Impacts of Migration

The U.S. Labor Market Impacts of Low-skill Migration from Mexico

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Introduction

Although in recent years a growing literature has focused on the economic effects of U.S. immigration (Borjas, 1994; Greenwood and McDowell, 1986; LaLonde and Topel, 1997; and Smith and Edmonston, 1997), little research has dealt directly with the migrant group from Mexico. An example of this gap is a recent study of the economic consequences of U.S. immigration by the National Academy of Sciences (Smith and Edmonston, 1997) that makes only passing reference to the Mexico-born population. By estimating the U.S. employment and wage effects of this population, the present study takes a step toward filling this research gap.

Four distinctive characteristics of Mexican migrants to the United States have implications for the nature and magnitude of their labor market impacts. First, the sheer volume of the migration flow and the size of the Mexico-born population in the United States set this foreign-born group apart. Second, a large share of the undocumented population is of Mexican origin. Third, the Mexico-born population in the United States has low education levels, which although improving have not kept pace with those of the U.S. population. Fourth, the Mexico-born population is highly concentrated in the Southwest and in several large cities.

Mexico contributes a larger share to the U.S. foreign born population than any other country—roughly as much as the entire continents of Asia and Europe. During 1994 alone the United States admitted as legal resident aliens 111,398 persons born in Mexico. Between 1989 and 1993, boosted by legalizations under terms of the Immigration Reform and Control Act of 1986 (IRCA), 2.4 million persons of Mexican birth were legally admitted to the United States. The size of the migrant flow is important for understanding impacts because arguments about scale economies and about magnitudes of impacts derive directly or indirectly from the volume of migration, depending, of course, on residential patterns, return migration rates, and other social and demographic characteristics we discuss below.

Not only is Mexico the single most important source of legal immigrants, it is also the primary source of unauthorized migrants. Data on undocumented migrants are necessarily sketchy. However, studies of legalization authorized by IRCA indicate that 70 percent of those who were legalized under the amnesty program were of Mexican origin (see Tienda, et al., 1991; Singer, 1994). Between 1989 and 1994, the U.S. Border Patrol located 6.4 million entries from Mexico who were deemed deportable. Legal status of migrants is important for understanding the impacts of Mexican migration because public attitudes and behavior toward migrants from Mexico are often driven by images, accurate or not, of undocumented migrants. Employers who fear sanctions for hiring migrants who entered the United States unlawfully may deliberately avoid hiring all workers who look and sound like foreigners. Such behavior could directly affect the employment and wage opportunities of earlier arrivals who entered legally, as well as some native residents who speak English with an accent or "look Mexican." Although these effects are difficult to quantify, there is little disagreement that the presence of a large share of undocumented migrants among the Mexican migrant population shapes the policy and social climate surrounding Mexican migration to the United States.

The Mexican migrant population comes to the United States with low levels of formal education. Male Mexican migrants average nine years of education, which is substantially less than most other native and migrant groups, who average a high school education. Because Mexico has been the single largest source of migrants to the U.S. for 30 years, and because migrants from Mexico have low levels of formal education, recent concerns about admitting immigrants with low skills have focused on migrant streams from Mexico. The skill composition of Mexican migrants has important implications for a study of impacts because it is central for addressing questions about labor market impacts, and in particular, whether Mexicans compete mainly with other low wage workers (e.g., native-born teens, unskilled women, blacks, Mexican Americans, and migrants who arrived earlier), or whether Mexican migrants fill labor market niches that domestic and other foreign-born workers do not want. In light of recent trends in U.S. wage inequality between skilled and unskilled labor groups, the question of whether large numbers of unskilled Mexican migrants can be absorbed in the labor market remains a central source of controversy about the economic impact of Mexican migrants.

In 1990, of 13.5 million Mexican-origin persons enumerated in the census, 45.3 percent resided in California and 28.8 percent resided in Texas.[1] California's share of national population was 12.0 percent in 1990 and Texas's was 6.8 percent. Such concentrations of Mexican-origin population suggest highly regionalized immediate impacts of the migrants, although several studies suggest that the effects of immigrants are quickly arbitraged across the nation (Borjas, 1994). A major advantage of the approach adopted here is that for simulation purposes we are able to distinguish areas with differing concentrations of Mexico-born persons rather than relying only on nation-wide estimates of the impacts.

The wage and employment impacts of the foreign born on native workers may differ according to race and national origin, but the findings of prior studies are highly variable. The empirical evidence generally indicates that immigrant groups tend to be substitutes for some domestic labor market groups and complements for other domestic workers (Borjas, 1987a). Specifically, Hispanic immigrants appear to be substitutes for white domestic male workers, but complements with native Hispanic workers. Mexican immigrants have a small negative impact on the earnings of both white and black native-born men. However, all immigrants have a sizable negative impact on their own wage levels (Borjas, 1986a, and 1986b). One important implication of earlier studies is that in attempting to assess substitution and complementarity relationships among the foreign born and the native born, investigators should disaggregate the study population as much as possible. The functional form of the production function used in this study allows for the specification of considerably more labor types than is found in the typical production-theory approach (Greenwood, Hunt, and Kohli, 1996; 1997).

This study employs cross-sectional 1990 Census data on metropolitan areas in the context of a production-theory approach that uses the Symmetric Normalized Quadratic functional form and that incorporates eight labor inputs and a measure of capital. The eight labor inputs, whose estimation is allowed by the functional form employed here, permit us to account not only for low-skill Mexico-origin labor, but also for certain skill groups with whom this group is likely to compete in U.S. labor markets (including native, low-skill labor distinguished by sex, as well as foreign-born, low-skill labor from parts of the world other than Mexico). The incorporation of capital into the empirical model avoids the assumption of separability of labor and capital that has been problematic in several earlier empirical studies. An advantage of cross-section data is that the model can be calibrated and simulated for specific metropolitan areas that differ in terms of their concentration of Mexico-born persons. Moreover, following the work of Greenwood and Hunt (1995), we incorporate into the model certain channels of influence in addition to the production channel. These other channels include labor force participation and aggregate demand.

Workers born in Mexico increase the supply of labor available in the United States. This increased labor supply clearly is not spread evenly across the United States, but rather is concentrated in proximity to the U.S.-Mexico border and in areas that offer those types of employment opportunities that are attractive to migrants from Mexico. Previous studies typically have shown that the wage and employment effects of increased immigration on native-born groups are not great (see Greenwood and Hunt, 1995; Greenwood, Hunt, and Kohli, 1996 and 1997). The largest impacts are on other foreign-born workers (like the immigrants themselves). The results of earlier studies, however, have been based on 1980 census data and on other data sources that are sufficiently old to throw into question their contemporary relevance. Moreover, the various studies that adopt a production function approach usually have not focused specifically on areas of high immigrant concentration.

In this paper, we disaggregate native workers by skill, gender, ethnicity, and nativity, and estimate the impacts of migrants from Mexico at the metropolitan area level in different regions of the U.S. including, especially, areas in the Southwest that are near to Mexico. We consider employment and wage effects stemming from both supply-side and demand-side effects of low-skill Mexican migration. Effects on the rental price of capital services also are explored.

Model Structure—An Overview

The model incorporates one aggregate output and nine inputs.[2] The relatively large disaggregation of inputs reflects the interest of this study in the effects of immigration by origin and skill level on native U.S. workers by skill level, gender, and ethnicity. Eight groups of labor are identified in the model: (1) native, low-skill, Mexican males; (2) native, low-skill Mexican females; (3) native, low-skill non-Mexican males; (4) native, low-skill, non-Mexican females; (5) native, high-skill males and females; (6) foreign-born, low-skill Mexican males and females; (7) foreign-born, low-skill non-Mexican males and females; and (8) foreign-born, high-skill males and females. The ninth input is capital. The methodology is the same as that reported in Greenwood, Hunt, and Kohli (1997), but the labor inputs are different. In this part of the model substitution and complementarity relationships between the various inputs are estimated.

The model contains 18 endogenous variables. For each of the nine inputs, a factor price equation is specified by setting the factor price of the input equal to the input's value marginal product (VMP). The VMP for each input is derived from production theory as described below. Eight more behavioral equations are specified for the labor force participation rates of the eight groups of labor. These equations also are treated in more detail below, but their basic purpose is to measure the degree to which own-wage changes influence the labor force participation of the various labor groups. Finally, a behavioral equation for aggregate absorption of area output (i.e., area aggregate demand) is specified.

In addition to the 18 equations for the corresponding 18 endogenous variables, the model contains several technical relations, such as an aggregate value added production function and numerous identities. Some of these identities translate variables from their indexed forms used in theoretical specification (e.g., normalized employment), to their more policy-relevant forms (e.g., employment). The model contains 46 such technical relations and identities. Altogether the model contains 64 behavioral equations, technical relations, and identities.

Data

Because it facilitates our later presentation of empirical results, the next section discusses the 1990 data used in this study. This section is followed by a discussion of the model structure. The various components of the model's structure are followed by a discussion of issues relating to econometric estimation, as well as the presentation of the estimates obtained for model parameters.

Factor Inputs and Prices

The 1990 Public Use Microdata Sample (PUMS) of the U.S. Census (U.S. Bureau of the Census, 1992a) is used in the estimation of labor inputs and prices. The five percent (state) sample is used because it contains more observations than the one percent (metropolitan area) sample, while still containing metropolitan area of residence. A number of steps were taken in preparing these data. First, a random sample was drawn from the PUMS for the estimation of Mincerian-style earnings equations. Second, a skill-quantity variable was computed from the earnings equations for all individual observations in the five percent PUMS. This skill-quantity variable is important in making the demographic disaggregations described below. The third step involved aggregating the individual observations to the Metropolitan Statistical Area (MSA) level to form aggregate area labor inputs and prices. Altogether 273 MSAs are identified from the 1990 PUMS five percent sample. As part of this third step, individual observations were grouped into eight demographic groups based on male/female, Mexican/non-Mexican, native-born/foreign-born, and high skill/low skill status. The criteria for assigning skill level are discussed below.

Earnings Equations

In preparing the data for estimation of earnings equations, a 10 percent random subsample of the five percent PUMS was taken. This was done following the subsampling procedures described in the PUMS Technical Documentation (U.S. Bureau of the Census, 1992b). Only those observations satisfying the following criteria were used: age between 16 and 65, not currently in school, not currently in the military, not self-employed, and 1989 earnings greater than zero. This process yields a national subsample of 456,202 observations.

