NATIVE INTERNAL MIGRATION AND THE LABOR MARKET IMPACT OF IMMIGRATION

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Abstract

Immigrants tend to cluster in a small number of geographic areas. Many studies use this clustering to estimate the wage impact of immigration by relating wage rates across labor markets to some measure of immigrant penetration. These spatial correlations may not measure the true impact of immigration because the internal migration response of native workers helps to re-equilibrate local labor markets. This paper presents a theoretical and empirical study of how immigrant supply shocks influence the joint determination of wages and internal migration decisions in local labor markets. The data indicate that immigration is associated with lower wages, lower in-migration rates, higher out-migration rates, and a decline in the growth rate of the native workforce. The native migration response is sufficiently strong to attenuate the measured impact of immigration on wages in a local labor market from 40 to 60 percent, depending on whether the labor market is defined at the state or metropolitan area level.

NATIVE INTERNAL MIGRATION AND THE LABOR MARKET
IMPACT OF IMMIGRATION

George J. Borjas[*]

I. Introduction

Immigrants in the United States cluster in a small number of geographic areas. In 2000, for example, 69.2 percent of working-age immigrants resided in six states (California, New York, Texas, Florida, Illinois, and New Jersey), but only 33.7 percent of natives lived in those states. Similarly, 38.4 percent of immigrants lived in four metropolitan areas (New York, Los Angeles, Chicago, and San Francisco), but only 12.2 percent of natives lived in the four metropolitan areas with the largest native-born populations (New York, Chicago, Los Angeles, and Philadelphia).

Economic theory suggests that immigration into a *closed* labor market affects the wage structure in that market by lowering the wage of competing workers and raising the wage of complements. Most of the empirical studies in the literature exploit the geographic clustering of immigrants to measure the labor market impact of immigration by defining the labor market along a geographic dimension—such as a state or a metropolitan area. Beginning with Grossman (1982), the typical study regresses a measure of native economic outcomes in the locality (or the change in that outcome) on the relative quantity of immigrants in that locality (or the change in

the relative number).[1] The regression coefficient, or "spatial correlation," is then interpreted as the impact of immigration on the native wage structure.

There are two well-known problems with this approach. First, immigrants may not be randomly distributed across labor markets. If immigrants tend to cluster in areas with thriving economics, there would be a spurious positive correlation between immigration and area outcomes either in the cross-section or in the time-series. This spurious correlation could attenuate or reverse whatever measurable negative effects immigrants might have had on the wage of competing native workers.[2]

The second problem is that natives may respond to the entry of immigrants into a local labor market by moving their labor or capital to other localities until native wages and returns to capital are again equalized across areas. A large immigrant flow arriving in Los Angeles might result in, say, fewer workers from Iowa or Ohio moving to California, and a reallocation of capital across states. An interstate comparison of the wage of native workers might show little or no difference because the effects of immigration are diffused throughout the national economy, and not because immigration had no economic effects.

In view of these potential problems it is not too surprising that the empirical literature has produced a confusing array of results. The measured impact of immigration on the wage of native workers in local labor markets fluctuates widely from study to study, but seems to cluster around zero. In recent work (Borjas, 2003), I show that by defining the labor market at the

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[1] See also Altonji and Card (1991), Borjas (1987), Card (2001), LaLonde and Topel (1991), and Schoeni (1997). De New and Zimmermann (1994) and Pischke and Velling (1997) provide similar studies for the German labor market. Card's (1990) case study of the impact of the Mariel immigrant flow into Miami is certainly the most influential study of this type. Friedberg and Hunt (1995) provide a good survey of the literature.

[2] Borjas (2001) argues that income-maximizing immigrants would tend to cluster in high-wage regions, helping to move the labor market towards a long-run equilibrium. The evidence does indeed suggest that, within education groups, new immigrants tend to locate in those states that offer the highest rate of return for their skills.

national level—which more closely approximates the theoretical counterpart of a closed labor market—the measured wage impact of immigration becomes much larger. By examining the evolution of wages in the 1960-2000 period within narrow skill groups (defined in terms of schooling and labor market experience), I concluded that an immigrant supply shock that increases the number of workers in a particular skill group by 10 percent reduces the wage of that skill group by 3 to 4 percent.

In this paper, I explore the disparate findings implied by the two approaches by focusing on a particular adjustment mechanism that native workers may use to avoid the adverse impacts of immigration on local labor markets: internal migration. A number of studies already examine if native migration decisions respond to immigrant supply shocks. As with the spatial correlation literature, these studies offer a cornucopia of findings, with some studies finding strong effects (e.g., Frey, 1995, and Borjas, Freeman, and Katz, 1997), and other studies finding little connection (Card, 2001; and Wright, Ellis, and Reibel, 1997).[3]

This paper can be viewed as a synthesis of two related, but so far unconnected, strands in the literature. I present and estimate a theoretical framework that jointly models wage determination in local labor markets and the native migration decision. The theory yields estimable equations that explicitly link the parameters measuring the wage impact of immigration at the national level, the spatial correlation between wages and immigration in local labor markets, and the native migration response. The model clearly shows that the larger the native migration response, the greater will be the difference between the estimates of the national wage effect and the spatial correlation. The model also implies that it is possible to use the

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[3] Other studies include Card and DiNardo (2000), Filer (1992), and White and Hunter (1993).

spatial correlations to calculate the "true" national impact of immigration as long as one has information on the elasticity measuring the migration response of native workers.

I use data drawn from all the Census cross-sections between 1960 and 2000 to estimate the key parameters of the model. The data indicate that the measured wage impact of immigration depends intimately on the geographic definition of the labor market, and is larger as one expands the size of the market—from the metropolitan area, to the state, to the Census division, and ultimately to the nation. In contrast, although the measured impact of immigration on native migration rates also depends on the geographic definition of the labor market, these effects become smaller as one expands the size of the market. These mirror-image patterns suggest that the wage effects of immigration on local labor markets are more attenuated the easier that natives find it to "vote with their feet." In fact, the native migration response can account for between 40 and 60 percent of the difference in the measured wage impact of immigration between the national and local labor market levels, depending on whether the local labor market is defined by a state or by a metropolitan area.

II. Theory

I use a simple economic model of the joint determination of the regional wage structure and the internal migration decision of native workers to show the types of parameters that spatial correlations identify, and to determine if these parameters can be used to identify the national labor market impact of immigration.[4] Suppose that the labor demand function for workers in skill group i residing in geographic area j at time t can be written as:

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[4] The model can be viewed as an application of the Blanchard and Katz (1992) framework that analyzes how local labor markets respond to demand shocks. The basic model presented here builds on a framework developed by Borjas, Freeman, and Katz (1997, unpublished appendix), and further elaborated in Borjas (1999). The

(1) $$w_{ijt} = X_{ijt} L_{ijt}^{\eta},$$

where w_{ijt} is the wage of workers in cell (i, j, t); X_{ijt} is a demand shifter; L_{ijt} gives the total number of workers (both immigrants, M_{ijt}, and natives, N_{ijt}); and η is the factor price elasticity (with $\eta < 0$). It is convenient to interpret the elasticity η as the "true" impact that an immigrant supply shock would have in a closed labor market in the short run, a labor market where neither capital nor labor responds to the immigrant influx.

For simplicity, I assume that the demand shifter is both time-invariant and region-invariant ($X_{ijt} = X_i$). This simplification implies that (within a particular skill group) wages differ across regions only when the stock of workers is not evenly distributed across regions. The extension of the model to incorporate differences in the level of the demand curve would complicate the presentation without substantially altering the basic insights provided by the model.[5] I also assume that the total number of native workers in a particular skill group in the national economy is fixed at $\bar{N}_i$. It would not be difficult (though it would be cumbersome) to extend the model to allow for differential rates of growth in the size of the native workforce.

Suppose that $N_{ij,-1}$ native workers in skill group i reside in region j in the pre-immigration period ($t = -1$). The sorting of native workers across regions in the pre-immigration regime does not represent a long-run equilibrium; some regions have too many workers and other regions too

few. The regional wage differentials induce a migration response by native workers even prior to the immigrant supply shock. In particular, region j experiences a net migration of ΔN_{ij0} natives belonging to skill group i between $t = -1$ and $t = 0$.

Beginning at time 0, the local labor market (as defined by a particular skill-region cell) experiences an immigrant supply shock of M_{ijt} immigrants. This immigrant supply shock continues in all subsequent periods. A convenient assumption that greatly simplifies the presentation is that region j receives the *same* number of immigrants in each year. The annual immigrant influx for a particular skill-region cell can then be represented by M_{ij}. The assumption that the immigrant supply shock is constant over time is not grossly contradicted by the data for the United States because the same regions have been the recipients of similar types of immigrants for several decades.[6]

For simplicity, I assume that immigrants do not migrate internally within the United States—they enter region j and remain there.[7] Natives continue to make relocation decisions, and region j experiences a net migration of ΔN_{ij1} natives in period 1, ΔN_{ij2} natives in period 2, and so on. The labor demand function given by equation (1) implies that the wage for skill group i in region j at time t is then given by:

(2) $$\log w_{ijt} = \log X_i + \eta \log [N_{ij,-1} + (t+1)M_{ij} + \Delta N_{ij0} + \Delta N_{ij1} + \ldots + \Delta N_{ijt}],$$

which can be rewritten as:

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[6] The model could be easily extended to incorporate a time-variant immigrant supply shock to each region as long as the growth rate of the immigrant influx was constant.

(3) $\qquad \log w_{ijt} \approx \log w_{ij,-1} + \eta \left[(t+1) \, m_{ij} + v_{ij0} + v_{ij1} + \ldots + v_{ijt} \right], \qquad$ for $t \geq 0,$

where $m_{ij} = M_{ij} / N_{ij,-1}$, the relative number of immigrants entering region j in each period; and v_{ijt} $= \Delta N_{ijt} / N_{ij,-1}$, the net migration rate of natives (relative to the initial population in the region). Note that $w_{ij,-1}$ gives the initial wage offered to workers in cell (i, j) in the pre-immigration period.

I assume that the internal migration response of native workers occurs with a lag. For example, immigrants begin to arrive at $t = 0$. The demand function in equation (3) implies that the wage response to immigration is immediate, so that wages fall in the immigrant-penetrated regions. The migration decisions of natives induced by this supply shock, however, are not observed until the next period. The lagged supply response that describes the migration decisions of native workers is given by:

(4) $\qquad v_{ijt} = \sigma \, (\log w_{ij,t-1} - \log \overline{w}_{i,t-1}),$

where σ is the supply elasticity ($\sigma > 0$); and $\log \overline{w}_{i,t-1}$ is the equilibrium wage (for skill group i) that will be observed throughout the national economy once all migration responses to the immigrant supply shocks that have occurred up to time $t - 1$ have been made.[8] It might seem

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[7] The evidence reported in Bartel (1989) suggests that the internal migration decisions of immigrants in the United States do not seem to be very sensitive to regional wage differences, but are instead more sensitive to the location decisions of earlier immigrant waves.

[8] More precisely, $\log \overline{w}_{i,t-1} = \log \overline{w}_{i,-1} + \eta(tm_i)$, where m_i gives the per-period number of immigrants in skill group i relative to the total number of natives in that skill group. Note that the model implicitly assumes that the native population is large enough (relative to the total immigrant supply shock) to be able to equalize the number of workers across labor markets through internal migration.

preferable to model the supply function so that natives take into account the expected impact of future immigration. However, the total supply shock up to time $t - 1$ is a "sufficient statistic" because we have assumed that the region receives the same number of immigrants in every period.

