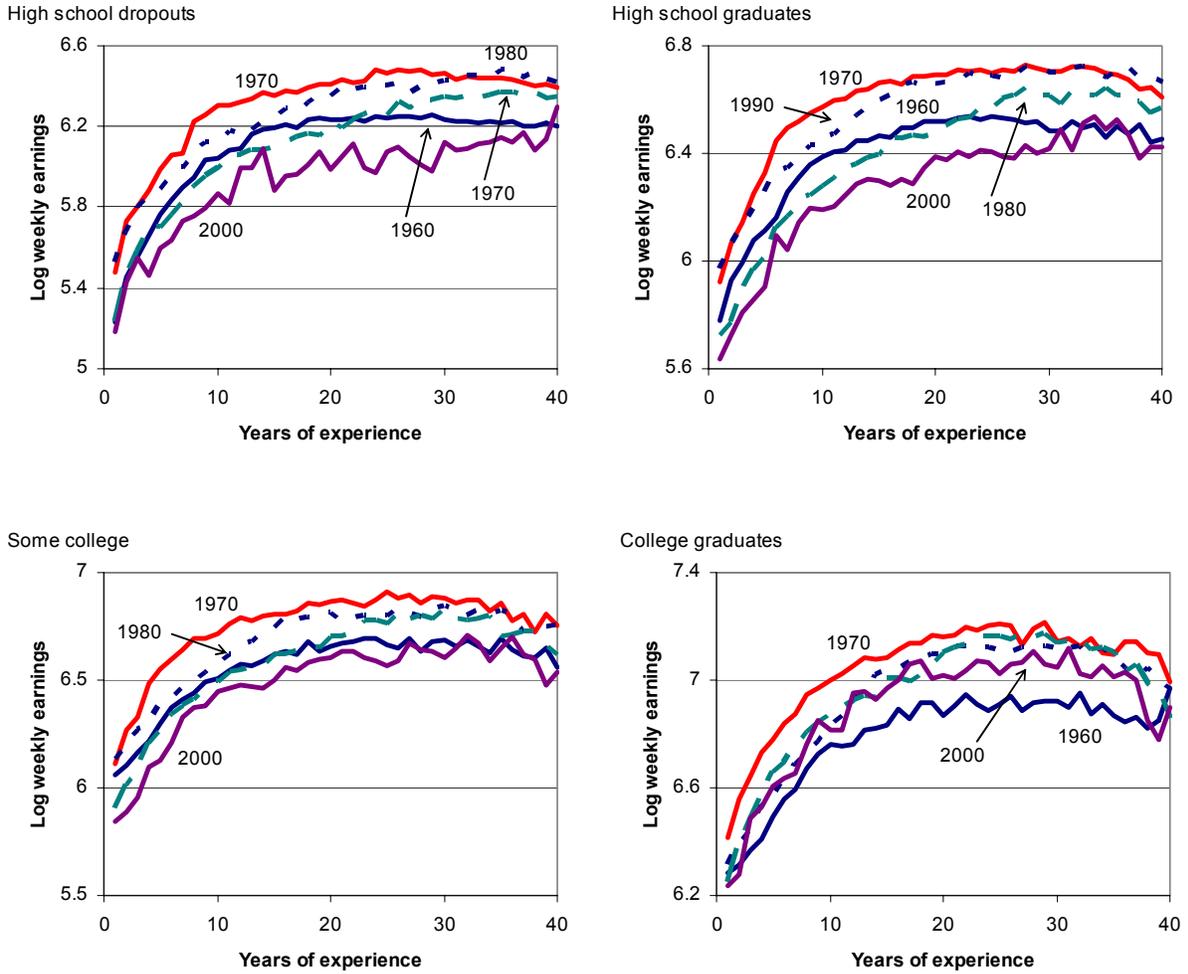
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**Figure 1. Immigration and the Labor Market**