Using this national subsample, Mincerian-style earnings equations were econometrically estimated separately for males (235,069 observations) and females (221,133 observations). For these earnings equations, an hourly wage variable was created by dividing 1989 earnings by hours worked in 1989 (computed as hours worked per week times weeks worked in 1989). The natural logarithm of the 1989 hourly wage served as the dependent variable.

The independent variables included: educational attainment, potential labor market experience (constructed as age less education less six) and its square, a dummy for metropolitan area residence, race and ethnicity dummies, a foreign-born dummy and its interaction with year of entry dummies, a set of census division dummies, a set of world region of origin dummies, a set of occupation dummies, and a set of industry dummies.

The OLS estimates produce reasonable results. For both males and females, the log of hourly earnings increases with education. It also increases with potential labor market experience, but at a decreasing rate. Foreign-born individuals have log-wages below those of natives, although this effect is not statistically significant. The adjusted-R^2 in the male earnings equation is 0.365 and that in the female equation is 0.252. The equation F-value for males is 2759.75 and for females is 1524.22.

Skill Quantity

Based on the results of the earnings equations, we predicted a “skill-quantity” variable or skill index for all individuals in the subsample. This skill index was predicted using the estimated coefficients on educational attainment, potential labor market experience and its square, the foreign-born dummy and the interactions between foreign-born and year of entry, and the world region of origin dummies, along with the actual values of each of these variables for each individual in the subsample. This predicted skill-index variable is designed to reflect skill quantity (a proxy for human capital) rather than various aspects of "skill price" such as racial or ethnic discrimination or compensating differentials due to industry, occupation, region of residence, or MSA residence. The skill-quantity estimates are made separately for males and females using the estimated coefficients from the appropriate regression equation.

Each individual in the subsample was coded as being in one of four skill quartiles by ranking all observations by predicted skill quantity and splitting them into four groups of equal size. Each individual was then designated as low skill or high skill depending on how the skill quartiles are grouped. In the analysis conducted in this paper, the lower two skill quartiles are designated as "low skill" whereas the upper two skill quartiles are designated as "high skill." This low skill/high skill segmentation is discussed further below.

Aggregation

Having created the skill quartiles from the earnings equations, we next aggregated the data to the MSA level. To do so, we used the complete five percent 1990 PUMS rather than the subsample used for the earnings equations. Observations were excluded from the data if they did not meet our "selection criteria." The skill-quantity variable was computed for all individuals as described above. The individuals were then coded as belonging to one of the four skill quartiles based on the value of this skill quantity variable and the quartile "break-points" determined from the 10 percent national subsample.

As indicated above, eight demographic groups were created for the Mexican model. Individuals were coded as native-born if they were born in the U.S. or in U.S. outlying areas (e.g., Guam, American Samoa, Puerto Rico). Otherwise, individuals were coded as foreign- born. Individuals were considered to be low-skill if they were in the lower two skill quartiles. The upper two skill quartiles accounted for high-skill individuals. Mexican status is conferred by birth in Mexico for the foreign-born and by Mexican origin (as reported on the PUMS Hispanic origin question) for the native born.

For each demographic group, several variables were created at the MSA level. These include total group population, number employed in the group, group labor force participation rates, total group earned income, total group non-labor income, total group welfare income, total group social insurance income, and total group hours worked. Furthermore, aggregate MSA population, employment, earnings, and non-labor income were created by summing across all eight demographic groups. The eight demographic groups exhaustively include area population, and therefore employment, earnings, and non-labor income.

This aggregation process was conducted MSA-by-MSA, in all states plus the District of Colombia, yielding 273 MSAs. Ten of these 273 cross state boundaries, and therefore represent the combination of data from multiple states. After deleting those MSAs in which one or more of the eight demographic groups have small or zero populations, we are left with 122 useable MSAs for the analysis conducted below.

Model Structure

Production Function and Factor Prices

We assume that in each metropolitan area, the technology can be represented by an aggregate production function. Let y be the quantity of output and assume J inputs,[3] the quantities of which are denoted by x_j. The production function is written as follows:

(1) $y = f(x_1, \ldots, x_J)$.

This function is assumed to be twice continuously differentiable, increasing, quasiconcave, and linearly homogeneous. Under profit maximization, we get the marginal product conditions (also known as the inverse input demand equations, or the wage equations) by differentiation:

(2) $$\frac{w_j}{p} = \frac{\delta f(\cdot)}{\delta x_j}, \quad j = 1, \ldots, J,$$

where p is the price of output and w_j is the price of the j^{th} input.

To describe the substitution and complementarity relationships between the J inputs, we can use the Hicksian elasticities of complementarity[4]:

(3) $$\psi_{j,k} \equiv \frac{f\, f_{j,k}}{f_j\, f_k}, \quad j,k = 1, \ldots, J,$$

where $f_j \equiv \delta f(\cdot) / \delta x_j$, $f_{j,k} \equiv \delta^2 f(\cdot) / (\delta x_j \delta x_k)$, and $f \equiv f(\cdot)$.

Quasiconcavity of the production function implies that $\psi_{j,j} \leq 0$. Furthermore $\psi_{j,k} > 0$ if inputs j and k are Hicksian q-complements, and $\psi_{j,k} < 0$ if inputs j and k are Hicksian q-substitutes.

The Hicksian elasticities of complementarity may seem to be somewhat difficult to assess, and it is sometimes more convenient to use quantity elasticities of inverse demands. These are defined as follows:

$$(4) \quad \eta_{j,k} \equiv \frac{\delta \ln w_j}{\delta \ln x_k}$$

Making use of Equations (2) and (3), one can easily show that:

$$(5) \quad \eta_{j,k} = \psi_{j,k} \cdot s_k,$$

where s_k is the cost share of the k^{th} input: $s_k \equiv x_k w_k /(py)$.

To describe the production function, we use the Symmetric Normalized Quadratic functional form introduced by Diewert and Wales (1987). It is as follows:

$$(6) \quad f(\cdot) = \sum_j a_j x_j = \frac{1}{2} \frac{\sum_j \sum_k b_{jk} x_j x_k}{\sum_j \beta_j x_j}$$

where $b_{jk} = b_{kj}$, $\sum b_{jk} = 0$, $\sum \beta_j = 1 \quad (j, k = 1, ..., J)$. As shown by Diewert and Wales (1987), this functional form is flexible, and it is globally concave as long as $B \equiv [b_{jk}]$ is negative semidefinite and $\sum \beta_j w_j > 0$. The negative semidefiniteness of B can be imposed by using the reparameterization of Wiley, Schmidt, and Bramble (1973). That is, we set $B = -TT$ where $T \equiv [\tau_{jk}]$ is a lower triangular matrix. As to $\sum \beta_j x_j$, this term can be interpreted as a Laspeyres input quantity index.

Assuming cost minimization, the inverse input demand functions are obtained by differentiation:

$$(7) \quad \frac{w_j}{p} = a_j + \frac{\sum_k b_{jk} x_k}{\sum_k \beta_k x_k} - \frac{1}{2} \beta_j \frac{\sum_k \sum_m b_{km} x_k x_m}{(\sum \beta_k x_k)^2}, \qquad j = 1, \ldots, J.$$

One difficulty with flexible functional forms is that their number of parameters increases very rapidly with the number of inputs. Even if one assumes linear homogeneity, the number of parameters in a N-input model is equal to $N + (N - 1) N / 2$. Thus, if $N = 2$, the number of parameters is 3; if $N = 4$, there are 10 parameters, and if $N = 16$, the number of parameters jumps to 136. This may lead to serious problems of multicollinearity, and it may lead to inefficient estimates. One way around this problem has been suggested by Diewert and Wales (1988), who introduce the concept of K-flexibility, or semiflexibility. A functional form $g(z)$ is said to be semiflexible at some point z^* if it has enough free parameters for $g(z^*)$, its gradient $\nabla g(z^*)$, and its Hessian $\nabla^2 g(z^*)$ to attain arbitrary values, provided that $\nabla^2 g(z^*)$ is restricted to have rank $K < N$. A semiflexible functional form therefore has less parameters than a flexible one, and, although it is not flexible, it does not impose any obvious *a priori* restrictions on the size or the signs of the elasticities of substitution or complementarity.

The concept of semiflexibility rests on some new results obtained by Diewert and Wales (1988). They show that any semi-definite $N \times N$ matrix of rank K, where K is less than the maximal possible rank N, has a K-column triangular decomposition. This means that $T \equiv [\tau_{mn}]$ is now such that $\tau_{mn} = 0$ for $1 \le m < n \le N$ and for $n = K + 1, \ldots, N$. Thus, T now is defined as a lower triangular $N \times N$ matrix which has zeros in its last $N - K$ columns. Note that T now has only $N(N + 1)/2 - (N - K)(N - K + 1)/2$ free parameters. This may mean a substantial reduction in the number of parameters to be estimated. Thus, if $N = 8$ and $K = 3$, the number of free parameters is 21, as opposed to 36 in the unrestricted case. This reparameterization applied to B in (6) yields the K-flexible—or semiflexible—version of the Symmetric Normalized Quadratic production function. In what follows, we will set $K = 3$; indeed, there is ample evidence that there is little to be gained in considering larger values of K.[5]

For empirical implementation the factor price equations have to be imbedded within a stochastic framework along with the other behavioral equations. We assume that the inverse input demand equations are stochastic due to errors in optimization. We define the optimization errors in the input demand equations at time t as $v_j(t)$ ($j = 1, \ldots, J$). We assume that the vector of disturbances is identically and independently, joint normally distributed with mean zero and non-singular covariance matrix Ω:

$$(8) \quad E[v(t)v(s)] = \begin{cases} \Omega \ \ \forall\, s,t \ \ if \ \ s = t \\ 0 \ \ if \ \ s \neq t, \end{cases}$$

where Ω is a $J \times J$ positive definite matrix.

The model is estimated by the algorithm of Berndt, Hall, Hall, and Hausman (1974) which is essentially a nonlinear version of the iterative Zellner (1962) method. All estimations were done on a Digital AXP 3000-800S computer, using SHAZAM,[6] version 7.0. The nine inputs of the model are identified above.