The model does not impose any restrictions on the value of the parameter σ (except that it is positive). If σ is sufficiently "small," the migration response of natives may not be completed within one period. Some workers may respond immediately, but other workers will take somewhat longer.[9] Note also that the migration decision is made by comparing the current wage in region j to the wage that region j will eventually attain. In this model, therefore, there is perfect information about the eventual outcome that results from the accumulation of immigrant supply shocks. Unlike the typical cobweb model, persons are not making decisions based on erroneous information. The lags arise simply because it is difficult to change locations immediately.

As noted above, the existence of regional wage differentials at time $t = -1$ implies that native internal migration was taking place even prior to the immigrant supply shock. It is useful to describe the determinants of the net migration flow v_{ij0}. In the pre-immigration period, the equilibrium wage that would be eventually attained in the economy is:

(5) $$\log \bar{w}_{i,-1} = X_i + \eta \log N_i^*,$$

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[9] In a sense, the migration behavior underlying equation (4) is analogous to the firm's behavior in the presence of adjustment costs (Hamermesh, 1993). One can justify this staggered response in a number of ways. The labor market is in continual flux, with persons entering and leaving the market. Because migration is costly, workers may find it optimal to time the lumpy migration decision concurrently with these transitions. Workers may also face

where N_i^* represent the number of native workers in skill group i that would live in each region once long-run equilibrium is attained.[10] The pre-existing net migration rate of native workers is then given by:

$$(6) \qquad v_{ij0} = \sigma \, (\log w_{ij,-1} - \log \bar{w}_{i,-1}) = \eta\sigma \, \lambda_{ij},$$

where $\lambda_{ij} = \log(N_{ij,-1} / N_i^*)$. By definition, the variable λ_{ij} is negative when the initial wage in region j is higher than the long-run equilibrium wage (in other words, there are fewer workers in region j than there will be after all internal migration takes place). Equation (6) then implies that the net migration rate in region j is positive (since $\eta < 0$).

Native net migration continues after the immigrant supply shock. In the mathematical appendix, I show that the native net-migration rate at year t can be written as:

$$(7) \qquad v_{ijt} = \eta\sigma \, (1 + \eta\sigma)^t \, \lambda_{ij} + [1 - (1 + \eta\sigma)^t] \, m_i - [1 - (1 + \eta\sigma)^t] \, m_{ij},$$

where $m_i = M_i / \bar{N}_i$, and M_i gives the per-period number of immigrants in skill group i. The restriction $0 < (1 + \eta\sigma) < 1$ is assumed to hold throughout the analysis.

The total number of native workers in cell (i, j, t) is then given by the sum of the initial stock $(N_{ij,-1})$ and the net migration flows defined by equation (7), or:

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constraints that prevent them from taking immediate advantage of regional wage differentials, including various forms of "job-lock" or short-term liquidity constraints.

$$\log N_{ijt} = \log N_{ij,-1} + [(1+\eta\sigma)^{t+1} - 1]\lambda_{ij}$$

(8)
$$+ \left[\frac{t}{t+1} + \frac{(1+\eta\sigma)}{\eta\sigma} \frac{[1-(1+\eta\sigma)^t]}{(t+1)} \right] \tilde{m}_{it}$$

$$- \left[\frac{t}{t+1} + \frac{(1+\eta\sigma)}{\eta\sigma} \frac{[1-(1+\eta\sigma)^t]}{(t+1)} \right] \tilde{m}_{ijt},$$

where $\tilde{m}_{it} = (t+1)m_i$, the relative number of immigrants with skill i who have migrated to the

United States as of time t; and $\tilde{m}_{ijt} = (t+1)m_{ij}$, the relative number of immigrants with skill i who

have migrated to region j as of time t.[11] The wage for workers in cell (i, j, t) is then given by:

$$\log w_{ijt} = \log w_{ij,-1} + \eta[(1+\eta\sigma)^{t+1} - 1]\lambda_{ij}$$

(9)
$$- \eta \left[\frac{t}{t+1} + \frac{(1+\eta\sigma)}{\eta\sigma} \frac{[1-(1+\eta\sigma)^t]}{(t+1)} \right] \tilde{m}_{it}$$

$$+ \eta \left[\frac{1}{t+1} - \frac{(1+\eta\sigma)}{\eta\sigma} \frac{[1-(1+\eta\sigma)^t]}{(t+1)} \right] \tilde{m}_{ijt}.$$

Consider equation (8), which describes the evolution of the size of the native workforce in a particular labor market. In addition to the initial size of the workforce, the current stock of native workers in cell (i, j, t) depends on three factors. First, there is a term in λ_{ij} that essentially gives the total net migration rate of natives that would have occurred in the absence of immigration. Second, there is a term that relates the size of the native workforce to the total immigrant supply shock in skill group i. The last term indicates how the current size of the native

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[10] This number, of course, equals the total number of natives in a skill group divided by the number of regions.

[11] A tilde above a variable indicating the size of the immigrant supply shock implies that the variable refers to the entire stock of immigrants up to a particular point in time (rather than to the per-period flow).

workforce depends on the size of the total region-specific immigrant supply shock. Equation (9) shows that the same three variables also affect the evolution of wages in the local labor market.

Equations (8) and (9) have a number of implications for empirical studies of the impact of immigration on native migration decisions or wages. Consider the behavior of the coefficients of the region-specific immigrant supply shock variable in the size of the native workforce and wage regressions. As t grows large, the coefficient in the native workforce regression (which should be negative) converges to -1, while the coefficient in the wage regression (which should also be negative) converges to zero. Put differently, the longer the time elapsed between the beginning of the immigrant supply shock and the measurement of native migration decisions and native wages, the more likely that natives have completely internalized the immigrant supply shock and the less likely that the spatial correlation approach will uncover *any* wage effect on local labor markets.

Most important, the coefficients of the region-specific (total) immigrant supply shock in the two equations can be used to identify the parameter of interest, η. In fact, these two coefficients indicate how the spatial correlation (i.e., the impact of immigration on wages that can be estimated by comparing local labor markets) relates to the national wage impact of immigration, the factor price elasticity η. In particular, let γ_{Nt} be the coefficient of the immigrant supply shock in the native workforce regression estimated at time t, and let γ_{Wt} be the respective coefficient in the wage regression. The definitions of these coefficients imply that:

(10) $\qquad \gamma_{Wt} = \eta \, (1 + \gamma_{Nt}).$

It is easy to show that the coefficient γ_{Nt} gives the number of natives who migrate out of a particular labor market for every immigrant who migrates there (i.e., $\gamma_{Nt} = \partial N / \partial \tilde{M}_t$). In effect, the factor price elasticity measuring the impact of immigration in the closed national labor market can be estimated from the spatial correlation by "blowing up" the coefficient from the cross-region wage regression by taking into account the relative number of natives who stay. To illustrate, suppose that the coefficient γ_{Nt} is -0.5, indicating that 5 fewer natives choose to reside in the local labor market for every 10 immigrants that enter that market. Equation (10) then implies that the spatial correlation that can be estimated by comparing native wages across local labor markets is only half the size of the true factor price elasticity.

Empirical Specification

In the next section, I will use data drawn from the 1960-2000 Censuses to estimate the key parameters of the model. These data, in essence, provide five wage and size-of-workforce observations (one for each Census cross-section) for labor markets defined by skill groups and geographic regions. The available data, therefore, are not sufficiently detailed to allow me to estimate the dynamic evolution of the size of the native workforce and wages as summarized by equations (8) and (9). These equations, after all, have time-varying coefficients for the variable measuring the immigrant supply shock, and these coefficients are highly nonlinear in time. I derive a simpler framework that can be applied to the available data by using the Taylor's approximation $(1 + x)^t \approx (1 + xt)$. Equations (8) and (9) can then be rewritten as:[12]

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[12] I also use the approximation that t is relatively large so that the ratio $t/(t+1) \approx 1$ and $1/t \approx 0$; in other words, the wage convergence process has been going on for some time before we observe the data points.

(11) $\log N_{ijt} = \log N_{ij,-1} + \eta\sigma\,\lambda_{ij} + \eta\sigma\,(t\,\lambda_{ij}) - \eta\sigma\,\tilde{m}_{it} + \eta\sigma\,\tilde{m}_{ijt}\,,$

(12) $\log w_{ijt} = \log w_{ij,-1} + \eta^2\,\sigma\,\lambda_{ij} + \eta^2\,\sigma\,(t\,\lambda_{ij}) - \eta\sigma\,\tilde{m}_{it} + \eta(1 + \eta\sigma)\,\tilde{m}_{ijt}\,.$

These equations can be estimated by stacking the available data on the size of the native workforce, wages, and immigrant supply shocks across skill groups, regions, and time. Many of the regressors in equations (11) and (12) can then be absorbed by including appropriately defined vectors of fixed effects in the regressions. For example, the inclusion of fixed effects indicating skill-region cells absorbs the vector of variables $(N_{ij,-1}, \lambda_{ij})$ in equation (11) and the vector $(w_{ij,-1}, \lambda_{ij})$ in equation (12). Similarly, interactions between skill and time fixed effects absorb the variable $\tilde{m}_{it}$ in both equations.

In addition to these fixed effects, the regression models in (11) and (12) indicate the presence of two regressors that vary by skill, region, and time. The first, of course, is the region-specific immigrant supply shock, the key independent variable in any empirical analysis that attempts to estimate spatial correlations. Note that the region-specific immigrant supply shock gives the *total* number of immigrants who have arrived in the region up to time *t* relative to the (initial) native population.

The second is the variable $(t\,\lambda_{ij})$, which is related to the (total) net migration rate of natives that would have been observed as of time $(t-1)$ had there been no immigration. This variable is not observable. In the empirical work reported below, I proxy for this variable by including in the regression either a lagged measure of the number of natives in the workforce or the lagged growth rate of the native workforce in the particular labor market.

The regression models in (11) and (12) provide some insight into why there may be some confusion in the empirical literature about the link between native internal migration and

immigration or between wages and immigration. Even abstracting from the interpretation of the

coefficient of the immigrant supply shock variable (which represent an amalgam of various

structural parameters), this amalgam is only estimated properly if the pre-existing conditions in

the local labor market are properly accounted for in the regression specification.

Suppose, for instance, that immigrants enter those parts of the country that pay high

wages, so that Cov (log w_{ij} , $\tilde{m}_{ijt}$) < 0. If the initial wage is left out of the wage regression, it is

easy to show that the observed impact of immigration on wages will be too positive, as the

immigrant supply shock is capturing unobserved pre-existing characteristics of high-wage areas.

Similarly, suppose that immigrants tend to enter those parts of the country that also attract native

migrants. If the regression equation does not control for the pre-existing migration flow, equation

(11) indicates that the impact of immigration on the size of the native workforce will be too

positive.[13]

The regression models also suggest that the geographic definition of a labor market is

likely to have a substantial impact on the magnitude of the measured spatial correlations. In both

regressions, the coefficient of the region-specific immigrant supply shock depends on the value

of the parameter σ, the elasticity measuring the native migration response. In particular, the

spatial correlation estimable in the native workforce regression depends negatively on σ, while

the spatial correlation estimable in the wage regression depends positively on σ. The supply

elasticity will probably be larger when migration is less costly, implying that σ will be greater

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[13] Borjas, Freeman, and Katz (1997) provide a good example of how controlling for pre-existing conditions can actually change the sign of the correlation between net migration and immigration. In particular, they show that the rate of change in the number of natives living in a state is positively correlated with a measure of concurrent immigrant penetration. But this positive correlation turns negative when they add a lagged measure of native population growth into the regression.

when the labor market is relatively small in geographic terms.[14] Equations (11) and (12) then

imply that the spatial correlation between the size of the native workforce and the immigrant

supply shock will be more negative when the model is estimated using geographically *smaller*

labor markets, and that the spatial correlation between the wage and the immigrant supply shock

will be more negative for *larger* labor markets. I will show below that the data indeed satisfy this

mirror-image implication of the theory.

