Does Immigration Crowd Natives Into or Out of Higher Education?

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Abstract

This paper investigates the impact of immigration on the college enrollment of natives. Existing studies have primarily focused on the effect of increased immigrant demand for schooling on native enrollment. However, changes in immigrant labor supply may also affect native enrollment if they alter the net benefit of higher education by changing local market prices. Using decadal U.S. Census microdata from 1970 to 2000, I find that state-level increases in immigrant college students do not significantly lower the rate of native college enrollment in those states. In contrast, state-level increases in relatively unskilled immigrant labor do significantly raise the proportion of natives in those states going to college. The identification of a crowd-in effect and the lack of a significant crowd-out effect are suggestive of college demand that is fairly wage-sensitive and college slots that are flexibly supplied over a decadal time horizon. Consistent with this, the crowd-in effect of immigrant labor inflows is larger for young natives, who may be more sensitive to college returns than older natives, as well as for natives on the margin of public school attendance, where college supply is likely more elastic.

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1 Introduction

Over the past several decades, the United States has experienced some of its largest immigrant inflows since the Great Depression. This higher level of immigration has generated significant academic and public policy debate on the effects that such inflows have on receiving markets and natives. Much of that discussion has centered around the impact of increased immigration on education and labor markets.

Focusing on the higher education market, Hoxby (1998) finds that inflows of immigrant students displace disadvantaged natives from college enrollment. Studies at other levels of education have found similar displacement effects for some although not all natives (Betts, 1998; Betts & Fairlie, 2003; Borjas, 2007; Gould, Lavy, & Paserman, 2009). Meanwhile, the labor literature has primarily examined the impact of immigrant labor inflows on the wages of similarly- and dissimilarly-skilled natives. However, findings have been mixed regarding the sign and magnitude of such a wage effect (Borjas, 2003; Card, 1990; Ottaviano & Peri, Forthcoming).

The lack of consensus amongst the wage studies has helped to generate a growing line of research on whether natives respond endogenously to immigrant worker inflows.[1] Studies in this area have, for instance, investigated whether in response to labor immigration, natives relocate, increase their labor supply, and specialize in occupations and tasks for which they have a comparative advantage (Card, 2001, 2005; Card & DiNardo, 2000; Cortes & Tessada, Forthcoming; Peri & Sparber, 2009). However, it remains unexplored whether native responses in the higher education market also factor in the absorption of immigrants into the labor market, and how this affects equilibrium in both markets.

This paper, in a unified framework of the education and labor markets, addresses the question of whether skill level via college enrollment is another margin on which natives endogenously adjust to immigrant inflows; not only when facing student immigration, but labor immigration as well.[2] There is reason to anticipate native responses to both types of immigrant inflows. Marginal benefits

[1] Immigration analyses that, more generally, highlight general equilibrium effects of immigration are also a recently expanding area (Cortes, 2008; Lewis, Forthcoming; Ortega & Peri, 2009).

[2] Betts (1998) also acknowledges the distinct effects on native skill acquisition that these heterogenous immigrant inflows may have, although he does not separately identify the effects. Eberhard (2009) also examines an endogenous native skill response to immigrant labor inflows in a general equilibrium framework, focusing more on welfare implications and less on explicitly modeling the college market than this paper. Finally, while studies prior to the current paper have linked labor and education markets, it has been to determine their joint role in some alternative outcome such as the growth in the college wage premium (Fortin, 2006).

of higher education can be framed as the skilled wage relative to the unskilled wage. Marginal costs of higher education can be thought of as college tuition and fees, net of grants and aid, and the opportunity cost (the unskilled wage).[3] Relatively unskilled labor immigration may increase or "crowd-in" native enrollment by raising the net benefits of college, while student immigration could decrease or "crowd-out" native enrollment by lowering net benefits.

Such analysis thus contributes to the understanding of how local markets respond to immigrant inflow shocks. By proposing immigration-induced market price movements as the mechanisms for a native skill response, the paper takes an alternative approach to examine immigration wage effects and the structure of the labor market. The native enrollment response to immigration is similarly important for understanding the structure of the higher education market and the elasticity of college supply, using an alternative demand shock than existing work (Bound & Turner, 2007). The paper also helps to evaluate the sensitivity of college demand to the relative wage of unskilled labor and college tuition/fees, adding to earlier investigations of the impact of labor and education market conditions on educational attainment (Black, McKinnish & Sanders, 2005; Dynarski, 2003; Kane, 1999; Neumark & Wascher, 1995).