Parameter estimates are shown in Table 1. Concavity is imposed globally, and it is therefore satisfied for all observations. Monotonicity is satisfied for all observations but one. Table 2 reports estimates of the Hicksian elasticities of complementarity (ψ_{jk}) at the sample mean, whereas Table 3 gives the sample-

Table 1
Mexican Model
Parameter Estimates (asymptotic t-values in parentheses)

τ_{11}	0.00312	(2.57)	τ_{33}	-0.00492	(-0.42)
τ_{21}	0.01077	(4.01)	τ_{43}	0.11402	(1.85)
τ_{31}	0.02289	(5.05)	τ_{53}	0.04357	(1.95)
τ_{41}	-0.01224	(-0.26)	τ_{63}	-0.00474	(-0.18)
τ_{51}	0.16173	(5.75)	τ_{73}	0.00116	(0.11)
τ_{61}	-0.00376	(-0.48)	τ_{83}	-0.05538	(-2.66)
τ_{71}	0.00155	(0.29)	a_1	0.00182	(30.21)
τ_{81}	0.00359	(0.21)	a_2	0.00475	(32.85)
τ_{22}	0.00400	(0.82)	a_3	0.02457	(114.88)
τ_{32}	-0.00513	(-0.66)	a_4	0.12130	(167.04)
τ_{42}	0.05863	(0.52)	a_5	0.36144	(222.94)
τ_{52}	0.04651	(0.54)	a_6	0.00739	(24.73)
τ_{62}	0.02403	(4.15)	a_7	0.01433	(76.91)
τ_{72}	0.01084	(2.86)	a_8	0.04335	(66.08)
τ_{82}	0.02055	(0.36)	a_9	0.41485	(178.14)

The subscripts refer to the inputs which are defined as follows:
(1) Native, low-skill, Mexican, male labor; (2) Native, low-skill, Mexican, female labor; (3) Native, low-skill, non-Mexican, male labor; (4) Native, low-skill, non-Mexican, female labor; (5) Native, high-skill labor; (6) Foreign-born, low-skill, Mexican labor; (7) Foreign-born, low-skill, non-Mexican labor; (8) Foreign-born, high-skill labor; (9) Capital.

mean values of the quantity elasticities of inverse input demands (η_{jk}). Capital is a Hicksian complement for all categories of labor, except foreign-born high-skill labor. Overall, however, and this is rather surprising, there appears to be far more substitution than complementarity relationships.

Most labor categories seem to be competing with each other. The strongest complementarity links are between native, low-skill men and low-skill migrants, as well as between native, low-skill, non-Mexican women and high-skill migrants. Judging from the elasticities shown in Table 3, an increase in the number of low-skill Mexican migrants would tend to benefit capital and low-skill native males, and hurt all other categories of labor; however, except for low-skill Mexican migrants themselves, these effects are very small.

Labor Force Participation

The modeling of labor force participation rates begins with a reservation wage equation and a market wage equation:

Table 2

Mexican Model

Elasticities of Complementarity (values at the sample mean)

$$\psi_{j,k} = \frac{f \bullet f_{j,k}}{f_j \bullet f_k}$$

	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9
j=1	-2.910	-3.858	-1.585	0.172	-0.761	0.866	-0.184	-0.141	0.769
j=2		-5.820	-1.926	-0.177	-1.117	-1.573	-0.878	-0.584	1.342
j=3			-0.946	0.381	-0.364	1.018	0.073	-0.233	0.294
j=4				-1.121	-0.130	-1.013	-0.428	0.974	0.350
j=5					-0.230	-0.112	-0.155	0.056	0.277
j=6						-11.171	-2.339	-2.304	0.869
j=7							-0.587	-0.263	0.356
j=8								-1.852	-0.068
j=9									-0.401

The subscripts are as defined at the bottom of Table 1.

Table 3

Mexican Model

Quantity Elasticities of Inverse Demand (values at the sample mean)

$$\eta_{j,k} \equiv \frac{\delta \ln w_j}{\delta \ln x_k}$$

	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9
j=1	-0.005	-0.018	-0.039	0.021	-0.277	0.006	-0.003	-0.006	0.321
j=2	-0.007	-0.028	-0.048	-0.022	-0.406	-0.012	-0.013	-0.025	0.560
j=3	-0.003	-0.009	-0.023	0.046	-0.132	0.008	0.001	-0.010	0.123
j=4	0.000	-0.001	0.009	-0.137	-0.047	-0.008	-0.006	0.042	0.146
j=5	-0.001	-0.005	-0.009	-0.016	-0.084	-0.001	-0.002	0.002	0.116
j=6	0.002	-0.008	0.025	-0.124	-0.041	-0.083	-0.034	-0.101	0.363
j=7	-0.000	-0.004	0.002	-0.052	-0.056	-0.017	-0.008	-0.011	0.149
j=8	-0.000	-0.003	-0.006	0.119	0.020	-0.017	-0.004	-0.081	-0.029
j=9	0.001	0.006	0.007	0.043	0.101	0.006	0.005	-0.003	-0.167

The subscripts are defined at the bottom of Table 1.

(9) $S = \gamma_0 + \gamma_1 H + \gamma_2 Z + u_1$

(10) $W = \beta_0 + \beta_1 X + u_2$

where S is the reservation wage (or shadow wage), H is hours worked, Z is a vector of other factors that influence the reservation wage, W is the market wage, and X is a vector of factors that influence the market wage. The gammas and betas are parameters. The u_1 and u_2 terms are zero mean, spherical, normally distributed stochastic errors. Equations (9) and (10) apply to individuals.

Let $\overline{W} = \beta_0 + \beta_1 \overline{X},$ where a bar over variables denotes a mean. Therefore,

(11) $W = \beta_0 + \beta_1 X + \overline{W} - \overline{W} + u_2,$

which implies

(12) $W = \beta_1 (X - \overline{X}) + \overline{W} + u_2.$

Assuming that W=S, Equations (9) and (10) can be equated and the following equation for hours can be derived:

(13) $H = \{[\beta_1 (X - \overline{X}) + \overline{W} - \gamma_0 - \gamma_2 Z] / \gamma_1\}.$

If H>0, then the individual participates. If H≤0, then the individual does not participate.

For participating individuals, H>0 implies that Eq.(13) becomes

(14) $\{[\beta_1 (X - \overline{X}) + \overline{W} - \gamma_0 - \gamma_2 Z] / \gamma_1\} + \{[u_2 - u_1] / y_1\} > 0.$

Equation (14) in turn implies the following:

(15) $\{[u_2 - u_1] / \gamma_1\} < \{[\beta_1 (X - \overline{X}) + \overline{W} - \gamma_0 - \gamma_2 z] / \gamma_1\}.$

Therefore, for participants, H>0, we have

(16) $u_2 - u_1 < \beta_1 (X - \overline{X}) + \overline{W} - \gamma_0 - \gamma_2 z.$

This implies that the probability of participating is

$$\text{(17) } \Pr ob(H > 0) = \Phi\{[\beta_1(X - \overline{X}) + \overline{W} - \gamma_0 - \gamma_2 z]/\sigma\}$$

where sigma is the standard deviation of $u_2 - u_1$. Each of the eight labor groups has a corresponding Equation (17) structure to represent its labor force participation rate behavior.

The sources of data used to estimate the participation rate equations for each of the eight labor groups are those described above for the labor quantity and price variables and the aggregate area output price variable. Specific variables utilized from the five percent PUMS include a labor force participation dummy variable as the dependent variable; and the following independent variables in the vector X (see Eq. (17)): white, black, years of schooling completed, potential experience and its square (as defined above), foreign-born dummy variable, and immigration cohort 1980-90. The vector Z (see Eq. (17)) contains the following independent variables: family income, black, white, number of children under six years of age present in the household, and number of children six to seventeen years of age present in the household. All income variables, including the average area wage for the labor group, are expressed in real terms by deflating by the aggregate area output price variable described above.

The stochastic assumptions made for the labor force participation rate equations flow from the theoretical discussion presented above. Each of the eight labor group's participation is modeled as a binary probit process. The maximum likelihood estimates of the probit equations for the eight labor groups are presented in Appendix Tables A1 through A8. It is notable that the estimated coefficients on the area average real wage for seven of the eight labor groups are positive and significant. The estimated effect of higher real wages on average is negative and significant only for the group of native, high skill persons.

Each estimated equation contains both area average variables and variables that represent deviations of individual observations from the area averages. The theoretical motivation for this structure is presented above. The deviations are represented by variable names beginning with the letter "D." The variable names in Appendix Tables A1 through A8 are associated with the following variables: AREARW, area real wage of group; RFAMINC, real household income of group; KIDLT6 and KID617, children less than six years of age in household and those between 6 and 17 years of age in household, respectively; BLACK and WHITE, dummy variables representing broad race of individuals; ED, years of schooling completed; X and XSQ, years of potential experience and its square, respectively; IMG8090, immigrant dummy variable interacted with entry cohort of 1980-90. In each of the eight corresponding tables of estimates, the marginal effects of each independent variable on the probability of participating (=1) or not participating (=0) is presented.

Aggregate Output Quantity and Price

Our methodology requires an index of real output (real value added). Let x_j^h and w_j^h be the quantity and the price of input j in region h. We first define $\tilde{w}_j$ as the mean price of input j across all regions:

$$(18)\ \tilde{w}_j \equiv \frac{\sum_h w_j^h x_j^h}{\sum_h x_j^h}$$

We next define s_j^h as the value-added share of input j in region h:

$$(19)\ s_j^h \equiv \frac{w_j^h x_j^h}{\sum_j w_j^h x_j^h}$$

We also define $\tilde{s}_j$ as the mean value added share of input j, that is the share of input j in the total of the value added by all regions:

$$(20)\ \tilde{s}_j \equiv \frac{\sum_h w_j^h x_j^h}{\sum_h \sum_j w_j^h x_j^h}.$$

The price of output in region h (p^h) is then calculated as a Tornqvist price index, where the prices in region h are compared to the corresponding mean prices:

$$(21)\ p^h = \exp\left[\sum_j \frac{1}{2}(s_j^h + \tilde{s}_j)\ln\frac{w_j^h}{\tilde{w}_j}\right].$$

Finally, the quantity of real value added in region h is obtained implicitly as:

$$(22)\ y^h = \frac{\sum_j w_j^h x_j^h}{p^h}.$$

The data used for the labor input quantities and prices are those discussed above. The data used to compute the quantity and price of capital services are a combination of the labor data and gross state product data obtained from the Bureau of Economic Analysis' *Regional Economic Information System (REIS) and a Jorgensonian measure of the cost of capital.* The gross state product data for each state were scaled to corresponding MSA-level data using one-digit SIC labor earnings at the state and MSA levels. The computation of the rental income for capital then was computed as the difference between MSA value added (i.e., gross product) and labor earnings. The rental price of capital services was estimated as the Jorgensonian user cost of capital services. Division of the rental income by the user cost yielded the estimate of the quantity of capital services used in this study.