Finally, it is worth stressing that the coefficients of the immigrant supply shocks in this

linearized version of the model satisfy the multiplicative property summarized in equation (10).

Therefore, the theory clearly provides a useful foundation for linking the results of very different

econometric frameworks in the study of the economic impact of immigration.

III. Data and Descriptive Statistics

The empirical analysis uses data drawn from the 1960, 1970, 1980, 1990, and 2000

Integrated Public Use Microdata Series (IPUMS) of the U.S. Census. The 1960 and 1970

samples used below represent a 1 percent random sample of the population, while the 1980,

1990, and 2000 samples represent a 5 percent sample.[15] The analysis is restricted to the sample

of men who do not reside in group quarters, are not enrolled in school, and worked in the

calendar year prior to the Census.[16] 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.

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[14] In other words, it is cheaper to migrate across metropolitan areas to escape the adverse affects of immigration than it is to migrate across Census divisions.

[15] The person weights provided in the 1990 and 2000 Censuses are used in all calculations involving these data.

[16] The analysis excludes persons in the military (as indicated by the variable indicating labor force status in the week of the survey).

As in my earlier work (Borjas, 2003), I use both educational attainment and work experience to sort workers into particular skill groups. The key idea underlying this classification is that similarly educated workers with very different levels of work experience are unlikely to be perfect substitutes (Welch 1979; Card and Lemieux 2001).

I classify the men into four distinct education groups: persons who are high school dropouts (i.e., they have less than twelve years of completed schooling), high school graduates (they have exactly twelve years of schooling), persons who have some college (they have between thirteen and fifteen years of schooling), and college graduates (they have at least sixteen years of schooling).[17]

The classification of workers into experience groups is more 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. I assume that the age of entry into the labor market is 17 for the typical high school dropout, 19 for the typical high school graduate, 21 for the typical person with some college, and 23 for the typical college graduate. Let A_T be the assumed entry age for workers in a particular schooling group. The measure of work experience is then given by (Age – A_T). I restrict the analysis to persons who have between 1 and 40 years of experience.[18] Welch (1979) suggests that workers in adjacent experience cells are more likely to influence each other's labor market opportunities than workers in cells that are further apart. I capture the similarity across workers with roughly similar years of experience by aggregating the data into

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[17] I use Jaeger's (1997, p. 304) algorithm for reconciling differences in the coding of the completed education variable across surveys.

[18] My definition of experience is reasonably accurate for native men, but would 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 will probably mis-measures "effective" experience in the sample of immigrants—i.e., the number of years of work

five-year experience intervals, indicating if the worker has 1 to 5 years of experience, 6 to 10

years, and so on. There are, therefore, 8 experience groups.

A skill group i is then defined by a particular combination of workers with a particular

level of schooling and a particular level of experience. There are 32 skill groups in the analysis

(4 education groups and 8 experience groups).

Consider a group of workers who have skills i, live in region j, and are observed in

calendar year t. The (i, j, t) cell defines a particular labor market at a point in time. I define the

measure of the immigrant supply shock affecting this labor market as:

(13) $$p_{ijt} = \frac{\tilde{M}_{ijt}}{\tilde{M}_{ijt} + N_{ijt}},$$

where $\tilde{M}_{ijt}$ gives the *total* number of foreign-born workers in skill group i who have entered

region j as of time t, and N_{ijt} gives the number of native workers in that cell. The variable p_{ijt} thus

measures the foreign-born share of the workforce in a particular labor market at a particular point

in time.

I begin the empirical analysis by describing how the immigrant supply shock affected

different labor markets in the past few decades. As indicated earlier, most of the immigrants in

the past 40 years have clustered in a relatively small number of states. Figure 1 shows the trends

in the immigrant share, by educational attainment, for three groups of states: California, the other

main immigrant-receiving states (Florida, Illinois, New Jersey, New York, and Texas), and the

rest of the country. Not surprisingly, the largest immigrant supply shock occurred in California

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experience that are valued by an American employer. Borjas (2003) finds that correcting for this problem does not
greatly affect the measured factor price elasticity.

for the least-educated workers. By 2000, almost 80 percent of high-school dropouts in California were foreign-born, as compared to only 50 percent in the other immigrant-receiving states, and 20 percent in the rest of the country. Although the scale of the immigrant supply shock is smaller for high-skill groups, there is still a large disparity in the size of the shock across the three "regions". In 2000, for example, a quarter of college graduates in California were foreign-born, as compared to 18 percent in the other immigrant-receiving states, and 8 percent in the rest of the country.

Figures 2 and 3 continue the descriptive analysis by showing the trends in the immigrant share for the specific schooling-experience groups used in my analysis. To conserve space, I only illustrate these profiles for the two education groups most affected by immigration: high school dropouts (Figure 2) and college graduates (Figure 3).

These figures show that there is significant dispersion in the immigrant supply shock over time and across experience groups, even within the same education group and within the same part of the country. In 1980, the immigration of high school dropouts in California was particularly likely to affect the labor market opportunities faced by workers with around 15 years of experience, where around half of the relevant population was foreign-born. In contrast, only 30 percent of the workers with more than 30 years of experience were foreign born. By 2000, however, over 80 percent of all high school dropouts with 10 to 35 years of experience were foreign-born. These patterns differed in other parts of the country. In the relatively non-immigrant rest of the country, for example, immigration of high school dropouts was relatively rare prior to 1990, accounting for less than 5 percent of the workers in the relevant labor market. By 2000, however, immigrants made up more than 30 percent of the high school dropouts with 5 to 15 years of experience.

The data summarized in these figures, therefore, suggest that there has been a great deal of dispersion in how immigration affects the various skill groups in particular regional labor markets. In some years, it affects workers in certain parts of the region-education-experience spectrum. In other years, it affects other workers. This paper exploits this variation to measure how wages and native worker migration decisions respond to immigration.

Before proceeding to a formal analysis, it is instructive to document that there are equally strong differences in the way that natives have chosen to sort themselves geographically across the United States. More important, these location choices seem to be correlated with the immigrant supply shocks. Figure 4 illustrates the aggregate trend. As is well known (Borjas, Freeman, and Katz, 1997), the share of the native population that has chosen to live in California stopped growing around 1970, at the same time that the immigrant supply shock began. This important trend is illustrated in the top panel of Figure 4. The data clearly show the relative numbers of native workers living in California first stalling, and eventually declining, as the scale of the immigrant supply shock increased rapidly.[19]

The middle panel of Figure 4 illustrates a roughly similar trend for the other immigrant states. As immigration increased in these states (the immigrant share rose from about 8 percent in 1970 to 22 percent in 2000), the fraction of natives who chose to live in those states declined, from 26 to 24.5 percent.

Finally, the bottom panel of the figure illustrates the trend in the relatively non-immigrant areas that form the rest of the country. Although immigration also increased over time in this region, the increase has been relatively small (the immigrant share rose from 2.5 percent in 1970 to 7.5 percent in 2000). At the same time, the share of natives living in this region experienced

an upward drift, from 64.5 percent in 1970 to 66.5 percent in 2000. Overall, therefore, the

evidence summarized in Figure 4 suggests a link between native location decisions and the

immigrant supply shock.

This link is also evident at more disaggregated levels of geography and skills. I used all

of the Census data available between 1960 and 2000 to calculate for each schooling-experience-

region group the growth rate of the native workforce during each decade (defined as the log of

the ratio of the native workforce at the decade's two endpoints) and the decadal change in the

immigrant share. The top panel of Figure 5 presents the scatter diagram relating these decadal

changes at the state level after removing decade effects. The plot clearly suggests a negative

relation between the growth rate of a particular class of native workers in a particular state and

immigration. The bottom panel of the figure illustrates the same pattern when the decadal

changes are calculated at the metropolitan area level. In sum, the raw data clearly reveal that the

native population grew fastest in those labor markets that were least affected by immigration.

Finally, Table 1 provides an alternative way of looking at the data that seems to also link

native migration decisions and immigrant supply shocks. Beginning in 1970, the Census contains

information not only on the person's state of residence as of the Census date, but also on the state

of residence five years prior to the Census. These data can be used to construct net-migration

rates for each of the skill groups in each geographic market, as well as in-migration and out-

migration rates. (The construction of these rates will be described in detail later in the paper). To

easily summarize the basic trends linking migration rates and immigrant supply shocks, I again

break up the United States into three regions: California, the other immigrant-receiving states,

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[19] Obviously, other factors also account for California's demographic trends during the last twenty years, such as the impact of the defense cutbacks of the late 1980s and the high-tech boom of the late 1990s.

and the rest of the country. A native worker is then defined to be an internal migrant if he moves across these three regions in the five-year period prior to the Census.[20]

The differential trends in the net-migration rate across the three regions are revealing. Within each education group, there is usually a steep decline in the net migration rate into California, a slower decline in the net migration rate into the other immigrant states, and a slight rise in the net migration rate into the rest of the country. In other words, the net migration of natives fell most in those parts of the country most heavily hit by immigration.

The other panels of Table 1 show that the relative decline in net migration rates in the immigrant-targeted states arises both because of a relative decline in the in-migration rate and a relative increase in the out-migration rate. For example, the in-migration rate of native high school dropouts into California fell from 7.6 to 4.0 percent between 1970 and 2000, as compared to a respective increase from 1.8 to 2.5 percent in the rest of the country. Similarly, the out-migration rates of high school dropouts rose from 7.8 to 9.5 percent in California and from 3.6 to 5.6 percent in the other immigrant states, but fell from 1.8 to 1.6 percent in those states least hit by immigration.

IV. Immigration and the Wage of Native Workers

In earlier work (Borjas, 2003), I showed that the labor market impact of immigration at the national level can be estimated by examining the wage evolution of skill groups defined in terms of educational attainment and experience. This section of the paper re-estimates some of

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[20] The same qualitative trends would be evident if the migration rates are defined in terms of interstate migration, and these interstate migration rates are aggregated upward to each of the three regions that I have defined.

the models presented in my earlier paper, and documents the sensitivity of the wage impact of immigration to the geographic definition of the labor market.

I measure the wage impact of immigration using four alternative definitions for the geographic area covered by the labor market. In particular, I assume that the labor market facing a particular skill group is: (1) a closed national labor market, so that the wage impact of immigration estimated at this level of geography measures the factor price elasticity η in the theoretical model; (2) a labor market defined by the geographic boundaries of the nine Census divisions; (3) a labor market that operates at the state level; or (4) a labor market bounded by the metropolitan area.[21]

Let $\log w_{ijt}$ denote the mean log weekly wage of *native* men who have skills i, work in region j, and are observed at time t.[22] I stack these data across skill groups, geographic areas, and Census cross-sections and estimate the model:

$$(14) \qquad \log w_{ijt} = \theta_W p_{ijt} + s_i + r_j + \pi_t + (s_i \times r_j) + (s_i \times \pi_t) + (r_j \times \pi_t) + \varphi_{ijt},$$

where s_i is a vector of fixed effects indicating the group's skill level; r_j is a vector of fixed effects indicating the geographic area of residence; and π_t is a vector of fixed effects indicating the time period of the observation. The linear fixed effects in equation (14) control for differences in labor market outcomes across skill groups, regions, and over time. The interactions $(s_i \times \pi_t)$ and $(s_j \times$

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[21] The metropolitan area is defined in a roughly consistent manner across Censuses beginning in 1980. The analysis conducted at the metropolitan area level, therefore, uses only the 1980-2000 cross-sections and deletes all observations of persons residing outside the identifiable metropolitan areas.