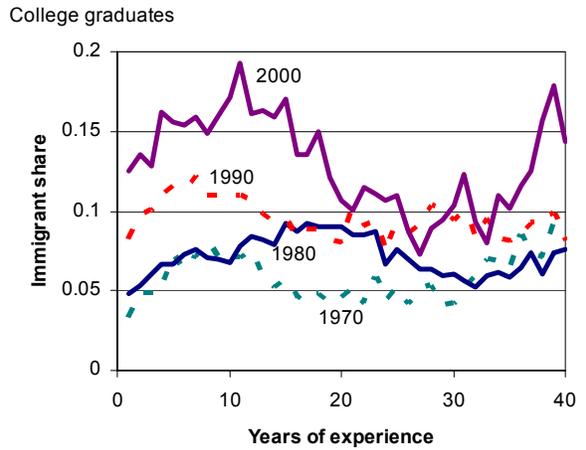
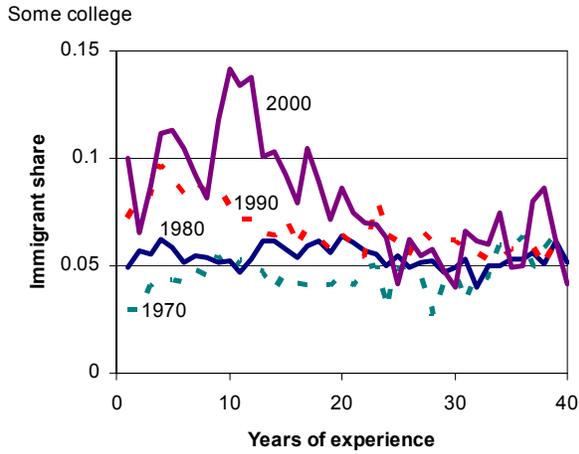
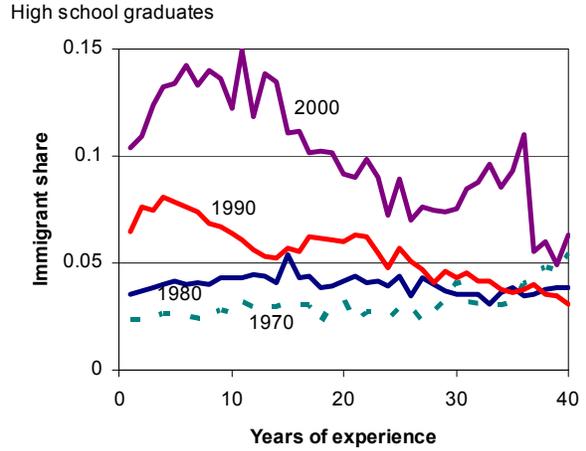
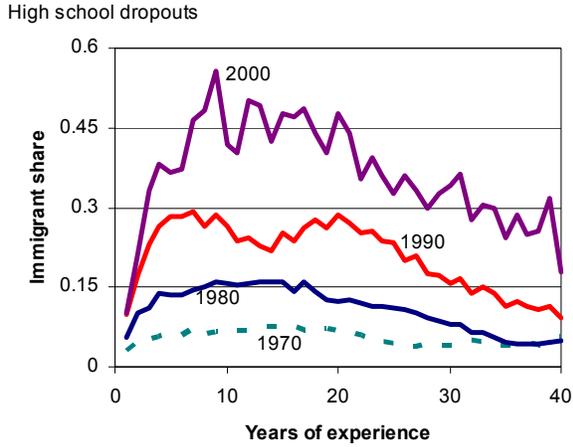
**Figure 2. The Immigrant Supply Shock on Schooling-Experience Groups, 1960-2000**