The paper first outlines a dual-market, supply-demand model that forms predictions on the reduced-form crowding effects of immigration on native college enrollment. The model also illustrates the underlying structural relationship of the crowding effects to market prices. The next sections of the paper describe the data and empirical strategy used to analyze these effects, including the approach to isolate the exogenous component of immigrant inflows. The final sections of the paper present estimates of immigration's effect on native enrollment and discuss the sensitivity and implications of these estimates.

A key finding of this paper is that while state-level increases in immigrant college students do not significantly lower native college enrollment rates, increases in relatively unskilled immigrant labor within a state do significantly raise rates. As such, these results provide indirect evidence of market price effects of immigration on natives. However, while the model and empirics suggest that unskilled immigrant labor inflows do lower the relative unskilled wage, they also show that this effect is mitigated by the positive enrollment response of natives. Crowd-in coupled with a lack of

[3]While resources per student may also vary across institutions and influence higher education demand, this paper will not focus on such school quality differences.

crowd-out is shown to imply that the native response arises primarily due to wage-sensitive college demand and highly elastic college supply, rather than large market price effects. Consistent with this assertion, the crowd-in effect is largely driven by young natives, who may be most sensitive to college returns, and is also moderately larger for natives on the margin of public school attendance, where enrollment slots are more flexibly supplied.

2 Conceptual Framework

I use a dual-market, supply-demand framework to model the impact of heterogenous immigrant inflows on native college enrollment. Native crowd-in and crowd-out from immigration occurs in the static model via the interaction of the labor and higher education markets and movements in prices that affect native skill choice. I focus on a graphical presentation of the model which captures much of its intuition (a more detailed discussion and version of the model can be found in Appendix A).

The geographic boundary of the local labor and higher education (college) markets is assumed to be a state.[4] I focus on the impact of immigration into each of these two markets for a given state,[5] still allowing for out-of-state migration by natives or immigrants. Individuals are considered skilled if they have at least some college education and are unskilled otherwise. Natives acquire skill domestically in the model, while immigrants may either acquire skill in the U.S. or in their home country before migrating.[6]

As mentioned earlier, the marginal benefits of college are the skilled wage relative to the unskilled wage, while the marginal costs of college are tuition/fees and the unskilled wage (the opportunity cost). Thus, in the college market, both the supply of and demand for college enrollment are potentially sensitive to changes in the relative unskilled wage and college tuition/fees.[7] Meanwhile, the supply of and demand for relatively unskilled labor in the labor market are potentially sensitive to changes in the relative unskilled wage only. The relative supply of unskilled labor is determined

[4]As Bound et al. (2004) discuss, because funding decisions at public institutions occur primarily at the state level, there is support for usage of the state as the appropriate geographic boundary of these markets. Washington, D.C. will be excluded as it is an atypical market with more flexible boundaries for both labor and educational purposes.

[5]Thus state-specific notation is suppressed in all versions of the model.

[6]Thus foreign-born individuals must decide whether to immigrate for college and/or employment. Jackson (2010) claims that immigrants make this college/employment decision jointly and explores whether cross-country differences in educational quality and informational asymmetries affect that choice.

[7]Without loss of generality, I use the relative unskilled wage rather than the relative skilled wage to aid in later interpretation. Also, for simplicity, I focus on price sensitivity rather than the roles that labor unemployment or college quality may also have on native enrollment.

by: equilibrium college enrollment and the retention of a state's college students in its labor market, labor immigration and native migration, and the sensitivity of labor supply to the relative unskilled wage.[8][9]

Figures 1a and 1b depict the impact on equilibrium native college enrollment of two types of immigrant inflows. In Figure 1a, an exogenous inflow of relatively unskilled immigrant labor increases the equilibrium relative supply of unskilled labor from L to $L^{'}$ and lowers the relative unskilled wage from w to $w^{'}$. This decrease in the relative wage return to being unskilled is associated with an equilibrium increase in college demand, which raises total enrollment from E to $E^{'}$ and tuition/fees from f to f'. Comparing the new equilibrium at point B to the old one at point A, native enrollment increases from E_N to $E_N^{'}$. In other words, the model predicts increases in relatively unskilled immigrant labor will crowd-in native college enrollment.