The approach taken in Greenwood and Hunt (1995) is taken in specifying the absorption equation. The aggregate demand for real value-added output produced in area h is:

$$(23)\ \ln(y^h) = \alpha_0 + \alpha_1 \ln(p^h) + \alpha_2 \ln[Y^h/(N^h p^h)]$$

where y^h is aggregate demand for real value-added output produced in area h^h, p^h is the corresponding aggregate price index, N^h is area population, Y^h is area household income, "ln" is the natural logarithm operator, and the alphas are parameters. Equation (23) can be expressed in inverse form by solving for $\ln(p^h)$.

The aggregate area output price and quantity variables are those defined above. Aggregate area household income and population are computed from the summation of the corresponding area aggregate group variables across the eight demographic groups delineated above.

In this study, instrumental variables estimation is not entertained. Based on the work of Greenwood and Hunt (1995), the estimation of the aggregate absorption equation requires instrumental variables to obtain the correct sign on the price coefficient. Therefore, the estimates from Greenwood and Hunt (1995) are used in this study with appropriate scaling.

Model Simulations

The model is organized into six blocks of equations: (1) production; (2) labor force; (3) input value shares; (4) income; (5) absorption; and (6) add factors. Block 1 consists of 11 equations. Nine represent the value marginal product equations for each of nine inputs: five categories of native labor, three categories of immigrant labor, and capital. The skill levels are defined as quartiles of the U.S. distribution of skills. The value marginal products are set equal to wage rates (i.e., skill prices). The value added production function is the tenth equation in the first block. The eleventh equation is for aggregate value added output in nominal terms. All of these variables are index numbers. The indexing procedure is discussed below.

Block 2 consists of 33 equations. There are eight labor force identities, one for each of the eight labor groups. These specify labor force size as the product of labor force participation rate and population of labor force age. Eight employment identities define a normalized (i.e., indexed) employment measure, described below, for each of the eight labor groups, and eight additional employment identities for the employment of each of the eight groups of labor. Each of the eight labor groups also has a labor force participation equation specified for it. Finally, there is an identity for aggregated population of labor force age, the sum of the corresponding variable across the eight groups.

Block 3 consists of nine input value share equations, one for each of the eight labor inputs and capital. Block 4 includes an aggregate income identity: the sum of labor earnings and nonlabor income; and it includes eight wage rate equations (actual wage rates and not index numbers). Block 5 consists of an absorption equation written in inverse form so that the area price index is on the lefthand side.

Block 6 consists of 18 equations, one for each of the model's add factors. The add factors are variables that are computed endogenously during the baseline simulation of the model to ensure that the baseline simulation solution values equal the observed sample values. There is an add factor for each structural/behavioral equation in the model. Add factors are not required for identities since the computed values for the corresponding variables will equal the observed sample values if the structural/behavioral variable values are forced (by add factoring) to equal the observed sample values. There are eight add factor equations for the eight labor force participation rate equations. There are nine add factor equations for the value marginal product conditions. Finally, there is an add factor equation for absorption.

The model simulations were accomplished in two steps. The first step was to generate an add-factored baseline simulation. The second step was to increase the "foreign-born, low-skilled, Mexican" labor group by 20 percent in each of the 122 metropolitan areas. Our basic assumption here is that Mexico-born migrants in the United States tend to have relatively low skill levels because, as noted above, they tend to have relatively low levels of education. The difference in the solution values of each of these two steps, in each area, represents our simulated impacts of a 20 percent increase in low-skilled, Mexican migrants.

All blocks of the model are "turned on" in the simulations. Consequently, both supply and demand-side effects on employment and real factor prices are captured. In order to understand the economics of the simulations, it is useful to disaggregate conceptually the simulations into three parts. In the first part, only the effects of immigration on the value marginal products of each input and on output are considered. Consequently, increased immigration results only in factor price effects and an output effect. Only the production block of the model is therefore "turned on.” Consequently, impacts are limited to those operating through the production structure channel of influence.

In the second part, employment effects in addition to factor price effects are considered. This is accomplished by “turning on” the production, labor force, input value shares, and income blocks of the model structure. Impacts are therefore limited to those operating through the production structure and labor force participation channels of influence.

Additional effects are “turned on” in the third part by considering aggregate demand in addition to the effects occurring through the production structure and labor force participation channels. The aggregate demand effects have two aspects. First, the impacts of changes in local wage and nonlabor income on local demand are incorporated. If the sum of changes in local wage and nonlabor income is positive due to immigration, then local demand will rise and the local price level will be supported. Second, the effects of changes in output on the local price level are incorporated. An increase in migration directly results in an increase in labor input locally and therefore to the production of more local output. If the labor force participation effects across all labor groups do not offset this positive direct output effect of increased migration, the level of locally produced output will rise. In parts one and two, such an output increase would be absorbed without a change in the price of locally produced output. In this way, the other two parts represent, by assumption, the operation of a small open economy. In this third part, local price is endogenized and a lower price of local output will be required to get the extra output absorbed, *ceteris paribus*.

Aggregate demand effects operate in two opposing directions on the local price level and therefore on value marginal products. If the local demand effect bolsters the local price level, then this will support value marginal products and factor prices. However, this positive effect could be offset to some extent, or outweighed, by the downward pressure on local price by any extra local output produced with increased immigration. In the simulation of the model, of course, both effects are computed, and the result for factor prices is incorporated. The simulation results presented below incorporate all three of these parts: the production structure channel of influence, the labor force participation channel, and the aggregate demand channel.[7]

In Table 4, the simulated effects on the real wages of the eight groups of labor are presented. For all 122 areas, the average real wage of the migrant group itself falls by 3.0 percent. As shown in Table 5, due to this lower wage rate, workers in this category withdraw from the labor force, so that ultimately employment of this group increases by 19.39 percent and not by 20 percent, which reflects a displacement effect of about 0.6 percent (20.0 percent - 19.4 percent). The wage rates of other labor categories are almost unchanged. For example, native, low-skill females of Mexican ancestry suffer a wage loss of only about 0.3 percent

Table 4

Percentage Change in Real Wage of Various Labor Skill Groups Due to a 20-Percent Increase in Low-skilled, Foreign-born Mexican Labor—Selected MSAs

	Low-skilled						High-skilled	
	Native				Foreign-born			
	Mexican		Non-Mexican					
MSA	Male	Female	Male	Female	Mexican	Non-Mexican	Native	Foreign-born
All areas (122)	0.34	-0.34	0.33	-0.15	-3.01	-0.45	0.06	-0.47
California areas (23)	0.75	-0.68	0.59	-0.41	-6.85	-1.05	0.05	-1.16
Texas areas (23)	0.64	-0.68	0.72	-0.16	-5.00	-0.65	0.22	-0.64
Arizona, New Mexico, Colorado areas (11)	0.43	-0.36	0.48	-0.16	-3.69	-0.56	0.12	-0.57
Areas in border states (52)	0.69	-0.66	0.67	-0.28	-5.90	-0.85	0.14	-0.90
Areas of high concentration of foreign born, low-skilled, Mexicans[a] (13)	1.42	-1.27	1.55	-0.23	-11.42	-1.38	0.59	-1.40
Areas of low concentration of foreign born, low-skilled, Mexicans[b] (43)	0.02	-0.02	0.02	-0.02	-0.19	-0.04	-0.00	-0.04
Santa Ana, CA	1.29	-0.48	0.51	-0.68	-7.37	-1.30	-0.39	-1.69
Bakersfield, CA	0.56	-0.72	0.57	-0.44	-8.89	-1.29	0.05	-1.32
Chico-Paradise, CA	0.13	-0.25	0.21	-0.14	-1.83	-0.37	0.00	-0.34
Fresno, CA	1.31	-1.11	1.12	-0.62	-12.24	-1.63	0.25	-1.49
Los Angeles, CA	2.30	-1.36	1.07	-1.59	-13.54	-1.53	-0.56	-3.43
Merced, CA	2.05	-0.94	1.41	-0.24	-14.24	-1.74	0.88	-1.75
Modesto, CA	0.18	-0.80	0.53	-0.36	-7.40	-1.23	0.09	-1.21

Table 4 (Continued)

	Low-skilled						High-skilled	
	Native				Foreign-born			
	Mexican		Non-Mexican					
MSA	Male	Female	Male	Female	Mexican	Non-Mexican	Native	Foreign-born
Oakland, CA	0.07	-0.25	0.10	-0.21	-1.50	-0.37	-0.09	-0.40
Oxnard-Ventura, CA	0.87	-0.69	0.63	-0.48	-6.98	-1.16	-0.09	-1.23
Redding, CA	0.01	-0.03	0.02	-0.02	-0.24	-0.06	0.00	-0.05
San Bernardino, CA	0.31	-1.24	0.16	-0.52	-7.09	-1.58	-0.16	-1.35
Sacramento, CA	0.11	-0.32	0.11	-0.19	-1.36	-0.30	-0.04	-0.26
Salinas, CA	1.29	-1.04	1.64	-0.42	-13.39	-1.81	0.59	-1.88
San Diego, CA	0.87	-0.81	0.61	-0.56	-5.90	-1.03	-0.14	-1.12
San Francisco, CA	0.15	-0.16	0.16	-0.18	-1.48	-0.27	-0.06	-0.39
San Jose, CA	0.50	-0.54	0.14	-0.38	-3.59	-0.80	-0.13	-0.92
Santa Barbara, CA	0.79	-0.84	0.82	-0.45	-8.80	-1.34	0.09	-1.37
Santa Cruz, CA	0.79	-0.84	0.90	-0.47	-8.82	-1.29	0.09	-1.32
Santa Rosa, CA	0.48	-0.43	0.22	-0.28	-2.63	-0.61	-0.03	-0.61
Stockton-Lodi, CA	0.66	-0.65	0.38	-0.39	-6.45	-1.07	0.05	-1.06
Vallejo, CA	0.22	-0.38	0.19	-0.20	-2.64	-0.51	0.00	-0.50
Visalia-Tulare, CA	2.05	-1.10	1.51	-0.36	-15.17	-1.95	0.73	-1.95
Yuba City, CA	0.23	-0.61	0.57	-0.28	-5.96	-0.98	0.12	-0.98
Abilene, TX	0.25	-0.24	0.18	-0.13	-2.17	-0.35	0.01	-0.30
Amarillo, TX	0.16	-0.25	0.15	-0.14	-1.58	-0.30	0.00	-0.37