[22] The mean log weekly wage for each cell is calculated in the sample of men who do not reside in group quarters, are not enrolled in school, participate in the civilian labor force (according to the information provided by the labor force status variable for the reference week), and provide a positive value for annual earnings, weeks worked, and usual hours worked in the calendar year prior to the Census.

π_t) control for secular changes in the returns to skills and in the regional wage structure during the 1960-2000 period. Finally, the inclusion of the interactions ($s_i \times r_j$) implies that the coefficient θ_W is being identified from within skill-region changes in wages and the immigrant supply shock.

Note that the various vectors of fixed effects included in (14) correspond to the vectors of fixed effects implied by the estimable equation derived from the theoretical model [equation (12)]. The only exception is that (14) also includes interactions between region and Census year. These interactions would clearly enter the theoretical model if I had allowed for demand shocks to differentially affect regions over time.

The regression coefficients reported in this section come from both weighted and unweighted regressions, where the weight is the sample size used to calculate the mean log weekly wage in the (i, j, t) cell. The standard errors are clustered by skill-region cells to adjust for the possible serial correlation that may exist within cells.

Finally, the specification I use in the empirical analysis uses the immigrant share, p, rather than the relative number of immigrants as of time t, $\tilde{m} = \tilde{M} / N$, as the measure of the supply shock. It turns out that the relation between the various dependent variables, including the mean log weekly wage, and the relative number of immigrants is highly nonlinear, and is not captured correctly by simply including a linear term in $\tilde{m}$. It is easy to show that the immigrant share approximates $\log \tilde{m}$, so that using the immigrant share introduces some of the required non-linearity into the regression model. In fact, the wage effects (appropriately interpreted) are very similar when including either $\log \tilde{m}$ or a second- or third-order polynomial in $\tilde{m}$ as the measure of the immigrant supply shock.

The first row of Table 2 presents the basic estimates of the adjustment coefficient θ_W estimated at the national level.[23] The coefficient is -0.532, with a standard error of 0.202. It is easier to interpret this coefficient by converting it to an elasticity that gives the percent change in wages associated with a percent change in labor supply. In particular, define the wage elasticity as:

$$(15) \qquad \frac{\partial \log w}{\partial \tilde{m}} = \theta_W (1-p)^2 .$$

By 2000, the immigrant share for working men was 14.7 percent. Equation (15) implies that the wage elasticity—evaluated at the mean value of the relative number of immigrants—can be obtained by multiplying θ by approximately 0.7. The wage elasticity for weekly earnings is then -0.37 (or -0.532×0.7). Put differently, a 10 percent immigrant supply shock (i.e., an immigrant flow that increases the number of workers in the skill group by 10 percent) reduces weekly earnings by about 4 percent.

Suppose now that the worker's state of residence defines the geographic area encompassed by the labor market. The data then consists of stacked observations on the immigrant share and the mean log weekly wage for cell (i, j, t). The first row of Panel III in Table 2 reports the estimated coefficient of the immigrant share variable when equation (14) is estimated at the state level. The adjustment coefficient is -0.214, with a standard error of .033. At

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[23] At the national level regression, the regression specification differs slightly from the generic model in equation (14). In particular, the regression equation includes the immigrant supply shock, fixed effects indicating the skill group, and fixed effects indicating the time period. Because it is impossible to introduce interactions between the skill group and the time period, I instead introduce all two-way interactions between the following three vectors: fixed effects indicating the group's educational attainment, fixed effects indicating the group's labor market experience, and fixed effects indicating the time period.

the mean relative number of immigrants, the state-level regression implies that a 10 percent increase in supply due to immigration reduces the native wage by only 1.5 percent, roughly 40 percent of the estimated impact at the national level. Note that the derivative in equation (15) is precisely the wage impact of immigration captured by the region-specific immigrant supply shock in equation (12). In terms of the parameters of the theoretical model, this derivative estimates the product of elasticities $\eta(1 + \sigma\eta)$.

As discussed earlier, the theoretical model suggests that the log wage regression—when estimated at the "local" labor market level—should include a variable that approximately measures the lagged relative number of natives who would have migrated in the absence of immigration. The second row of the panel adds a variable measuring the log of the number of native workers 10 years prior to the Census date.[24] The inclusion of lagged employment does not alter the quantitative nature of the evidence. The adjustment coefficient is -0.217 (0.033). Finally, the third row of the panel introduces an alternative variable to control for the counterfactual native migration flow, namely the rate of growth in the size of the native workforce in the 10 year period prior to the Census date. Again, the estimated wage effects are roughly similar.

The remaining panels in Table 2 document the behavior of the adjustment coefficient as the geographic boundary of the labor market is either expanded (to the Census division level) or narrowed (to the metropolitan area level). The key result implied by the comparison of the various panels is that the adjustment coefficient grows larger as the size of the labor market expands. Using the simplest specification in row 1 in each of the panels, for example, the adjustment coefficient is -0.036 (0.025) at the metropolitan area level; increases to -0.214 (0.033)

at the state level; increases further to -0.268 (0.053) at the division level; and converges to -0.532 (0.202) at the national level.

The theoretical model presented earlier suggests one interesting interpretation for this negative correlation between the geographic size of the labor market and the adjustment coefficient θ_W. As the geographic region becomes smaller, there is more spatial arbitrage—due to interregional flows of labor—that tends to equalize opportunities for workers of given skills across regions.

An alternative explanation for the pattern is that the smaller wage effects measured in smaller geographic units may be due to attenuation bias. The variable measuring the immigrant supply shock will likely contain more measurement errors when it is calculated at more disaggregated levels of geography. As I will show in the next section, however, it is unlikely that attenuation bias can explain the important differences among the various adjustment coefficients.

Overall, the weight of the evidence seems to indicate that even though immigration has a sizable adverse effect on the wage of competing workers at the national level, the analysis of wage differentials across regional labor markets conceals much of the impact. The remainder of this paper examines if these disparate findings can be attributed to native internal migration decisions.

V. Immigration and Native Internal Migration

I now estimate a variety of models—closely linked to the theoretical discussion in Section II—that investigate if the evolution in the size of the native workforce or the internal

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[24] I used the 1950 Census to calculate the lagged workforce variable pertaining to the (i, j, t) cells drawn form the 1960 cross-section.

migration behavior of natives can be linked to immigrant supply shocks in the respective labor markets.

The Size of the Native Workforce

I estimate the following regression model:

(16) $$\log N_{ijt} = X_{ijt}\beta + \theta_N p_{ijt} + s_i + r_j + \pi_t + (s_i \times \pi_t) + (r_j \times \pi_t) + (s_i \times r_j) + \varepsilon_{ijt},$$

where X is a vector of control variables discussed below. As with the wage regression, the various vectors of fixed effects absorb any region-specific, skill-specific, and time-specific factors that affect the evolution of the workforce in a particular labor market. Similarly, the interactions allow for decade-specific changes in the number of workers in particular skill groups or in particular states caused by shifts in aggregate demand. Finally, the interaction between the skill and region fixed effects implies that the coefficient of the immigrant supply shock is being identified from changes that occur within a specific labor market. As before, all standard errors are adjusted for any clustering that may occur at the skill-region level.[25]

I estimate the model using three alternative definitions for the geographic area encompassed by the labor market: a Census division, a state, and a metropolitan area. Table 3 presents alternative sets of regression specifications that show how the immigrant supply shock affects the evolution of the size of the native workforce under the three definitions.

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[25] The regressions presented in this section are not weighted by the size of the sample in a particular skill-region-time cell, as the weight is proportionately identical to the dependent variable in some of the cross-sections, and differs only slightly in others (due to the presence of sampling weights in the 1990 and 2000 Censuses).

Consider initially the regressions estimated at the state level, reported in the middle panel of the table. Specification (1) does not include any variables in the vector X. The estimated coefficient for the immigrant share variable is -0.376, with a standard error of 0.093. This simple regression model, therefore, confirms that there is a numerically important and statistically significant negative relation between immigration and the rate of growth of the native workforce at the state level. The coefficient is easier to interpret numerically by calculating the derivative $\partial N / \partial \tilde{M}$, which gives the change in the size of the native workforce when one more immigrant enters the labor market. It is easy to show that the derivative of interest is:

$$(17) \qquad \frac{\partial N}{\partial \tilde{M}} = \theta_N (1-p)^2.$$

As before, the derivative in equation (17) can be evaluated at the mean value of the immigrant share by multiplying the regression coefficient θ_N by around 0.7. The simplest specification reported in Panel II of Table 3 implies that 2.6 fewer native workers chose to live in a particular state for every 10 additional immigrants that enter that state. In terms of the theoretical model, equation (11) implies that the derivative reported in (17) estimates the product of elasticities $\eta\sigma$.

The remaining rows of the middle panel of Table 3 estimate more general specifications of the regression model. As noted earlier, I adjust for pre-existing migration flows by including either the lagged log of the number of native workers or the lagged rate of growth in the size of the native workforce. [26] In the most general specification, I also include variables measuring the

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[26] To avoid re-introducing the dependent variable on the right-hand-side, the regressions presented in this section use the lagged growth rate of the native workforce 10 to 20 years prior to the Census date. For example, the lagged growth rate for the observation referring to high school graduates in Iowa in 1980 would be the growth rate

mean log weekly wage in the labor market and the unemployment rate.[27] These additional

variables further control for factors that motivate income-maximizing native workers to move

from one labor market to another.

Specifications (2) and (3) reported in the middle panel of Table 3 yield very similar

results, so the evidence is not sensitive to which variable is chosen to proxy for the lagged size of

native net migration in the absence of immigration. Not surprisingly, lagged measures of the size

of the native workforce or its growth rate have a positive impact on the current number of native

workers. Similarly, the mean log wage has a positive (sometimes insignificant coefficient), while

the unemployment rate has a negative (and sometimes insignificant coefficient). The coefficient

of the immigrant share variable falls to around −0.27 in the most general specification.[28] This

estimate implies that around 2 fewer native workers choose to reside in a particular state for

every additional 10 immigrants who enter that state.

The other panels of Table 3 re-estimate the regression models at the division and

metropolitan area levels. The estimated impact of the immigrant supply shock typically has the

wrong sign at the division level, but with large standard errors. In contrast, the adjustment

coefficient is very negative (and significant) at the metropolitan area level. The obvious

conclusion that can be drawn by comparing the three panels of the table is that the negative

impact of the immigrant supply shock gets numerically stronger the smaller the geographic

region that defines the labor market. In the general specification reported in row 2, for example,

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in the number of high school graduates in Iowa between 1960 and 1970. This definition of the lagged growth rate implies that the regression models using this specification do not include any cells drawn from the 1960 Census.

[27] The mean log weekly wage and unemployment rate for each cell are calculated from the data available in each Census cross-section.

[28] The coefficient would be virtually identical if both the lagged level and growth rate of the native workforce were included in the most general specification.

the estimated coefficient of the immigrant share variable is 0.058 (0.121) at the Census division level; -0.278 (.081) at the state level; and -0.836 (0.090) at the metropolitan area level.[29] The large size of the coefficient of the metropolitan area regression implies that 5.9 fewer native workers choose to reside in a particular metropolitan area for every 10 additional immigrants who enter that area.

It is worth noting that the geographic variation in the measured spatial correlation between the size of the native workforce and immigration is an exact mirror image of the geographic variation in the spatial correlation between wages and immigration reported in Table 2. As implied by the model, the wage effects are larger when the impact of immigration on the growth of the native workforce is weakest (at the Census division level); and the wage effects are smallest when the impact of immigration on the size of the native workforce is largest (at the metropolitan area level).