In Figure 1b, an exogenous inflow of immigrant students increases the demand for higher education. This increases tuition/fees and induces some natives to no longer enroll in college. Additionally, if the enrolled immigrant students join the local labor market as skilled labor, this decreases the equilibrium relative supply of unskilled labor and raises the relative return to being unskilled. In equilibrium, these effects result in total enrollment increasing from E to $E^{'}$ and tuition/fees rising from f to $f^{'}$. Those changes in the higher education market are associated with a decrease in the relative supply of unskilled labor from L to $L^{'}$ and a rise in the relative unskilled wage from w to $w^{'}$. Again comparing the new equilibrium at point B to the old one at point A, native enrollment here, contrary to total enrollment, decreases from E_N to $E_N^{'}$. Therefore, increases in immigrant students are predicted to crowd-out native college enrollment.

In addition to these sign predictions, the magnitudes of the above comparative statics from the immigrant shocks are also of interest. The magnitudes depend on demand and supply elasticities in the labor and college markets, which determine how much prices (i.e., wages and tuition/fees) are affected by immigrant inflows, as well as depend on the sensitivity of native college demand to changes in those prices. Let β and α represent the sensitivity of native enrollment demanded to inflows of relatively unskilled immigrant labor and immigrant students, respectively, in equilib-

[8]Bound et al. (2004) estimate that approximately 30 percent of students college-educated in a state remain there for employment in the long-run.

[9]Labor supply sensitivity to the relative unskilled wage here reflects within-state outside options and the marginal utility of leisure, as well as the sensitivity of interstate migration to the relative wage.

rium. Then as Appendix A details, the following can be derived for those crowd-in and crowd-out elasticities:

$$\beta = (-\epsilon_{wL})(\eta^N) + (-\epsilon_{fL})(\phi^N) \in [0, \infty) \qquad [Crowd - in], \tag{1}$$

$$\alpha = (-\epsilon_{wE})(\eta^N) + (-\epsilon_{fE})(\phi^N) \in [-1, 0] \qquad [Crowd - out], \tag{2}$$

where η^N and ϕ^N are, respectively, the relative unskilled wage and tuition/fee elasticities of native college enrollment demand. Parameters ϵ_{wL} and ϵ_{fL} are elasticities of relative unskilled wages and tuition/fees to exogenous inflows of relatively unskilled immigrant labor, while ϵ_{wE} and ϵ_{fE} are elasticities for the sensitivity of relative unskilled wages and tuition/fees to exogenous inflows of immigrant students.

Both $|\beta| > |\alpha|$ and $|\beta| < |\alpha|$ are possible depending on structural parameter values. The lower bound on β occurs for several scenarios, such as perfectly inelastic college supply or frictionless labor mobility across states, while the upper bound on β requires perfectly inelastic labor demand, perfectly elastic college supply, very large immigrant population shares, and immobile labor with no labor supply sensitivity to wage changes. The upper bound on α occurs when there is perfectly elastic college supply combined, for instance, with perfectly elastic labor demand, while the lower bound on α simply requires perfectly inelastic college supply. This highlights that markets with a more flexible supply of college enrollment slots, such as those with a larger proportion of two-year and four-year public universities (Bound & Turner, 2007), should experience both amplified crowd-in effects and diminished crowd-out effects.

A key assumption made throughout the model to allow for a causal interpretation of the crowding parameters is that the state-level immigrant inflows are exogenous. However, variation across states, time, or within states over time in local labor and college market conditions may be confounded with variation in immigrant flows. This would bias estimates and misinform interpretation of the impact of immigrant flows on native college enrollment.

For instance, outward shifts in the demand for relatively unskilled labor tend to lower native college enrollment, but may also be associated with inflows of unskilled immigrant labor who are choosing markets with good prospects. As a result, measurements of the crowd-in effect would be downward biased, as increases in relatively unskilled immigrant labor would appear to cause decreases (or else, mitigated increases) in native enrollment. More generally, correlations between immigrant inflows and relative labor demand or college supply can bias each of the crowding estimates upward or downward, depending on the signs of the correlations. The magnitude of such bias depends on how strongly correlated the immigrant flows are with labor demand or college supply.