**Figure 3. Experience-Earnings Profiles, by Schooling and Year**

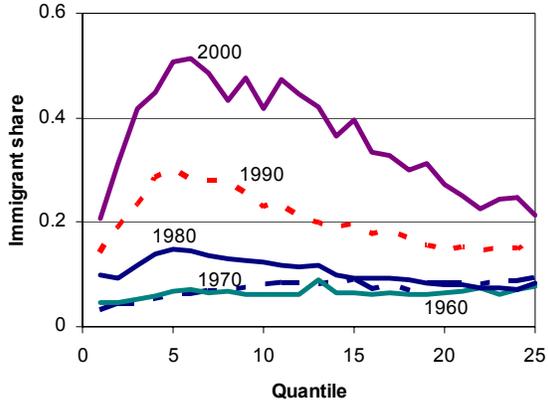


**Figure 4. The Immigrant Supply Shock Using Effective Experience, 1970-2000**

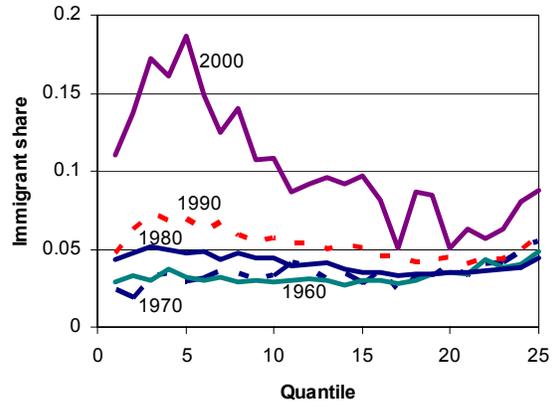


**Figure 5. The Immigrant Supply Shock  
By Quantile of the Wage Distribution, 1960-2000**

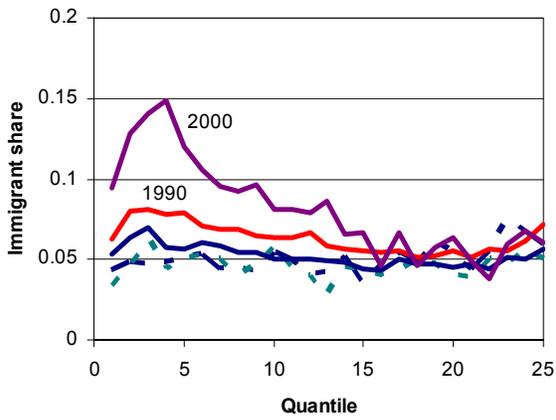
High school dropouts



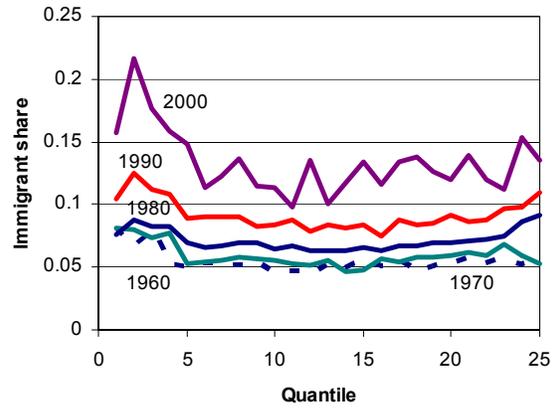
High school graduates



Some college



College graduates



**Table 1. Basic Estimates of Adjustment Coefficients**

| <u>Dependent variable:</u>   | Specification   |                 |                 |
|--|-----------------|-----------------|-----------------|
|  | (1)             | (2)             | (3)             |
| 1. Log annual earnings   | -.714<br>(.091) | -.813<br>(.072) | -.805<br>(.122) |
| 2. Log weekly earnings   | -.345<br>(.058) | -.392<br>(.059) | -.481<br>(.090) |
| 3. Log weeks worked  | -.369<br>(.051) | -.421<br>(.029) | -.324<br>(.073) |
| 4. Probability of work during year                                   | -.284<br>(.027) | -.313<br>(.023) | -.227<br>(.026) |
| Fixed effects included in regression:                                |                 |                 |                 |
| Education ( $s_i$ ), experience ( $v_j$ ), calendar year ( $\pi_t$ ) | Yes             | Yes             | Yes             |
| ( $s_i \times v_j$ ) interactions                                    | No              | Yes             | Yes             |
| ( $s_i \times \pi_t$ ) and ( $v_j \times \pi_t$ ) interactions       | No              | No              | Yes             |

Notes: The standard errors are reported in parentheses. All regressions have 800 observations, and are weighted by the sample size of the education-experience-time cell.

**Table 2. Adjustment Coefficients Estimated in Each Decade  
(Full Interaction Model)**

| <u>Dependent variable:</u>         | Period           |                  |                  |                  |
|------------------------------------|------------------|------------------|------------------|------------------|
|                                    | <u>1960-1970</u> | <u>1970-1980</u> | <u>1980-1990</u> | <u>1990-2000</u> |
| 1. Log annual earnings             | -.692<br>(.310)  | -1.017<br>(.246) | -.405<br>(.285)  | -.708<br>(.223)  |
| 2. Log weekly earnings             | -.454<br>(.260)  | -.263<br>(.214)  | -.212<br>(.214)  | -.340<br>(.173)  |
| 3. Log weeks worked                | -.238<br>(.094)  | -.754<br>(.155)  | -.192<br>(.141)  | -.368<br>(.107)  |
| 4. Probability of work during year | -.054<br>(.064)  | -.142<br>(.051)  | -.326<br>(.053)  | -.201<br>(.074)  |

Notes: The standard errors are reported in parentheses. All regressions have 320 observations, and are weighted by the sample size of the education-experience-time cell. The regression specification includes vectors of fixed effects indicating the group's educational attainment, work experience, and survey year, as well as interactions among all of these vectors.