Table 4 (Continued)

	Low-skilled						High-skilled	
	Native				Foreign-born			
	Mexican		Non-Mexican					
MSA	Male	Female	Male	Female	Mexican	Non-Mexican	Native	Foreign-born
Austin, TX	0.30	-0.40	0.32	-0.23	-2.55	-0.46	0.01	-0.42
Beaumont, TX	0.05	-0.08	0.04	-0.04	-0.47	-0.11	-0.01	-0.10
Brazoria, TX	0.17	-0.27	0.11	-0.16	-1.96	-0.36	-0.03	-0.37
Brownsville, TX	2.70	-2.14	3.88	-0.25	-20.34	-1.94	1.68	-1.87
Bryan-College Station, TX	0.21	-0.26	0.27	-0.15	-2.43	-0.41	0.02	-0.43
Corpus Christi, TX	0.21	-0.44	0.23	-0.20	-3.08	-0.48	0.00	-0.47
Dallas, TX	0.69	-0.03	0.60	-0.40	-3.21	-0.57	-0.05	-0.61
El Paso, TX	2.69	-2.89	2.98	0.20	-19.44	-2.04	1.14	-2.09
Ft. Worth-Arlington, TX	0.30	-0.27	0.25	-0.22	-2.47	-0.52	-0.02	-0.42
Galveston, TX	0.13	-0.18	0.14	-0.11	-1.51	-0.28	-0.02	-0.23
Houston, TX	1.02	-0.12	0.79	-0.25	-3.89	-0.48	-0.07	-0.86
Killeen-Temple, TX	0.14	-0.17	0.12	-0.08	-1.47	-0.23	0.01	-0.23
Longview-Marshall, TX	0.14	-0.22	0.11	-0.11	-1.20	-0.32	-0.01	-0.26
Lubbock, TX	0.11	-0.18	0.12	-0.10	-1.13	-0.24	0.00	-0.21
McAllen-Edinberg-Mission, TX	3.75	-4.03	4.33	0.22	-25.44	-1.79	2.29	-2.05
Midland, TX	0.54	-0.64	0.31	-0.32	-4.46	-0.79	-0.04	-0.63
Odessa, TX	0.30	-0.63	0.41	-0.35	-4.49	-0.92	0.04	-0.97

Table 4 (Continued)

MSA	Low-skilled						High-skilled	
	Native				Foreign-born			
	Mexican		Non-Mexican					
	Male	Female	Male	Female	Mexican	Non-Mexican	Native	Foreign-born
San Antonio, TX	0.29	-1.28	0.46	-0.37	-4.66	-0.87	0.02	-0.65
Tyler, TX	0.24	-0.45	0.27	-0.21	-3.22	-0.59	0.00	-0.46
Waco, TX	0.25	-0.35	0.27	-0.19	-2.50	-0.47	0.02	-0.46
Wichita Falls, TX	0.06	-0.16	0.14	-0.09	-1.24	-0.34	0.00	-0.24
Yakima, WA	1.55	-0.98	1.32	-0.38	-11.26	-1.67	0.37	-1.61
Yuma, AZ	2.03	-0.91	2.10	-0.26	-15.85	-1.83	0.87	-2.06
Las Cruces, NM	1.06	-0.93	1.47	-0.33	-10.35	-1.43	0.50	-1.68
Richland-Kennewick-Pasco, WA	0.65	-0.64	0.67	-0.32	-6.35	-0.98	0.07	-0.88
Greeley, CO	0.33	-0.43	0.32	-0.25	-3.24	-0.71	0.02	-0.62

[a] Refers to MSAs for which at least 60 percent of the foreign born are low-skilled persons born in Mexico.

[b] Refers to MSAs for which less than 10 percent of the foreign born are low-skilled persons born in Mexico.

Table 5

Percentage Change in Employment of Various Labor Skill Groups Due to a 20-Percent Increase in Low-Skilled, Foreign-born Mexican Labor—Selected MSAs

	Low-skilled						High-skilled	
	Native				Foreign-born			
	Mexican		Non-Mexican					
MSA	Male	Female	Male	Female	Mexican	Non-Mexican	Native	Foreign-born
All areas (122)	0.00	-0.15	-0.01	-0.06	-0.61	-0.17	-0.01	-0.07
California areas (23)	-0.01	-0.39	-0.05	-0.16	-1.30	-0.44	-0.03	-0.19
Texas areas (23)	0.02	-0.24	-0.01	-0.08	-1.11	-0.24	-0.02	-0.11
Arizona, New Mexico, Colorado areas (11)	0.02	-0.13	0.00	-0.05	-0.82	-0.22	-0.01	-0.08
Areas in border states (52)	0.00	-0.30	-0.02	-0.11	-1.22	-0.34	-0.03	-0.15
Areas of high concentration of foreign born, low-skilled, Mexicans	0.07	-0.40	0.01	-0.12	-2.41	-0.51	-0.04	-0.20
Areas of low concentration of foreign born, low-skilled, Mexicans	0.00	-0.01	-0.00	-0.00	-0.04	-0.01	-0.00	-0.01
Santa Ana, CA	-0.08	-0.70	-0.11	-0.27	-1.40	-0.53	-0.05	-0.33
Bakersfield, CA	-0.01	-0.37	-0.03	-0.18	-1.53	-0.44	-0.03	-0.20
Chico-Paradise, CA	0.01	-0.05	0.00	-0.04	-0.43	-0.16	0.00	-0.04
Fresno, CA	0.02	-0.57	-0.06	-0.24	-2.04	-0.87	-0.05	-0.27
Los Angeles, CA	-0.25	-1.96	-0.44	-0.70	-3.06	-0.73	-0.16	-0.76
Merced, CA	0.17	-0.29	0.03	-0.11	-2.53	-0.82	-0.04	-0.22
Modesto, CA	-0.04	-0.32	-0.02	-0.13	-1.45	-0.48	-0.02	-0.18

Table 5 (Continued)

MSA	Low-skilled						High-skilled	
	Native				Foreign-born			
	Mexican		Non-Mexican					
	Male	Female	Male	Female	Mexican	Non-Mexican	Native	Foreign-born
Oakland, CA	-0.04	-0.20	-0.04	-0.08	-0.40	-0.17	-0.02	-0.08
Oxnard-Ventura, CA	0.02	-0.30	-0.03	-0.16	-1.25	-0.41	-0.02	-0.17
Redding, CA	0.00	-0.01	0.00	0.00	-0.04	-0.03	0.00	-0.01
San Bernardino, CA	-0.13	-0.89	-0.13	-0.29	-1.68	-0.72	-0.05	-0.30
Sacramento, CA	-0.02	-0.16	-0.02	-0.07	-0.33	-0.14	-0.01	-0.06
Salinas, CA	0.05	-0.40	0.00	-0.19	-2.43	-0.67	-0.04	-0.26
San Diego, CA	-0.05	-0.69	-0.11	-0.25	-1.42	-0.46	-0.05	-0.27
San Francisco, CA	-0.02	-0.16	-0.03	-0.07	-0.34	-0.11	-0.01	-0.08
San Jose, CA	-0.03	-0.34	-0.06	-0.14	-0.80	-0.33	-0.02	-0.15
Santa Barbara, CA	0.03	-0.26	0.00	-0.13	-1.51	-0.48	-0.02	-0.18
Santa Cruz, CA	0.03	-0.24	0.01	-0.12	-1.38	-0.41	-0.02	-0.16
Santa Rosa, CA	0.00	-0.17	0.00	-0.07	-0.55	-0.23	-0.01	-0.06
Stockton-Lodi, CA	0.02	-0.30	-0.02	-0.14	-1.20	-0.56	-0.02	-0.16
Vallejo, CA	0.00	-0.10	-0.01	-0.06	-0.54	-0.18	-0.01	-0.07
Visalia-Tulare, CA)	0.12	-0.43	0.02	-0.15	-2.58	-0.78	-0.05	-0.28
Yuba City, CA	0.01	-0.12	0.02	-0.08	-1.00	-0.34	-0.01	-0.12
Abilene, TX	0.02	-0.04	0.01	-0.03	-0.35	-0.10	0.00	-0.04
Amarillo, TX	0.01	-0.04	0.00	-0.03	-0.36	-0.10	0.00	-0.04

Table 5 (Continued)

MSA	Low-skilled						High-skilled	
	Native				Foreign-born			
	Mexican		Non-Mexican					
	Male	Female	Male	Female	Mexican	Non-Mexican	Native	Foreign-born
Austin, TX	0.00	-0.12	-0.01	-0.06	-0.47	-0.15	-0.01	-0.07
Beaumont, TX	0.00	-0.02	0.00	-0.01	-0.10	-0.04	0.00	-0.01
Brazoria, TX	0.01	-0.05	0.00	-0.04	-0.37	-0.12	0.00	-0.04
Brownsville, TX	0.13	-0.74	0.03	-0.21	-4.57	-0.66	-0.08	-0.32
Bryan-College Station, TX	0.01	-0.04	0.01	-0.03	-0.43	-0.13	0.00	-0.06
Corpus Cristi, TX	0.00	-0.11	-0.01	-0.06	-0.67	-0.20	-0.01	-0.07
Dallas, TX	-0.01	-0.33	-0.06	-0.15	-0.64	-0.23	-0.04	-0.16
El Paso, TX	0.04	-1.11	-0.06	-0.18	-4.68	-0.97	-0.10	-0.41
Ft. Worth-Arlington, TX	-0.01	-0.18	-0.02	-0.08	-0.47	-0.19	-0.01	-0.08
Galveston, TX	0.01	-0.04	0.00	-0.03	-0.28	-0.08	0.00	-0.03
Houston, TX	-0.05	-0.58	-0.10	-0.18	-0.93	-0.25	-0.05	-0.23
Killeen-Temple, TX	0.01	-0.03	0.00	-0.02	-0.30	-0.08	0.00	-0.03
Longview-Marshall, TX	0.01	-0.03	0.00	-0.02	-0.21	-0.06	0.00	-0.03
Lubbock, TX	0.01	-0.03	0.00	-0.02	-0.29	-0.08	0.00	-0.03
McAllen-Edinberg-Mission, TX	0.13	-1.27	0.05	-0.23	-6.10	-0.77	-0.13	-0.42
Midland, TX	0.05	-0.08	0.01	-0.07	-0.81	-0.22	0.00	-0.06
Odessa, TX	0.02	-0.13	0.01	-0.08	-1.11	-0.26	-0.01	-0.11