It would seem as if this mirror-image variation is not consistent with an attenuation hypothesis: more measurement error for data estimated at smaller geographic units would lead to smaller coefficient estimates at the metropolitan area level in both Tables 2 and 3. However, there is one possible source of measurement error that could potentially explain the mirror-image pattern. In particular, note that the adjustment coefficient θ_N estimated by equation (16) could suffer from division bias. The dependent variable appears (in transformed form) as part of the denominator in the immigrant share variable. If the size of the native workforce were measured with error, the division bias would lead to downward biased estimates of the adjustment coefficient. One could argue that such measurement error would be more severe at the metropolitan area level than in larger geographic regions.

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[29] The metropolitan area regressions cannot be estimated with the lagged growth rate because that would

I will show in the next section, however, that division bias does not play an important role in generating the mirror-image pattern of coefficients in Tables 2 and 3. Instead, the mirror-image pattern revealed by the two tables provides some support for the hypothesis that there is indeed a behavioral response by the native population that is contaminating the measured impact of immigration on local labor markets.

Migration Rates

Since 1970 the U.S. Census contains detailed information on the person's state of residence five years prior to the Census, and since 1980 there is similar information for the metropolitan area of residence. These data, combined with the information on geographic location at the time of the Census, can be used to compute in-, out-, and net-migration rates for the various skill-region-time cells. In this subsection, I examine how these native migration rates respond to the immigrant influx. Therefore, the results presented in this section, which examine the flows of *actual* native movers, can be interpreted as providing independent confirmation of the findings presented earlier that link the evolution of the native workforce to the immigrant supply shock.

To illustrate the calculation of the net migration rate, consider the data available at the state level in a particular Census. The worker is an out-migrant from the "original" state of residence (i.e., the state of residence five years prior to the Census) if he lives in a different state by the time of the Census. The worker is an in-migrant into the current state of residence if he lived in a different state five years prior to the Census. I define the in-migration and out-migration rates by dividing the total number of in-migrants or out-migrants in a particular skill-

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then leave only one cross-section with sufficient data to estimate the model.

state-time cell by the relevant workforce in the baseline state.[30] The net migration rate is then

defined as the difference between the in-migration and the out-migration rate. To make the

results in this section comparable to those reported in Table 3, I multiply the various migration

rates by two—this adjustment converts the various rates into decadal changes (which was the

unit of change implicitly used in the native workforce regressions).

I concluded the presentation of the theoretical model in Section II by deriving estimable

equations that relate the size of the native workforce and the native wage to the immigrant supply

shock. In this section, I use a variation of the model with a different dependent variable.

Equation (7) gives the theoretical expression for the net migration rate for cell (i, j, t). By using

the Taylor's approximation that $(1 + x)^t \approx 1 + xt$, the equation determining the net-migration rate,

v_{ijt}, can be written in estimable form as:

(18) $\qquad v_{ijt} = \eta\sigma\,\lambda_{ij} + (\eta\sigma)^2\,(t\,\lambda_{ij}) - \eta\sigma\,\tilde{m}_{it} + \eta\sigma\,\tilde{m}_{ij}$.

A regression of the net migration rate on various vectors of fixed effects, variables proxying for

lagged native net migration in the absence of immigration, and the region-specific immigrant

supply shock estimates the product of elasticities $\eta\sigma$.

As before, the regression model that I actually use to analyze how migration rates

respond to the immigrant supply shock is:

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[30] The baseline state is the original state of residence when calculating out-migration rates and the current state of residence when calculating in-migration rates. Let N_a be the number of native workers in the baseline state (in a particular skill group) five years prior to the Census, and let N_b be the number of workers in the same state at the time of the Census. The denominator of the in- and out-migration rates is then given by $(N_a + N_b)/2$.

$$(19) \qquad y_{ijt} = X_{ijt}\beta + \theta_N p_{ijt} + s_i + r_j + \pi_t + (s_i \times \pi_t) + (r_j \times \pi_t) + (s_i \times r_j) + \varepsilon_{ijt},$$

where y_{ijt} represents the net-migration, in-migration, or out-migration rate for cell (i, j, t).

Table 4 summarizes the evidence. To conserve space, I only report the general specification that includes all of the variables in the vector X. Consider initially the regression results reported in Panel II, where the dependent variable is the net migration rate estimated at the state level. Since the dependent variable in this regression model already approximates a *change* in the native population, I use the lagged native employment growth rate as a preferred way of controlling for pre-existing conditions.[31] The estimated coefficient of the immigrant supply shock in the net migration rate regression is -0.282, with a standard error of .064. This coefficient is more easily interpretable by multiplying it by 0.7, indicating that around 2 fewer native workers (on net) move to a particular state for every 10 immigrants who enter that state. The estimated product of elasticities $\eta\sigma$ is very similar to the corresponding estimate reported in Table 3, when the dependent variable was the log of the size of the native workforce.

Rows 3 and 4 of the middle panel show that the effect of immigration on net migration rates arises both because immigration induces fewer natives to migrate into the immigrant-penetrated labor markets, and because immigration induces more natives to migrate out of those markets. The coefficient of the immigrant supply shock in the in-migration regression is -0.150 (.042), while the respective coefficient in the out-migration regression is 0.132 (.049). In rough terms, each additional 10 immigrants in a state induces 1 fewer native worker to migrate there and induces 1 native worker already living there to move out.

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[31] In Table 4, the lagged employment growth rate is given by the log change in the size of the native workforce in a particular skill group in a particular geographic area in the 5-year period prior to the Census midpoint.

The top and bottom panels of Table 4 reconfirm the result that the negative impact of immigration on native migration is larger as the geographic area that encompasses the labor market becomes smaller. The estimated coefficient of the immigrant share variable on the net migration rate is -0.076 (0.046) at the division level; -0.282 (0.064) at the state level; and -0.404 (0.084) at the metropolitan area level.[32] The evidence, therefore, again suggests that natives find it much easier to respond to immigration by voting with their feet when the geographic area is relatively small, and that this response is attributable to both fewer in-migrants and more out-migrants.

Moreover, this mirror image trend (relative to the respective trend in the spatial correlations between wages and immigration) *cannot* be attributed to measurement error or division bias. In particular, any division bias that would be present in the regressions reported in Table 4 would tend to make the coefficients of the immigrant share variable more *positive*. After all, both the dependent variable (the net migration rate) and the independent variable (the immigrant share) have a measure of the native workforce as of Census year t in the denominator. If the size of the native workforce is measured with error, the resulting bias would induce a positive bias in the adjustment coefficient θ_N. It seems plausible to argue that this bias would be most severe at the metropolitan area level—where the adjustment coefficient (although not as negative as the respective coefficient in Table 3) is still negative and numerically large. In short, the mirror-image pattern in the spatial correlations that is evident when comparing Tables 2 and 4, cannot be attributed to measurement error. It is the result of a systematic behavioral response

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[32] The inclusion of the lagged native workforce variable in the metropolitan area regressions implies that the regressions can only include the 1990 and 2000 cross-sections, as the 1970 Census does not contain the required information.

by native workers that help to attenuate the wage impact of immigration on geographically smaller labor markets.

Sensitivity of the Results

It is worth examining if the evidence summarized in Tables 3 and 4 is sensitive to significant changes in model specification. Table 5 summarizes some of the sensitivity experiments that I conducted on the various regression models. To conserve space, the table only reports the adjustment coefficients estimated at the state level of aggregation and using the most general specification that includes all of the control variables in the vector X. For convenience, the top row of the table replicates the "baseline" results obtained from the most general specification.

As I showed earlier, the state of California plays a central role in the resurgence of large-scale immigration in the past few decades. California has atypical labor market characteristics; it is a very large state with high in-migration rates, a high-skill workforce, and a huge immigrant supply shock. These characteristics may contaminate many of the results presented above. It is important, therefore, to determine if the sign or magnitude of the estimated coefficients are driven by the outlying observations that describe the outcomes of specific skill groups in California. The second row of Table 5 re-estimates the regression models in the sample of skill-state-time cells that do not include any of the California observations. The estimated coefficients when the dependent variable is the log of the native workforce or the net migration rate are slightly more negative than in the baseline specification, hovering around -0.3.

The third row of the table re-estimates the model using cells that do not include workers who are high school dropouts. As I showed earlier, some of the largest immigrant supply shocks

observed over the past few decades occurred in this group of low-skill workers, and these outlying observations may be driving some of the estimation results. It turns out, however, that the coefficient of the immigrant share variable in the native workforce regression becomes even *more* negative (-0.82, with a standard error of 0.18) when the high school dropouts are dropped from the sample, but the respective coefficient in the net migration regression is stable at around -0.28.

Up to this point, the analysis has concentrated on analyzing the behavioral responses of native men to the immigrant supply shock. I have excluded women from the analysis because of the inherent difficult in correctly measuring their labor market experience and because of the possibility that many women may be tied movers or tied stayers. Row 4 of Table 5 includes women in the right-hand-side of the equation, by calculating the immigrant share in the total population of workers. The results are quite similar to those reported in the first row. Row 5 re-estimates the model using the log of the female native workforce or the migration rates of native women as the dependent variable.[33] Despite the measurement problems, the resulting coefficients in both sets of regressions are negative and significant. Finally, the last row of the table reports the results when I simply pool all working men and women in particular skill groups and re-estimate the various models using this pooled sample. The pooled sample results are quite similar to those first reported in the male baseline.

In sum, the sensitivity experiments summarized in Table 5 indicate that major specification changes in the regression models do not alter the qualitative nature of the results. Immigrant supply shocks are associated with lower native net migration rates, lower in-migration

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[33] The immigrant share used as the independent variable in the rows 4, 5, and 6 is calculated using the entire sample of male and female workers.

rates, higher out-migration rates, and a smaller growth rate in the size of the native workforce in particular labor markets.

Synthesis

The theoretical model presented in Section II suggests that the national wage effect of migration (i.e., the wage effect that would be observed in a closed labor market) and the spatial correlations estimated between wages and immigration across local labor markets are linked through a parameter that measure the native migration response. I now examine whether the large difference actually estimated in Section III in the wage impacts for different geographic definitions of the labor market can be "explained" by the impact of immigration on native location decisions.

Table 6 summarizes the key results of the analysis. The first row of the table reports that the wage effect at the national level was estimated to be -0.372 (or the coefficient of -0.532 in Table 2 times 0.7, as indicated by equation 15). I assume that the national labor market approximates the concept of a closed economy, so that this coefficient estimates the factor price elasticity η.[34] The model presented in Section II implies that the estimated wage effect of immigration will not equal this factor price elasticity whenever the equivalent wage regression is estimated in local labor markets where natives can respond to the immigrant supply shock by incurring the cost of internal migration. The spatial correlation will be smaller, and the gap between the spatial correlation and the true factor price elasticity reflects the native migration effect.

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[34] Put differently, I assume that the supply elasticity $\sigma = 0$ at the national level.

Row 2 of Table 6 summarizes the estimated migration effects reported earlier (again multiplied by 0.7, as indicated by equation 17). The row, therefore, reports the value of the derivative $\gamma_N = \partial N / \partial \tilde{M}$. These migration responses allow me to predict what the spatial correlations should be by using the multiplicative property of the model summarized in equation (10). In particular, let $\gamma_W = \partial \log w / \partial \tilde{m}$, the wage effect of immigration at a particular geographic level. The theory then predicts that the spatial correlation between wages and immigration at that level, $\hat{\gamma}_W$, will be:

$$(20) \qquad \hat{\gamma}_W = \eta(1 + \gamma_N).$$

Row 3 of Table 6 uses this equation to predict the spatial correlations that should be observed if the *only* adjustment mechanism contaminating the estimation procedure was the internal migration flow of native workers. If I use the coefficient estimated in the simplest specification of the size-of-workforce regression, the observed migration response at the state level implies that the estimated wage effect of immigration declines from the -0.37 observed at the national level to around -0.27, roughly a cut of one-quarter in the estimated wage effect. At the metropolitan area level, the migration response is quite large, implying that the spatial correlation between wages and immigration measurable at the metropolitan area level should be at most -0.17. If I use the migration response estimated in the complete specification of the net migration regressions, the predicted spatial correlations are -0.30 and -0.27, at the state and metropolitan levels respectively.