**Table 3. Adjustment Coefficients,  
Using Alternative Definitions of an Experience Group**

| <u>Definition and dependent variable:</u>                            | Specification   |                 |                  |
|--|-----------------|-----------------|------------------|
|  | (1)             | (2)             | (3)              |
| Five-year moving average:  |                 |                 |                  |
| 1. Log annual earnings   | -.761<br>(.093) | -.843<br>(.073) | -1.002<br>(.139) |
| 2. Log weekly earnings   | -.366<br>(.061) | -.406<br>(.060) | -.629<br>(.103)  |
| 3. Log weeks worked  | -.395<br>(.053) | -.437<br>(.029) | -.373<br>(.084)  |
| 4. Probability of work during year                                   | -.302<br>(.027) | -.324<br>(.024) | -.272<br>(.030)  |
| Using five-year experience groupings:                                |                 |                 |                  |
| 1. Log annual earnings   | -.772<br>(.197) | -.860<br>(.158) | -.794<br>(.257)  |
| 2. Log weekly earnings   | -.374<br>(.127) | -.418<br>(.129) | -.579<br>(.165)  |
| 3. Log weeks worked  | -.397<br>(.112) | -.442<br>(.064) | -.215<br>(.179)  |
| 4. Probability of work during year                                   | -.309<br>(.059) | -.332<br>(.052) | -.258<br>(.046)  |
| Fixed effects included in regression:                                |                 |                 |                  |
| Education ( $s_i$ ), experience ( $v_j$ ), calendar year ( $\pi_t$ ) | Yes             | Yes             | Yes              |
| ( $s_i \times v_j$ ) interactions                                    | No              | Yes             | Yes              |
| ( $s_i \times \pi_t$ ) and ( $v_j \times \pi_t$ ) interactions       | No              | No              | Yes              |

Notes: The standard errors are reported in parentheses. The regressions that use the five-year moving average have 800 observations; the regressions that use the five-year experience grouping have 160 observations. All regressions are weighted by the sample size of the education-experience-time cell.

**Table 4. Impact of Labor Market Experience on the Log Weekly Earnings of Natives and Immigrants**

| <u>Coefficient of:</u>   | <u>Group</u>    |                         |                         |
|--|-----------------|-------------------------|-------------------------|
|  | <u>Natives</u>  | <u>Child immigrants</u> | <u>Adult immigrants</u> |
| Source country experience  | ---             | ---                     | .015<br>(.001)          |
| Source country experience squared ÷ 10   | ---             | ---                     | -.003<br>(.000)         |
| U.S. experience  | .068<br>(.000)  | .071<br>(.001)          | .037<br>(.001)          |
| U.S. experience squared ÷ 10   | -.012<br>(.001) | -.012<br>(.001)         | -.004<br>(.001)         |
| Mean value of:   |                 |                         |                         |
| Source country experience  | ---             | ---                     | 10.4                    |
| U.S. experience  | 16.7            | 12.0                    | 10.5                    |
| Marginal value of an additional year of experience for immigrants:   |                 |                         |                         |
| Source country experience  | ---             | ---                     | .008<br>(.001)          |
| U.S. experience  | ---             | .041<br>(.001)          | .028<br>(.001)          |
| Marginal value of an additional year of experience for natives, evaluated at mean value of relevant sample of immigrants | ---             | .039<br>(.000)          | .017<br>(.000)          |

Notes: The standard errors are reported in parentheses. The regression pools data from the 1980 and 1990 Census and has 1,260,844 observations. The dependent variable is the log of weekly earnings. The regressors include: dummy variables indicating if the worker is an adult immigrant or a child immigrant; a vector of educational attainment, interacted with variables indicating if the worker is an adult immigrant or a child immigrant; experience (and its squared) for native workers; experience in the U.S. (and its square) for immigrants who arrived as children; source country experience (and its squared) for immigrants who arrived as adults; experience in the U.S. (and its squared) for immigrants who arrived as adults; dummy variables indicating the calendar year in which the immigrant arrived, and the interaction of this vector with a dummy variable indicating if the immigrant arrived as an adult; and a dummy variable indicating if the observation was drawn from the 1990 Census.