Table 5 (Continued)

MSA	Low-skilled						High-skilled	
	Native				Foreign-born			
	Mexican		Non-Mexican					
	Male	Female	Male	Female	Mexican	Non-Mexican	Native	Foreign-born
San Antonio, TX	-0.04	-0.43	-0.05	-0.15	-1.12	-0.34	-0.03	-0.16
Tyler, TX	0.01	-0.03	0.01	-0.04	-0.55	-0.18	0.00	-0.06
Waco, TX	0.01	-0.06	0.01	-0.04	-0.49	-0.17	0.00	-0.05
Wichita Falls, TX	0.00	-0.02	0.00	-0.02	-0.24	-0.08	0.00	-0.03
Yakima, WA	0.09	-0.19	0.04	-0.10	-1.78	-0.49	-0.02	-0.19
Yuma, AZ	0.12	-0.30	0.05	-0.12	-3.44	-0.64	-0.04	-0.23
Las Cruces, NM	0.08	-0.27	0.04	-0.10	-2.57	-0.73	-0.02	-0.19
Richland-Kennewick-Pasco, WA	0.04	-0.14	0.01	-0.07	-1.00	-0.27	-0.01	-0.11
Greeley, CO	0.03	-0.07	0.01	-0.05	-0.61	-0.20	0.00	-0.07

and their employment falls by about 0.2 percent. Thus, for the average U.S. region, even relatively large increases in Mexican-born labor do not appear to have large impacts on native workers.

Metropolitan areas in California and Texas have relatively heavy concentrations both of Mexican-born persons and of native-born persons of Mexican ancestry. Each of these states contains 23 metropolitan areas in the sample. The major impact of a 20-percent increase in foreign born, low-skill Mexican labor in California is on this group, whose wages fall by 6.9 percent (Table 4) and whose employment declines by 1.3 percentage points (20 percent less 18.7 percent) (Table 5). The largest wage impacts on other groups occur to foreign-born, low-skill, non-Mexicans and to foreign-born, high-skill persons, but in each case the effects amount only to about one percent. The labor displacement effect is never more than 0.5 percent for any group (Table 5).

The results for Texas are similar to those for California, but for the most part are slightly more moderate. For example, when their employment is increased by 20 percent, foreign-born, low-skill Mexican workers in Texas suffer a 5.0 percent wage decline (Table 4) and about 1.1 percentage point job displacement (Table 5). Comparable effects for Arizona, New Mexico, and Colorado (11 areas) are a 3.7 percent wage reduction and approximately 0.8 percent displacement. Areas of high concentration of foreign-born, low-skill Mexican workers clearly experience the largest impacts of a 20-percent increase in this labor category. For 13 areas for which this labor group constitutes 60 percent or more of the foreign-born population, the wage effect for a 20-percent increase in this group represents a decline of 11.4 percent. Employment of the group is reduced by 2.4 percentage points. Native, low-skill females of Mexican ancestry suffer a 1.3 percent wage decline and a 0.4 percent job displacement effect. Even these last effects are not large.

Three possibilities have been suggested for the repeated empirical finding that the effects of even relatively large increases in foreign-born labor do not appear to have great impacts on native workers. First, the foreign-born population is a relatively small fraction of the population and the labor force, and thus the effects may not be detectable. The results presented above suggest that even in areas with heavy concentrations of foreign-born, low- skill, Mexican labor, the wage and employment displacement effects of relatively large increases in this labor group are not great either for the native-born groups or for other foreign-born groups. The only noteworthy impact is on the own-wage rate because the members of the group are very good labor market substitutes for one another. A second possible explanation for the relatively small impacts of the foreign born on wages and employment is that offsetting increases occur in labor demand and supply relationships with the effect that the wage changes tend to cancel. A third explanation is that efficient U.S. markets result in the effects quickly arbitraging themselves across the nation, with the result that the effects are difficult to detect.

A closer examination of specific metropolitan areas in California and Texas and of other areas of high foreign-born, low-skilled Mexican concentration, indicate that the simulated wage and employment effects vary substantially. For example, among metropolitan areas in California, the own-wage reduction resulting from the 20-percent increase in foreign-born, low-skilled Mexican workers reaches as high as 15.2 percent in Visalia-Tulare and as low as 0.24 percent in Redding (Table 4). Employment of foreign-born, low-skilled Mexicans is reduced by as much as 3.1 percent in Los Angeles and as little as 0.04 percent in Redding (Table 5).

Similar variation in the magnitude of wage and employment effects is apparent among metropolitan areas in Texas. The wage reduction experienced by foreign-born, low-skilled Mexicans varies between 25.4 percent for McAllen-Edinberg-Mission and 0.5 percent for Beaumont (Table 4). The group experiences employment reductions of between 6.1 percent in McAllen-Edinberg-Mission and 0.1 percent in Beaumont (Table 4). Also of note, wages of foreign-born, low-skilled Mexicans fall by 15.9 percent in Yuma, Arizona, while employment falls by 3.4 percent. Greeley, Colorado, also has a high concentration of foreign-born, low-skilled Mexicans, although the own-wage reduction there is only 3.2 percent and the employment reduction is just 0.6 percent.

The range of the wage and employment effects on other groups resulting from a 20-percent increase in foreign-born, low-skilled Mexican workers is much smaller. Among metropolitan areas in California, the wages of native, low-skilled males (both Mexican and non-Mexican) increase, though this increase is relatively small and varies between 0.0 percent in Redding and 2.3 percent in Los Angeles (Table 4). The wage effect is similar for metropolitan areas in Texas, reaching a high of 4.3 percent in McAllen-Edinberg-Mission. The employment effect on this group varies little across metropolitan areas in California and Texas and is nearly zero in most cases.

To the extent that wages and job opportunities of the native born are influenced by low-skill migrants from Mexico, females and especially Mexican ancestry females bear the impacts. However, these effects are not great even in areas with high concentrations of foreign-born, low-skill Mexicans. For example, in areas where at least 60 percent of the foreign-born population consists of low-skill migrants from Mexico, a 20 percent increase in this population reduces the real wage of native-born Mexican ancestry females by 1.3 percent and their employment by 0.4 percent (Tables 4 and 5).

As discussed above, native, low-skilled females (both Mexican and non-Mexican) and other foreign-born groups tend to suffer wage and employment decreases as a result of the 20-percent increase in foreign-born, low-skilled Mexican workers. Although the effects are quite small on average for metropolitan areas in California and Texas (around 1 percent or less), some areas of high foreign-born, low-skilled Mexican concentration display relatively large effects. For example, in

Los Angeles, California, the wages of foreign-born, high-skilled workers fall by 3.4 percent while employment falls by 0.8 percent. In McAllen-Edinberg-Mission, Texas, the wages of native, low-skilled, Mexican females fall by 4.0 percent, accompanied by a 1.3 percent reduction in employment.

A general presumption is that the two groups most likely to enjoy benefits due to migration from Mexico to the United States are the migrants themselves and their U.S. employers. However, because most models that focus on the U.S. impacts of immigration assume separability of labor and capital, as well as not incorporating capital explicitly in the empirical framework, empirical models typically do not allow any assessment of the returns to capital. In the model described above, we explicitly introduce capital and therefore we are able to perform simulation exercises that relate to the return to capital.

Table 6 reports the percentage change in the real rental price of capital due to a 20-percent increase in foreign-born, low-skilled Mexican labor. Among all of the inputs, capital is the clearest winner. In California areas in general the real rental price of capital increases by 0.82 percent, but the increases are somewhat larger in agricultural areas like Merced (1.7 percent), Salinas (1.7 percent), and Visalia-Tulare (1.4 percent). However, the largest increase (2.5 percent) occurs in Los Angeles. The average increase in the real rate of return to capital in Texas is 0.3, but for many areas close to the border the return is considerably higher (Brownsville—1.4 percent; El Paso—1.6 percent; McAllen-Edinberg-Mission—1.8 percent). Another border area that experiences a large increase in the rate of return to capital is Yuma, Arizona (1.7 percent). These results provide confirmation that the U.S. owners of capital benefit due to low-skill migration from Mexico.

Conclusions

In summary, labor market impacts are the most intensively studied effects of the foreign born in the United States. Although these effects may be mitigated or reinforced through less-highly studied channels of influence, the following conclusions have the strongest support. First, in both 1980 and 1990 the foreign born had a tendency to put downward pressure on the wage rates of the native born and a tendency to displace them from their jobs, but the effects were not large at the national level. The Mexican-born had similarly small impacts at the national level. Second, the foreign born are highly concentrated regionally, and although internal migration and trade tend to distribute the consequences over broader regions, the economic consequences also are concentrated. The largest impacts of low-skilled migration from Mexico are on other low-skilled migrants from Mexico, because the two groups are good labor market substitutes. In areas of high concentration of new migrants from Mexico, such as El Paso, other migrants from Mexico suffer

Table 6
Percentage Change in the Real Rental Price of Capital Due to a 20-Percent Increase in Foreign-born, Low-skilled Mexican Labor—Selected Areas

Area	Percentage Change
All areas (122)	0.27
California areas (23)	0.82
Texas areas (23)	0.33
Arizona, New Mexico, Colorado areas (11)	0.30
Areas in border states (52)	0.56
Areas of high concentration of foreign-born, low-skilled, Mexicans (13)	0.88
Areas of low concentration of foreign-born, low-skilled, Mexicans (43)	0.02

Santa Ana, CA	1.31	Beaumont, TX	0.06
Bakersfield, CA	0.74	Brazoria, TX	0.12
Chico-Paradise, CA	0.12	Brownsville, TX	1.44
Fresno, CA	1.04	Bryan-College Station, TX	0.14
Los Angeles, CA	2.54	Corpus Christi, TX	0.12
Merced, CA	1.66	Dallas, TX	0.23
Modesto, CA	0.74	El Paso, TX	1.58
Oakland, CA	0.27	Ft. Worth-Arlington, TX	0.17
Oxnard-Ventura, CA	0.89	Galveston, TX	0.08
Redding, CA	0.02	Houston, TX	0.27
San Bernardino, CA	1.04	Killeen-Temple, TX	0.07
Sacramento, CA	0.15	Longview-Marshall, TX	0.05
Salinas, CA	1.68	Lubbock, TX	0.06
San Diego, CA	0.80	McAllen-Edinberg-Mission, TX	1.75
San Francisco, CA	0.19	Midland, TX	0.25
San Jose, CA	0.69	Odessa, TX	0.26
Santa Barbara, CA	0.45	San Antonio, TX	0.48
Santa Cruz, CA	0.93	Tyler, TX	0.16
Santa Rosa, CA	0.29	Waco, TX	0.13
Stockton-Lodi, CA	0.58	Wichita Falls, TX	0.07
Vallejo, CA	0.31	Yakima, WA	0.81
Visalia-Tulare, CA	1.43	Yuma, AZ	1.66
Yuba City, CA	0.42	Las Cruces, NM	0.70
Abilene, TX	0.10	Richland-Kennwick-Pasco, WA	0.48
Amarillo, TX	0.09	Greeley, CO	0.22
Austin, TX	0.16		

job displacement and significant downward pressure on their wage rates. Such effects impede the upward economic mobility of less-skilled migrants themselves. Finally, owners of capital and land are the primary U.S. beneficiaries from the presence of less-skilled migrants from Mexico.