Finally, row 4 of Table 6 reports the actual spatial correlations estimated in the data (and first reported in Table 2). At the state level, the wage impact of immigration is around -0.15. The

evidence summarized in Table 6, therefore, indicate that the internal migration response of native workers accounts for about 40 percent of the gap between the wage effects estimated at the state level and at the national level. At the metropolitan area level, the data indicate that the native internal migration response may account for as much as 60 percent of the difference.

This synthesis fails to explain the difference between the national wage effect and the spatial correlation between wages and immigration estimated at the Census division level. Much of the migration that takes place in the United States is within Census divisions. Between 1995 and 2000, for example, 11.6 percent of the working-age population migrated across metropolitan areas; 9.4 percent migrated across states; and 6.8 percent migrated across divisions. The regression coefficients reported in Tables 3 and 4 indeed indicate that the native migration response to immigrant supply shocks is negligible at the division level. Nevertheless, the evidence reported in Table 2 indicates that markets at this level of geographic aggregation do tend to re-equilibrate somewhat after an immigrant supply shock. It would be interesting to measure precisely which types of flows are most responsible for the long-run equalization of labor market conditions across Census divisions.[35]

VI. Summary

The empirical literature that attempts to estimate the labor market impact of immigration contains an important puzzle. Studies that examine how immigration alters economic opportunities across local labor markets tend to find that immigration has a negligible impact on the wage of competing native workers, while studies that examine how immigration alters

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[35] It is also possible that the endogeneity bias that arises whenever immigrants choose to cluster in high-wage localities is more severe at the Census division level than in smaller geographic units.

economic opportunities at the national level tend to find substantial wage effects. This paper

presented a theoretical and empirical analysis of one possible adjustment mechanism that can

explain the disparate findings: the internal migration decisions made by native workers.

The theoretical model presented in this paper illustrates how native migration flows

diffuse the impact of immigration across the entire economy, making it difficult to measure the

"true" wage impact of immigration by comparing conditions across local labor markets. More

importantly, the theory provides a framework that explicitly links the parameters measuring the

national wage effect of immigration, the spatial correlation estimated across local labor markets,

and the impact of immigration on native migration decisions.

The empirical analysis used data drawn from the 1960-2000 decennial Censuses. The

evidence indicates that native internal migration decisions are sensitive to immigrant supply

shocks. The native population in a particular skill group grew slowest in those parts of the

country that experienced the largest immigrant supply shocks. This native supply response is

evident both in terms of in-migration rates, with the targeted immigrant areas facing a decline in

native in-migration, and in out-migration rates, with the targeted immigrant areas facing an

increase in native out-migration. The native migration response is sizable, indicating that for

every 10 immigrants who enter a particular state two fewer natives choose to live in that state.

The response is even larger at the metropolitan area level: for every 10 immigrants who choose

to enter a particular metropolitan area between 3 and 6 natives will choose not to live in that

locality.

These migration responses are sufficiently large to explain an important part of the

disparate findings obtained in studies that estimate the wage effects of immigration at the

national and local labor market levels. At the state level, the native migration response explains

about 40 percent of the gap in wage effects. At the metropolitan area level, the migration response may explain as much as 60 percent of the gap.

Naturally, labor markets adjust in many other ways to immigrant supply shocks. Although native migration can explain a great deal of the adjustment mechanism, it is likely that flows of capital or goods are also important parts of the story. The magnitude, economic significance, and labor market consequences of these flows are yet to be determined.

Mathematical Appendix

To simplify the mathematical derivations, it is useful to start with a simpler version of the supply shock, a one time supply increase. In particular, M_{ij0} immigrants enter region j at time 0. Native migration will then occur for two reasons: a response to the initial disequilibrium, and a response to the impact of immigrants on the wage structure. It is useful to consider these two responses separately. As a result of the initial disequilibrium, equation (6) in the text shows that $v_{ij0} = \eta\sigma\,\lambda_{ij}$. By solving the model recursively, it is easy to show that $v_{ijt} = \eta\sigma\,(1 + \eta\sigma)^t\,\lambda_{ij}$.

The native response to the one-time immigrant supply shock will depend on the geographic sorting of immigrants relative to the geographic sorting of the native population. Suppose region j has (in the pre-immigration regime) a fraction q_{ij} of the native population in skill group i and receives a fraction ρ_{ij} of the immigrants in that skill group. The region-specific supply shock is then given by:

$$(A\text{-}1) \qquad m_{ij0} = \frac{M_{ij0}}{N_{ij0}} = \frac{\rho_{ij}\,M_i}{q_{ij}\,N_i} = k_{ij}\,m_i\,,$$

where $k_{ij} = \rho_{ij}\,/\,q_{ij}$, a measure of the penetration of immigrants into region j *relative* to the region's pre-immigration size (for a given skill group). Immigration is distributed neutrally if $k_{ij} = 1$.

The impact of the one-time immigrant supply on native migration can be solved recursively. In particular, the supply shock induces $\eta\sigma(k_{ij} - 1)m_i$ natives to move in period 1,

$\eta\sigma(1 + \eta\sigma)(k_{ij} - 1)m_i$ in period 2, and $\eta\sigma(1 + \eta\sigma)^t(k_{ij} - 1)m_i$ in period t. Combining both sources

of native migration flows, the native net migration rate in year t is then given by:

(A-2) $\qquad v_{ijt} = \eta\sigma(1+\eta\sigma)^t \lambda_{ij} - \eta\sigma(1+\eta\sigma)^{t-1}(1-k_{ij})m_i .$

I assume that $0 < (1 + \eta\sigma) < 1$.

      The *total* net migration rate of natives at time t is then given by:

(A-3)
$$V_{ijt} = \sum_{\tau=0}^{t} \eta\sigma(1+\eta\sigma)^\tau \lambda_{ij} - \sum_{\tau=1}^{t} \eta\sigma(1+\eta\sigma)^{\tau-1}(1-k_{ij})m_i$$
$$= [(1+\eta\sigma)^t - 1]\lambda_{ij} + [1-(1+\eta\sigma)^t](1-k_{ij})m_i .$$

      The model can now be more easily extended to the case where the immigrant supply

shock continues indefinitely. The last term of equation (A-3), call if Y_{ijt}, gives the (total) net

migration rate of natives as of time t induced by a period-0 immigrant supply shock. Consider

now what the native response would be to a similarly-sized supply shock occurring at $t = 1$. The

net migration rate of natives induced by the period-1 migration flow would be $Y_{ij,t-1}$. The total net

migration of natives in period t attributable to a supply shock of $k_{jj}m_i$ in region j between periods

0 and t-1 is then given by:

(A-4) $\quad V_{ijt}^* = [(1+\eta\sigma)^t - 1]\lambda_{ij} + \sum_{\tau=0}^{t-1} Y_{ijt} = [(1+\eta\sigma)^t - 1]\lambda_{ij} + \left[t + \frac{(1+\eta\sigma)}{\eta\sigma}[1-(1+\eta\sigma)^t] \right](1-k_{ij})m_i$

Equation (7) in the text can be obtained by differencing (A-4), while equations (8) and (9) follow

directly by substituting (A-4) in both the equation that determines the current size of the

workforce in a particular labor market and in the labor demand function.

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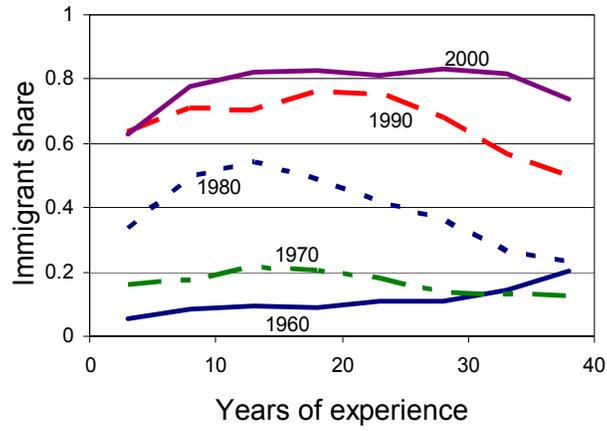
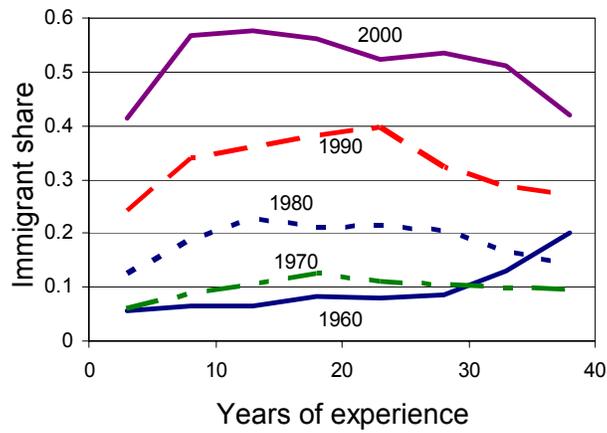**Figure 1. The Immigrant Supply Shock, By Education and Region of Country**
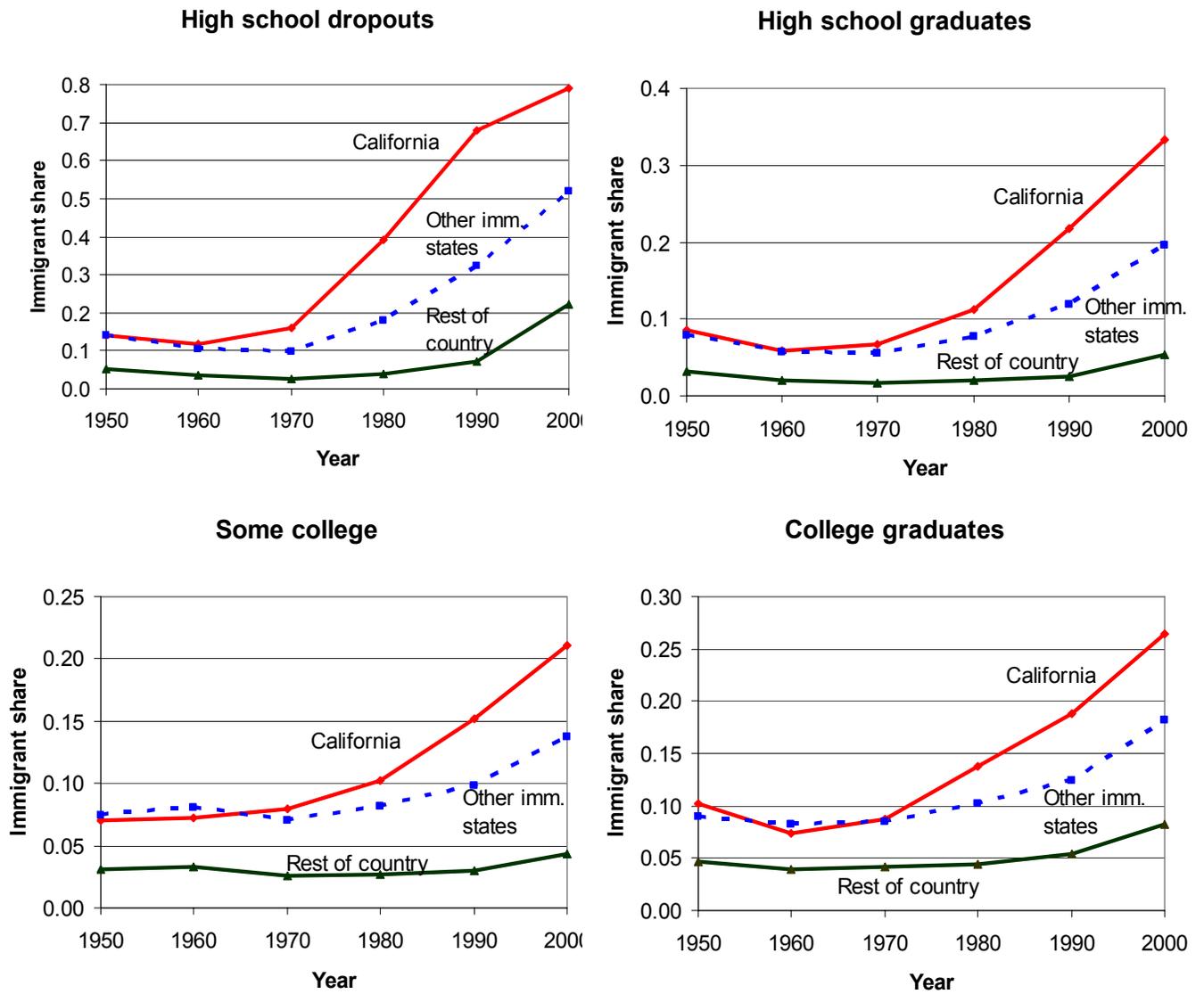
High school dropouts

High school graduates

Some college

College graduates

Note: The "other immigrant states" include Florida, Illinois, New Jersey, New York, and Texas.