**Table 5. Adjustment Coefficients,  
Using Effective Experience**

| <u>Dependent variable:</u>   | Specification   |                 |                 |
|--|-----------------|-----------------|-----------------|
|  | <u>(1)</u>      | <u>(2)</u>      | <u>(3)</u>      |
| 1. Log annual earnings   | -.942<br>(.108) | -.908<br>(.095) | -.822<br>(.142) |
| 2. Log weekly earnings   | -.439<br>(.069) | -.431<br>(.078) | -.308<br>(.104) |
| 3. Log weeks worked  | -.503<br>(.064) | -.477<br>(.038) | -.514<br>(.082) |
| 4. Probability of work during year                                   | -.325<br>(.029) | -.350<br>(.028) | -.230<br>(.032) |
| Fixed effects included in regression:                                |                 |                 |                 |
| Education ( $s_i$ ), experience ( $v_j$ ), calendar year ( $\pi_t$ ) | Yes             | Yes             | Yes             |
| ( $s_i \times v_j$ ) interactions                                    | No              | Yes             | Yes             |
| ( $s_i \times \pi_t$ ) and ( $v_j \times \pi_t$ ) interactions       | No              | No              | Yes             |

Notes: The standard errors are reported in parentheses. All regressions have 640 observations, and are weighted by the sample size of the education-experience-time cell.

**Table 6. Adjustment Coefficients for Immigrant Workers**

| <u>Sample and dependent variable:</u>                                | Specification   |                 |                 |
|--|-----------------|-----------------|-----------------|
|  | (1)             | (2)             | (3)             |
| All immigrants   |                 |                 |                 |
| 1. Log annual earnings   | -.667<br>(.061) | -.731<br>(.065) | -.109<br>(.137) |
| 2. Log weekly earnings   | -.609<br>(.051) | -.626<br>(.056) | -.073<br>(.119) |
| 3. Log weeks worked  | -.058<br>(.026) | -.105<br>(.023) | -.032<br>(.060) |
| 4. Probability of work during year                                   | .013<br>(.019)  | -.016<br>(.016) | -.065<br>(.040) |
| Immigrants in U.S. less than 10 years                                |                 |                 |                 |
| 1. Log annual earnings   | -.678<br>(.085) | -.805<br>(.089) | -.441<br>(.221) |
| 2. Log weekly earnings   | -.620<br>(.070) | -.608<br>(.076) | -.367<br>(.189) |
| 3. Log weeks worked  | -.056<br>(.040) | -.197<br>(.040) | -.074<br>(.112) |
| 4. Probability of work during year                                   | .025<br>(.031)  | -.074<br>(.030) | -.139<br>(.074) |
| Immigrants in U.S. less than 10 years, with effective experience     |                 |                 |                 |
| 1. Log annual earnings   | -.674<br>(.088) | -.813<br>(.095) | -.332<br>(.228) |
| 2. Log weekly earnings   | -.626<br>(.073) | -.611<br>(.081) | -.199<br>(.204) |
| 3. Log weeks worked  | -.046<br>(.039) | -.202<br>(.038) | -.133<br>(.101) |
| 4. Probability of work during year                                   | .042<br>(.030)  | -.107<br>(.029) | -.225<br>(.074) |
| Fixed effects included in regression:                                |                 |                 |                 |
| Education ( $s_i$ ), experience ( $v_j$ ), calendar year ( $\pi_t$ ) | Yes             | Yes             | Yes             |
| ( $s_i \times v_j$ ) interactions                                    | No              | Yes             | Yes             |
| ( $s_i \times \pi_t$ ) and ( $v_j \times \pi_t$ ) interactions       | No              | No              | Yes             |

Notes: The standard errors are reported in parentheses. The regressions estimated in the sample of all immigrants have 800 observations; the regressions estimated in the sample of recent immigrants have 639 observations; the regressions estimated in the sample of recent immigrants using effective experience have 493 observations. All regressions are weighted by the sample size of the education-experience-time cell.

**Table 7. Adjustment Coefficients,  
Defining Skill Groups as Quantiles of Wage Distribution  
(Full Interaction Model)**

| <u>Dependent variable:</u> | Sample          |                       |                          |
|----------------------------|-----------------|-----------------------|--------------------------|
|                            | <u>Natives</u>  | <u>All immigrants</u> | <u>Recent immigrants</u> |
| 1. Log annual earnings     | -.906<br>(.188) | -.461<br>(.187)       | -.153<br>(.278)          |
| 2. Log weekly earnings     | -.457<br>(.133) | -.814<br>(.120)       | -.988<br>(.159)          |
| 3. Log weeks worked        | -.449<br>(.160) | .353<br>(.174)        | .835<br>(.277)           |

Notes: The standard errors are reported in parentheses. The regressions estimated in the native sample have 496 observations; the regressions estimated in the sample of all immigrants have 495 observations; and the regressions estimated in the sample of recent immigrants (who have been in the United States less than 10 years) have 397 observations. All regressions are weighted by the sample size of the education-quantile-time cell. The regression specification includes vectors of fixed effects indicating the group's educational attainment, quantile of the wage distribution, and survey year, as well as interactions among all of these vectors.