Based on our econometric results the most surprising finding is probably that Hicksian complementarity relationships are much fewer than one might have expected. One tends to think that an increase in the supply of one factor increases the marginal products of the other factors. Indeed, one common argument in favor of immigration often is that more low-skill immigrants would make most other factors more productive, even if previous low-skill immigrants unavoidably get hurt. On average, Hicksian cross-elasticities of complementarity tend to be positive. Actually, they *must* be positive in the two-input case. They will also be positive, even if there are many inputs, if the functional form is Cobb-Douglas or CES, for instance. Yet, our results indicate that, even though capital is definitely a Hicksian complement for labor, Hicksian substitution relationships by far dominate among the different categories of labor. In the model, some complementarity relationships between various labor categories are evident, but they tend to be scarce and weak. These often involve low-skill native males and females, high-skill native females, and low- and high-skill migrants. As far as an increase in low-skill immigration is concerned, the clear winner is capital, but low-skill males and high-skill females are also likely to benefit.

The simulation results indicate that the largest adverse impacts of additional low-skilled, Mexican migrants falls on low-skilled, Mexican migrants themselves. Although small relative declines and advances are observed in the real wages and employment of other labor groups, the size of these effects is usually small. Capital's real rental price rises in the simulations, with the magnitude varying directly with the concentration of low-skilled, Mexican migrants in the various areas, as does the absolute value of the negative real wage effects on the migrants themselves and the various impacts on the labor market outcomes of other labor groups. These findings highlight the importance of demographic and geographic disaggregation in immigrant impact analyses.

Relative to other foreign-born groups and relative to the native born, persons born in Mexico have relatively low rates of U.S. internal migration (Greenwood, Henning and McDowell, 1997). Indeed, the native born of Mexican ancestry have low rates of internal migration in general. For example, among those household heads born in Mexico who entered the United States between 1970 and 1974, only 4.1 percent made an interstate move between 1985 and 1990. During the same period 5.2 percent of native-born heads of Mexican ancestry made such a move. In contrast, the same entry cohort from other countries of origin had much higher rates of internal migration over the 1985-1990 period. Representative rates of internal migration for these other groups are as follows: Philippines—12.3 percent;

Germany—18.0 percent; United Kingdom—19.7 percent; India—21.7 percent; Korea—15.8 percent; and Vietnam—15.2 percent. Among these countries, only for Mexico do the foreign born have lower rates of internal migration than the native born of each respective ancestry.

Neuman and Tienda (1994) also confirmed that undocumented migrants from Mexico are less likely to move across state lines than undocumented migrants from other regions. An analysis of administrative records (Legalization Application Processing System, or LAPS) revealed that just over one-quarter of amnestied immigrants changed residence at least once between the time of most recent entry and application for amnesty, but the likelihood of inter-state moves as undocumented migrants varied by place of birth. Mexicans were least likely to move subsequent to their initial entry, whereas Asians and Africans were most likely to do so. Specifically, only 19 percent of undocumented Mexicans who applied for legal status had moved across state lines before soliciting amnesty compared to over two-thirds of undocumented migrants from Asia and Africa, and over half of undocumented migrants from other Latin American countries (except Salvadorans, whose inter-state migratory behavior was similar to that of Mexicans).

If secondary migration leads to greater residential dispersion throughout the country, the social impacts of undocumented migration ultimately will be less severe in the states that serve as gateways for initial entry. Overall, unauthorized Mexican migrants who moved across state lines were less residentially concentrated at the time of application for amnesty than were nonmovers. For Mexicans, California and Texas were the main gateways for unauthorized entry. However, limited evidence suggests dispersal of impacts through inter-state moves of unauthorized Mexican migrants; nonmovers were more than twice as likely as movers to have entered through California (three out of four nonmovers from Mexico entered through California compared to just over one-third of movers). Mexicans who entered without inspection through Texas were more likely to have changed their state of residence by the time of application for amnesty, thereby attenuating impacts in this state. Specifically, just over half of Mexican movers entered through Texas compared to more than one-fifth of nonmovers.

These low rates of internal migration among persons born in Mexico are due to many factors, such as relatively low levels of education, lack of English language skills, and strong ties to areas with high concentrations of persons born in Mexico. Like education, migration is a form of investment in human capital and as such migration presumably yields higher future returns. Historically, internal migration has been a mechanism through which Americans have taken advantage of employment and wage opportunities elsewhere to improve their economic status. Thus, the low internal migration rates of both those born in Mexico and those born in the United States of Mexican ancestry may restrict their access to areas that provide favorable economic opportunities. Lack of internal mobility also perpetuates high concentrations of the Mexican-born population. The continued entry of migrants from Mexico who are good labor market substitutes for earlier migrants results in continued job competition between the groups, which in turn restricts wage growth for them.

Notes

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1. Other foreign-born groups also are highly concentrated. For example, 64.6 percent of the Cuban-origin population resided in Florida in 1990. However, these groups have absolute numbers that are low in comparison to the Mexican-origin population. The Cuban group, for example, numbered 1.0 million in 1990, or 7.7 percent of the Mexican group.

2. We are presently unable to estimate the model with more than nine inputs, but this is five more inputs than is found in the typical production-theory approach.

3. J = 9 in all models.

4. See Hicks (1970), Sato and Koizumi (1972), and Syrquin and Hollender (1982).

5. See Diewert and Wales (1988), Kohli (1994), and Greenwood, Hunt and Kohli (1996).

6. See White (1988).

7. Separate results associated with the opening of each channel are available from the authors on request.

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Appendix Table A1
Mexican Model Labor Force Participation ML Probit Estimates
Native, Lower-skilled, Mexican Males

Parameter	Estimate	Standard Error	t-statistic
AREARW	376.176	258.669	1.45427
RFAMINC	61.3785	13.6618	4.49271
KIDLT6	.265769	.055806	4.76241
KID617	.076358	.054201	1.40879
BLACK	1.01195	1.03761	.975270
WHITE	-.242839	.151583	-1.60202
DBLACK	-.942278	1.07299	-.878178
DWHITE	.327015	.162248	2.01552
DED	.097896	.012121	8.07632
DX	.061153	.980902E-02	6.23438
DXSQ	-.124580E-02	.163513E-03	-7.61896
DIMG8090	1.40544	1.22085	1.15120
C	.631353	.267986	2.35592

Standard Errors computed from analytic second derivatives (Newton)

	dP/dX 0	dP/dX 1
AREARW	-80.45346	80.45346
RFAMINC	-13.12714	13.12714
KIDLT6	-0.056841	0.056841
KID617	-0.016331	0.016331
BLACK	-0.21643	0.21643
WHITE	0.051936	-0.051936
DWHITE	-0.069939	0.069939
DED	-0.020937	0.020937
DX	-0.013079	0.013079
DXSQ	0.00026644	-0.00026644
DIMG8090	-0.30058	0.30058
C	-0.13503	0.13503

Log of Likelihood Function	=	-1480.12
Number of Observations	=	3808
Number of Positive Observations	=	3198
Fraction of Positive Observations	=	0.839811
Sum of Squared Residuals	=	453.344
R-squared	=	0.115128
Fraction of Correct Predictions	=	0.839548

Appendix Table A2
Mexican Model Labor Force Participation ML Probit Estimates
Native, Lower-skilled, Mexican Females

Parameter	Estimate	Standard Error	t-statistic
AREARW	157.074	111.311	1.41112
RFAMINC	107.314	6.66555	16.0999
KIDLT6	-.370276	.018081	-20.4792
KID617	-.070952	.013506	-5.25354
BLACK	1.13268	.612932	1.84796
WHITE	-.141244	.085478	-1.65239
DBLACK	-1.20283	.635434	-1.89293
DWHITE	.120051	.089450	1.34210
DED	.085264	.558204E-02	15.2746
DX	.024808	.355593E-02	6.97662
DXSQ	-.866736E-03	.740739E-04	-11.7010
DIMG8090	-1.16845	.510514	-2.28878
C	.192903	.118596	1.62655

Standard Errors computed from analytic second derivatives (Newton)

	dP/dX 0	dP/dX 1
AREARW	-51.34042	51.34042
RFAMINC	-35.07622	35.07622
KIDLT6	0.12103	0.12103
KID617	0.023191	-0.023191
BLACK	-0.37022	0.37022
WHITE	0.046166	-0.046166
DBLACK	0.39315	-0.39315
DWHITE	-0.039239	0.039239
DED	-0.027869	0.027869
DX	-0.0081087	0.0081087
DXSQ	0.00028330	-0.00028330
DIMG8090	0.38191	-0.38191
C	-0.063051	0.063051

Log of Likelihood Function	=	-6993.56
Number of Observations	=	12182
Number of Positive Observations	=	7708
Fraction of Positive Observations	=	0.632737
Sum of Squared Residuals	=	2359.90
R-squared	=	0.166572
Fraction of Correct Predictions	=	0.707273