Figure 2. Immigrant Supply Shock for High School Dropouts, by Experience
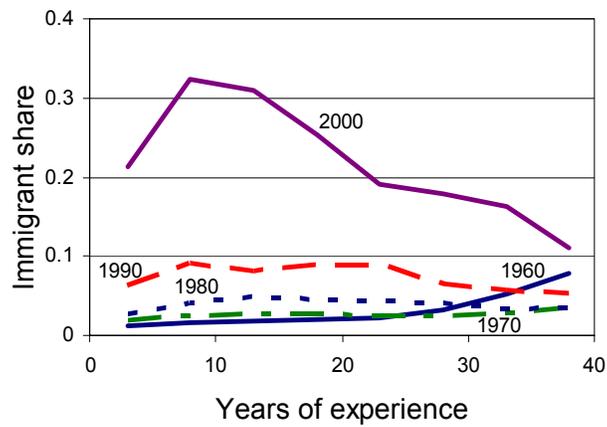
A. California

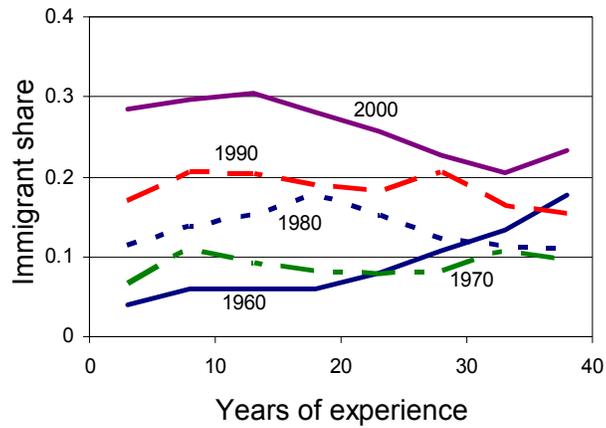**B. Other Immigrant States**
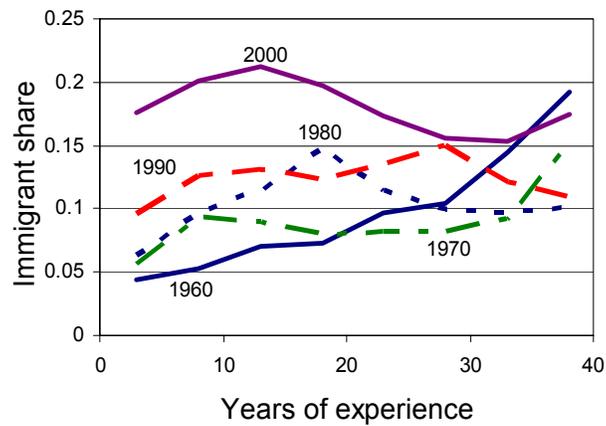

C. Rest of the Country

Note: The "other immigrant states" include Florida, Illinois, New Jersey, New York, and Texas.

Figure 3. Immigrant Supply Shock for College Graduates, By Experience

A. California

B. Other Immigrant States

C. Rest of the Country

Note: The "other immigrant states" include Florida, Illinois, New Jersey, New York, and Texas.

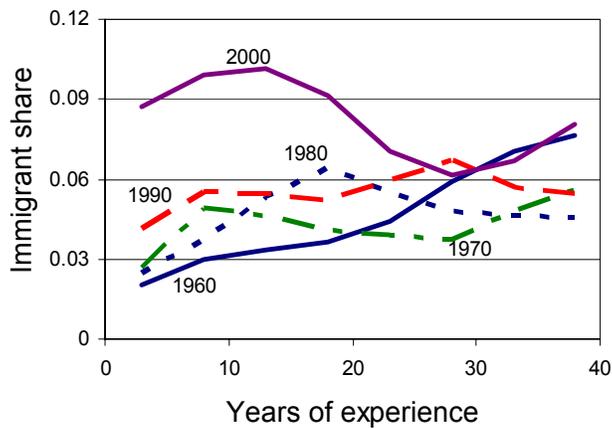# Figure 4. Geographic Sorting of Native Population and Immigration

A. California
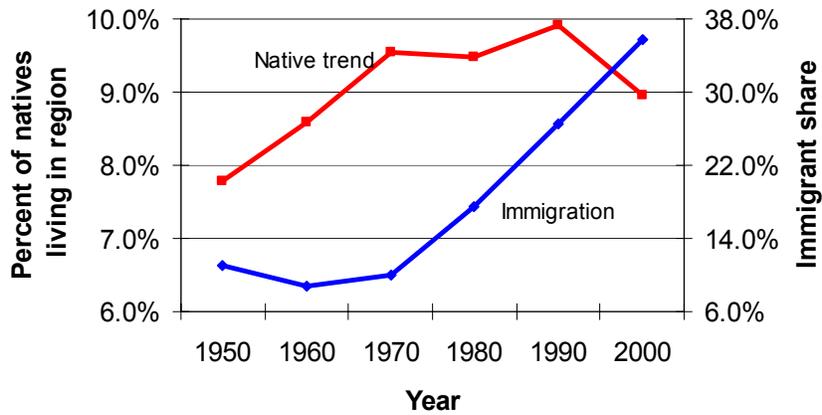
B. Other Immigrant States
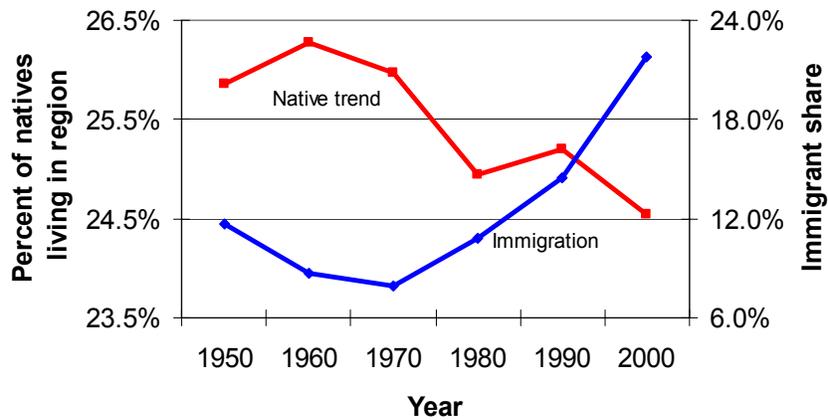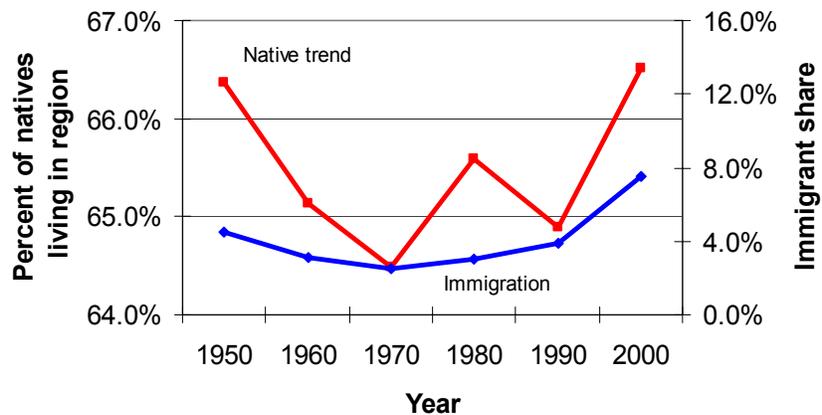
C. Rest of the Country

Note: The "other immigrant states" include Florida, Illinois, New Jersey, New York, and Texas.

**Figure 5. Scatter Diagram Relating the Growth Rate
of the Native Workforce and Immigration**

A. State Level Data
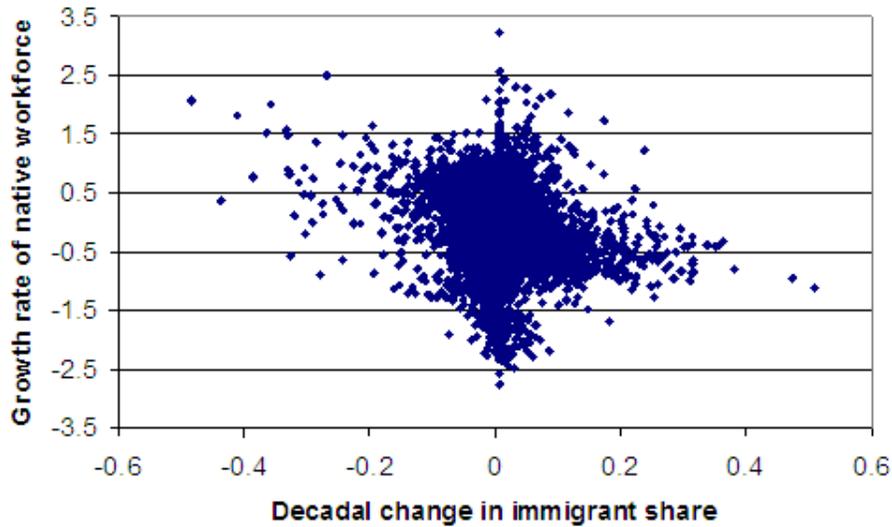
B. Metropolitan area level data
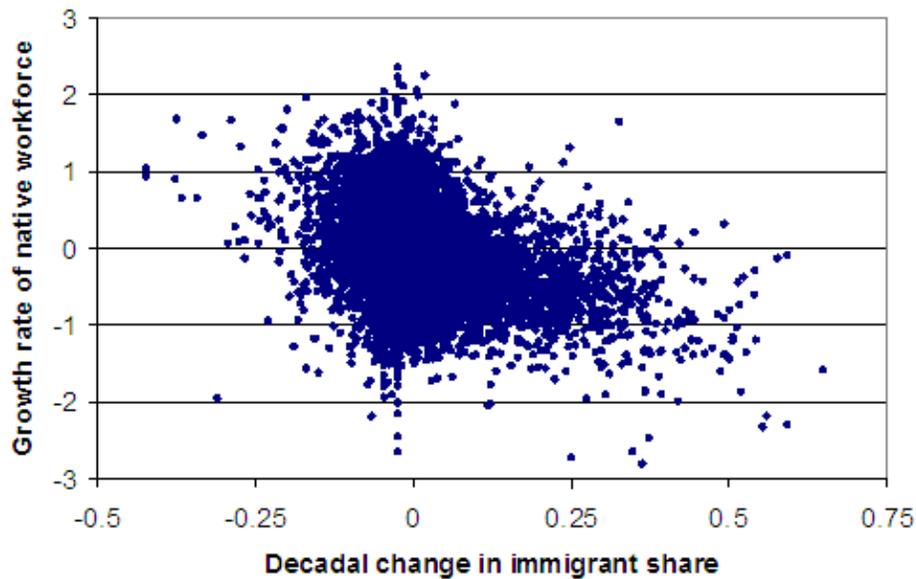
Notes: Each data point represents the decadal change (between 1960 and 2000) observed in the log size of the native workforce and the change in the immigrant share for a particular skill group in a particular geographic area. Both plots remove decade effects from the data.