Appendix Table A3

Mexican Model Labor Force Participation ML Probit Estimates

Native, Lower-skilled, Non-Mexican Males

Parameter	Estimate	Standard Error	t-statistic
AREARW	229.311	99.3298	2.30858
RFAMINC	63.4894	3.83384	16.5603
KIDLT6	.157440	.019434	8.10124
KID617	.079847	.025122	3.17833
BLACK	.202275	.129982	1.55617
WHITE	1.05712	.113347	9.32637
DBLACK	-.361712	.138173	-2.61783
DWHITE	-.795073	.121111	-6.56481
DED	.146418	.396335E-02	36.9430
DX	.068899	.339693E-02	20.2826
DXSQ	-.136488E-02	.589171E-04	-23.1661
DIMG8090	.865882E-02	.088712	.097606
C	-.079648	.162948	-.488793

Standard Errors computed from analytic second derivatives (Newton)

	dP/dX 0	dP/dX 1
AREARW	-41.73207	41.73207
RFAMINC	-11.55438	11.55438
KIDLT6	-0.028652	0.028652
KID617	-0.014531	0.014531
BLACK	-0.036812	0.036812
WHITE	-0.19238	0.19238
DBLACK	0.065828	-0.065828
DWHITE	0.14469	-0.14469
DED	-0.026646	0.026646
DX	-0.012539	0.012539
DXSQ	0.00024839	-0.00024839
DIMG8090	-0.0015758	0.0015758
C	0.014495	-0.014495

Log of Likelihood Function	=	-14934.2
Number of Observations	=	4472
Number of Positive Observations	=	38642
Fraction of Positive Observations	=	0.863914
Sum of Squared Residuals	=	4440.56
R-squared	=	0.155589
Fraction of Correct Predictions	=	0.867446

Appendix Table A4
Mexican Model Labor Force Participation ML Probit Estimates
Native, Lower-Skilled, Non-Mexican Females

Parameter	Estimate	Standard Error	t-statistic
AREARW	304.171	24.8732	12.2289
RFAMINC	23.8142	1.14345	20.8266
KIDLT6	-.530727	.474732E-02	-111.795
KID617	-.149499	.351399E-02	-42.5440
BLACK	.578658	.061099	9.47082
WHITE	.670588	.058886	11.3880
DBLACK	-.468357	.064083	-7.30856
DWHITE	-.655242	.061658	-10.6270
DED	.104957	.169158E-02	62.0469
DX	.020743	.878380E-03	23.6151
DXSQ	-.104941E-02	.179880E-04	-58.3393
DIMG8090	-.461973	.049749	-9.28605
C	-.305222	.072614	-4.20337

Standard Errors computed from analytic second derivatives (Newton)

	dP/dX 0	dP/dX 1
AREARW	-93.11224	93.11224
RFAMINC	-7.28994	7.28994
KIDLT6	0.16247	-0.16247
KID617	0.045764	-0.045764
BLACK	-0.17714	0.17714
WHITE	-0.20528	0.20528
DBLACK	0.14337	-0.14337
DWHITE	0.20058	-0.20058
DED	-0.032129	0.032129
DX	-0.0063498	0.0063498
DXSQ	0.00032124	-0.00032124
DIMG8090	0.14142	-0.14142
C	0.093434	-0.093434

Log of Likelihood Function	=	-134647.
Number of Observations	=	248369
Number of Positive Observations	=	170964
Fraction of Positive Observations	=	0.688347
Sum of Squared Residuals	=	45110.8
R-squared	=	0.153350
Fraction of Correct Predictions	=	0.730216

Appendix Table A5
Mexican Model Labor Force Participation ML Probit Estimates
Native, Higher-skilled

Parameter	Estimate	Standard Error	t-statistic
AREARW	-46.0643	20.2122	-2.27903
RFAMINC	19.9034	1.14656	17.3592
KIDLT6	-.194098	.596017E-02	-32.5658
KID617	-.025811	.413460E-02	-6.24266
BLACK	.134839	.070952	1.90042
WHITE	.355892	.062215	5.72038
DBLACK	-.328959	.074482	-4.41660
DWHITE	-.301183	.065311	-4.61152
DED	-.025589	.146034E-02	-17.5228
DX	.019869	.146036E-02	13.6055
DXSQ	-.107197E-02	.278087E-04	-38.5480
DIMG8090	-.322939	.074837	-4.31526
C	1.12338	.084711	13.2614

Standard Errors computed from analytic second derivatives (Newton)

	dP/dX 0	dP/dX 1
AREARW	7.57394	-7.57394
RFAMINC	-3.27253	3.27253
KIDLT6	0.031914	-0.031914
KID617	0.0042438	-0.0042438
BLACK	-0.022170	0.022170
WHITE	-0.058516	0.058516
DBLACK	0.054088	-0.054088
DWHITE	0.049521	-0.049521
DED	0.0042074	-0.0042074
DX	-0.0032669	0.0032669
DXSQ	0.00017625	-0.00017625
DIMG8090	0.053098	-0.053098
C	-0.18471	0.18471

Log of Likelihood Function	=	-83604.3
Number of Observations	=	275623
Number of Positive Observations	=	247762
Fraction of Positive Observations	=	0.898916
Sum of Squared Residuals	=	23336.4
R-squared	=	0.684925E-01
Fraction of Correct Predictions	=	0.899257

Appendix Table A6
Mexican Model Labor Force Participation ML Probit Estimates
Foreign-born, Lower-skilled, Mexicans

Parameter	Estimate	Standard Error	t-statistic
AREARW	326.612	188.085	1.73651
RFAMINC	45.8073	5.53054	8.28261
KIDLT6	-.280559	.016288	-17.2252
KID617	-.049781	.010875	-4.57762
BLACK	.201741	.783226	.257577
WHITE	-.450715	.081139	-5.55482
DBLACK	.125994	.807753	.155981
DWHITE	.428945	.084985	5.04731
DED	.018887	.354467E-02	5.32841
DX	.024408	.373495E-02	6.53513
DXSQ	-.782044E-03	.683280E-04	-11.4454
DIMG8090	-.259368	.027825	-9.32129
C	.090804	.156783	.579172

Standard Errors computed from analytic second derivatives (Newton)

	dP/dX 0	dP/dX 1
AREARW	-121.91581	121.91581
RFAMINC	-17.09870	17.09870
KIDLT6	0.1047	-0.10473
KID617	0.018582	-0.018582
BLACK	-0.075305	0.075305
WHITE	0.16824	-0.16824
DBLACK	-0.047030	0.047030
DWHITE	-0.16011	0.16011
DED	-0.0070502	0.0070502
DX	-0.0091110	0.0091110
DXSQ	0.00029192	-0.00029192
DIMG8090	0.096815	-0.096815
C	-0.033895	0.033895

Log of Likelihood Function	=	-7487.86
Number of Observations	=	11498
Number of Positive Observations	=	6045
Fraction of Positive Observations	=	0.525744
Sum of Squared Residuals	=	2638.10
R-squared	=	0.798307E-01
Fraction of Correct Predictions	=	0.621673

Appendix Table A7
Mexican Model Labor Force Participation ML Probit Estimates
Foreign-born, Lower-skilled, Non-Mexicans

Parameter	Estimate	Standard Error	t-statistic
AREARW	513.323	99.4405	5.16212
RFAMINC	18.8780	2.33006	8.10194
KIDLT6	-.415248	.011742	-35.3655
KID617	-.104216	.795639E-02	-13.0983
BLACK	.272277	.084406	3.22580
WHITE	-.238858	.045165	-5.28853
DBLACK	.025034	.088216	.283778
DWHITE	.053862	.047700	1.12920
DED	.016021	.201185E-02	7.96320
DX	.017073	.209490E-02	8.14958
DXSQ	-.824776E-03	.399819E-04	-20.6288
DIMG8090	-.338545	.015629	-21.6615
C	.103879	.102992	1.00861

Standard Errors computed from analytic second derivatives (Newton)

	dP/dX	
	0	1
AREARW	-171.81270	171.81270
RFAMINC	-6.31858	6.31858
KIDLT6	0.13899	0.034882
BLACK	-0.091133	0.091133
WHITE	0.079947	-0.079947
DBLACK	-0.0083790	0.0083790
DWHITE	-0.018028	0.018028
DED	-0.0053623	0.0053623
DX	-0.0057143	0.0057143
DXSQ	0.00027606	-0.00027606
DIMG8090	0.11331	-0.11331
C	-0.034769	0.034769

Log of Likelihood Function	=	-23111.0
Number of Observations	=	39239
Number of Positive Observations	=	25519
Fraction of Positive Observations	=	0.650348
Sum of Squared Residuals	=	7897.68
R-squared	=	0.114888
Fraction of Correct Predictions	=	0.692219

Appendix Table A8
Mexican Model Labor Force Participation ML Probit Estimates
Foreign-born, Higher-skilled

Parameter	Estimate	Standard Error	t-statistic
AREARW	286.908	44.3974	6.46226
RFAMINC	97.4366	4.44469	21.9220
KIDLT6	.100829	.015647	6.44418
KID617	.051002	.999703E-02	5.10176
BLACK	-.206484	.111559	-1.85089
WHITE	-.027063	.066818	-.405023
DBLACK	.151424	.118472	1.27815
DWHITE	.063638	.069625	.914010
DED	.237935E-02	.206830E-02	1.15039
DX	.036828	.236676E-02	15.5603
DXSQ	-.109184E-02	.441550E-04	-24.7274
DIMG8090	-.147804	.019277	-7.66733
C	.505518	.090778	5.56875

Standard Errors computed from analytic second derivatives (Newton)

	dP/dX 0	dP/dX 1
AREARW	-42.39572	42.39572
RFAMINC	-14.39800	14.39800
KIDLT6	-0.014899	0.014899
KID617	-0.0075365	0.0075365
BLACK	0.030512	-0.030512
WHITE	0.0039990	-0.0039990
DBLACK	-0.022376	0.022376
DWHITE	-0.0094036	0.0094036
DED	-0.00035159	0.00035159
DX	-0.0054419	0.0054419
DXSQ	0.00016134	-0.00016134
DIMG8090	0.021841	-0.021841
C	-0.074699	0.074699

Log of Likelihood Function	=	-12770.3
Number of Observations	=	46536
Number of Positive Observations	=	42335
Fraction of Positive Observations	=	0.909726
Sum of Squared Residuals	=	3536.00
R-squared	=	0.747712E-01
Fraction of Correct Predictions	=	0.910327