Table 1. Trends in inter-region migration rates of native workers

		Year			
Education group	Region	1970	1980	1990	2000
Net migration rates					
High school dropouts	California	-0.2%	-2.2%	-2.3%	-5.4%
	Other immigrant states	0.3	-0.2	-1.6	-1.4
	Rest of country	-0.1	0.3	0.8	1.0
High school graduates	California	0.3	-1.4	-0.8	-4.5
	Other immigrant states	0.0	-0.1	-0.8	-0.9
	Rest of country	0.0	0.2	0.4	0.7
Some college	California	1.3	-1.0	0.3	-3.4
	Other immigrant states	-0.4	-0.3	-0.9	-0.8
	Rest of country	-0.2	0.4	0.3	0.9
College graduates	California	4.4	3.3	4.5	1.9
	Other immigrant states	0.3	-0.3	-0.8	-0.4
	Rest of country	-1.0	-0.4	-0.5	-0.1
In-migration rates					
High school dropouts	California	7.6	6.9	6.2	4.0
	Other immigrant states	3.8	4.7	4.5	4.2
	Rest of country	1.8	2.3	2.6	2.5
High school graduates	California	8.7	8.3	7.7	4.9
	Other immigrant states	5.4	6.0	5.2	4.6
	Rest of country	2.7	2.8	2.6	2.5
Some college	California	8.6	8.8	7.9	5.3
	Other immigrant states	7.0	8.1	6.8	6.2
	Rest of country	4.4	4.8	4.0	3.6
College graduates	California	14.3	14.1	13.0	11.1
	Other immigrant states	11.9	11.9	10.0	9.4
	Rest of country	6.2	6.3	5.4	4.8
Out-migration rates					
High school dropouts	California	7.8	9.1	8.5	9.5
	Other immigrant states	3.6	4.9	6.1	5.6
	Rest of country	1.8	2.0	1.9	1.6
High school graduates	California	8.3	9.7	8.5	9.5
	Other immigrant states	5.4	6.1	6.0	5.5
	Rest of country	2.7	2.6	2.3	1.7
Some college	California	7.3	9.8	7.5	8.7
	Other immigrant states	7.4	8.4	7.7	7.0
	Rest of country	4.6	4.4	3.7	2.8
College graduates	California	9.9	10.8	8.4	9.2
	Other immigrant states	11.7	12.1	10.8	9.8
	Rest of country	7.2	6.7	5.9	4.9

Notes: This table breaks up the country into three distinct regions, California, the other immigrant states, and the rest of the country. The "other immigrant states" include Florida, Illinois, New Jersey, New York, and Texas.
A native worker is defined to migrate if he moves from one of these regions to another in the five-year period prior to the Census.

**Table 2. Impact of immigration on log weekly earnings,
by geographic definition of the labor market**

Regression model:	Weighted specification			Unweighted specification		
	Immigrant share	Lagged native employment	Lagged native employment growth	Immigrant share	Lagged native employment	Lagged native employment growth
I. National						
(1)	-.532	---	---	-.608	---	---
	(.202)			(.199)		
II. Census division						
(1)	-.268	---	---	-.281	---	---
	(.053)			(.051)		
(2)	-.267	-.043	---	-.283	-.019	---
	(.053)	(.019)		(.052)	(.018)	
(3)	-.264	---	.048	-.284	---	.040
	(.053)		(.014)	(.015)		(.013)
III. State						
(1)	-.214	---	---	-.099	---	---
	(.033)			(.049)		
(2)	-.217	-.027	---	-.106	-.005	
	(.033)	(.007)		(.046)	(.009)	
(3)	-.212	---	.033	-.103	---	.009
	(.033)		(.005)	(.046)		(.008)
IV. Metropolitan area						
(1)	-.036	---	---	-.012	---	---
	(.025)			(.041)		
(2)	.032	-.016	---	.009	.001	---
	(.048)	(.012)		(.068)	(.016)	
(3)	.057	---	.030	.017	---	.006
	(.047)		(.008)	(.067)		(.010)

Notes: Standard errors are reported in parentheses and are clustered by the region-skill group level. The regressions estimated at the national level have 160 observations; the regressions estimated at the region level have 1,440 observations; the regressions estimated at the state level have 8,154 observations; and the regressions estimated at the metropolitan area level have 25,150 observations (14,848 observations when lagged native employment is included). The regressors in the national-level regression include a vector of skill fixed effects, a vector of time fixed effects, and all possible two-way interactions between a vector of educational attainment fixed effects, a vector of experience fixed effects, and a vector of time fixed effects. All regressions presented in the bottom three panels include a vector of skill fixed effects, a vector of (appropriately defined) region fixed effects, a vector of time fixed effects, and all possible two-way interactions among these vectors.

Table 3. Impact of Immigration on the Size of the Native Workforce
(Dependent variable = Log of Number of Natives in Labor Force)

Geographic area and specification	Immigrant share	Lagged native employment	Lagged native employment growth	Mean log wage	Unemployment rate
I. Census divisions					
(1)	-.016 (.158)	---	---	---	---
(2)	.058 (.121)	.244 (.042)	---	.172 (.115)	-1.342 (.439)
(3)	.143 (.145)	---	.096 (.031)	.263 (.157)	-1.509 (.531)
II. State					
(1)	-.376 (.093)	---	---	---	---
(2)	-.278 (.081)	.056 (.015)	---	.020 (.048)	-.388 (.195)
(3)	-.269 (.085)	---	.038 (.011)	.117 (.056)	-.649 (.211)
III. Metropolitan area					
(1)	-.781 (.060)	---	---	---	---
(2)	-.836 (.090)	-.403 (.023)	---	.075 (.044)	-.303 (.154)

Notes: Standard errors are reported in parentheses and are clustered by the region-skill group level. The regressions estimated at the region level have 1,440 observations (1,152 observations when the lagged native employment growth is included); regressions estimated at the state level have 8,158 observations (6,434 observations when the lagged native employment growth is included); and the regressions estimated at the metropolitan area level have 25,151 observations (14,848 observations when the lagged native employment is included). All regressions include a vector of skill fixed effects, a vector of (appropriately defined) region fixed effects, a vector of time fixed effects, and all possible two-way interactions among these vectors.

Table 4. Impact of Immigration on Native Migration Rates

Geographic area and dependent variable	Immigrant share	Lagged native employment growth	Lagged native employment	Mean log wage	Unemployment rate
I. Census division					
1. Net migration rate	-.076	.061	---	.150	-.035
	(.046)	(.023)		(.056)	(.207)
2. Net migration rate	-..066	---	.050	.164	-.117
	(.042)		(.023)	(.057)	(.200)
3. In-migration rate	-.102	-.015	---	.113	.159
	(.034)	(.010)		(.040)	(.143)
4. Out-migration rate	-.027	-.076	---	-.037	.194
	(.033)	(.018)		(.041)	(.166)
II. State					
1. Net migration rate	-.282	-.018	---	.010	.270
	(.064)	(.014)		(.070)	(.211)
2. Net migration rate	-.288	---	-.067	.013	.310
	(.064)		(.018)	(.069)	(.209)
3. In-migration rate	-.150	-.054	---	.020	.042
	(.042)	(.009)		(.035)	(.126)
4. Out-migration rate	.132	-.035	---	.010	-.228
	(.049)	(.013)		(.052)	(.170)
III. Metropolitan area					
1. Net migration rate	-.404	-.089	---	-.045	.046
	(.084)	(.014)		(.041)	(.140)
2. Net migration rate	-.289	---	-.065	-.068	.081
	(.086)		(.020)	(.041)	(.140)
3. In-migration rate	-.116	-.076	---	-.015	.032
	(.055)	(.009)		(.027)	(.094)
4. Out-migration rate	.288	.012	---	.030	-.014
	(.062)	(.010)		(.028)	(.097)

Notes: Standard errors are reported in parentheses and are clustered by the region-skill group level. The regressions estimated at the region level have 1,152 observations; the regressions estimated at the state level have 6,524 observations; and the regressions estimated at the metropolitan area level have 14,847 observations. All regressions include a vector of skill fixed effects, a vector of (appropriately defined) region fixed effects, a vector of time fixed effects, and all possible two-way interactions among these vectors.

Table 5. Sensitivity of Results
(Coefficient of immigrant share variable in state-level regressions)

Specification	Log (Native Workforce)	Migration Regressions		
		Net migration	In-migration	Out-migration
1. Baseline (Men)	-.278	-.282	-.150	.132
	(.081)	(.064)	(.042)	(.049)
2. Men outside California	-.313	-.299	-.148	.151
	(.086)	(.069)	(.045)	(.052)
3. Men with at least a high school degree	-.820	-.279	-.248	.031
	(.176)	(.218)	(.123)	(.158)
4. Men, but includes women in counts of workers	-.228	-.268	-.127	.141
	(.086)	(.071)	(.046)	(.053)
5. Women	-.360	-.166	-.048	.118
	(.102)	(.073)	(.048)	(.054)
6. Men and women	-.298	-.232	-.100	.132
	(.082)	(.057)	(.036)	(.039)

Notes: Standard errors reported in parentheses; all standard errors are clustered by skill and region. The baseline male regressions on the log of the native workforce have 8,158 observations (6,524 observations in the migration regressions); the non-California regressions have 7,903 observations (6,396); the regressions for workers with at least a high school education have 6,039 observations (4,892); the regressions estimated in the sample of women have 8,030 observations (6,526); and the regressions in the sample of all workers have 8,083 observations (6,528). The regressions include a vector of skill fixed effects, a vector of (appropriately defined) region fixed effects, a vector of time fixed effects, all possible two-way interactions among these vectors, and the mean log weekly wage and unemployment rate in the labor market. In addition, the regressions on the native workforce include the lagged value of the log of the native workforce, while the migration regressions include the lagged value of the growth rate of the native workforce.

Table 6. Synthesis of Wage and Migration Effects

	Census division	State	Metropolitan area
1. Estimate of factor price elasticity (in national labor market)	-.372	-.372	-.372
2. Estimate of migration effect:			
Simple specification: native workforce	-.011	-.263	-.547
Complete specification: native workforce	.041	-.195	-.585
Complete specification: net migration	-.053	-.197	-.283
3. Predicted estimate of spatial correlation:			
Simple specification: native workforce	-.367	-.274	-.169
Complete specification: native workforce	---	-.299	-.154
Complete specification: net migration	-.352	-.299	-.270
4. Spatial correlation actually estimated at local level:			
Simple specification	-.188	-.150	-.025
Complete specification	-.187	-.152	.022

Notes: The synthesis is based on the theory-based interpretation of the coefficients reported in Tables 2, 3, and 4.