Another possible source of bias is the existence of exogenous shifts in native college demand that are correlated with immigrant inflows. Growth in the native population, for example, increases native demand for college enrollment and likely varies across states, time, or both for a number of reasons (e.g., persistent climate differences between states). If immigrants tend to locate in states where such native population growth is occurring, it may lead to a spurious relationship between immigrant inflows and increases in native enrollment.

The model thus highlights problematic sources of identifying variation in measuring the crowding effects it predicts will occur from exogenous immigration (see Appendix A for more details). These potential biases help to motivate and are addressed by the estimation strategy of the paper, discussed later.

3 Data

The analysis uses population samples from the Integrated Public Use Microsamples (IPUMS) of the decennial U.S. census for the 1970 to 2000 period (Ruggles et al., 2009). All individuals are classified as either immigrants or natives. Empirically, an immigrant is defined as an individual born abroad who is currently either a non-citizen or a naturalized citizen.[10] I oversample immigrants such that the census data on immigrants constitutes 1 percent population samples in 1970 and 5 percent population samples in 1980-2000, while data on natives are 1 percent population samples over the entire data range 1970-2000. The sample consists of working-age individuals ages 18 to 64 not living in group quarters (e.g., correctional facilities) unless those quarters are schooling-related (e.g., boarding schools). All fifty U.S. states are included (Washington, D.C. is excluded) and I define as the local labor and higher education markets. There are 7,400,855 individual-level observations,

[10]Exceptions (i.e., those coded as natives) are: a) individuals born in U.S. territories or possessions (e.g., Puerto Rico, American Samoa); b) individuals born in countries where they are granted automatic U.S. citizenship due to political unions with the U.S. if not already deemed natives under exception (a) (e.g., Northern Mariana Islands); and c) individuals born abroad of American parents.

consisting of 2,319,597 immigrants and 5,081,258 natives.

To create a pseudo-panel for each state j and year t, aggregations of this data are taken over individuals in each state-year, incorporating census individual sample weights so that the aggregates in each state-year cell are nationally representative, and resulting in 200 state-year observations. Skill is a binary measure, where individuals with four years of high school education or less are classified as unskilled, while individuals with some college education or more are classified as skilled, all based on census information on the highest grade attended (Jaeger, 1997).[11] Additionally, individual-level observations of 59,084 immigrants from 1960 census data are used in estimation via the prediction of immigrant college demand and the formation of historical immigrant enclaves (see section 4).

The top panel of Figure 2 shows the relative skilled wage, or skill premium, over the sample period. Initially, the mean wage of skilled workers relative to unskilled workers fell, dropping from 1.5 times as large in 1970 to 1.4 times as large in 1980. Median relative wages exhibited a similar albeit less drastic decrease. However, over the remainder of the sample period from 1980 to 2000, both the mean and median skill premia increased substantially, far surpassing their 1970 initial values. This fall and subsequent rise in the relative wages of skilled workers has been well-documented in the labor literature and is the source of policy debates regarding how best to combat the rising wage inequality across skill groups (Fortin, 2006).

The lower panel of Figure 2 shows that the relative supply of skilled labor measured in the census has been increasing for both natives and immigrants.[12] This implies that the relative demand for skilled labor outpaced relative supply from 1980 to 2000 (Johnson, 1997), consequently generating a considerable amount of research to investigate the cause of that demand increase (Autor, Katz, & Krueger, 1998; DiNardo & Pischke, 1997; Krueger, 1993). Figure 3 further corroborates an upward trend in individuals' skill levels over this period, as college enrollment increased steadily across various subgroups of the population.

There are a couple of points worth noting from the displayed trends. First, given the negative causal relationships outlined between immigrant skill and native skill in the model of section 2, the

[11] Jaeger's (1997) recommendations for coding are of particular importance here, since it is this margin of unskilled and skilled labor where the differences exist between the census coding and his. Specifically, in the census consistent recode of educational attainment, respondents who are attending their first year of college or who did not complete that first year are identified with '12th grade' as their highest attended grade of education, whereas I categorize the highest grade attended for these individuals as 'some college'.

[12] This would be an overstatement of the skill increase amongst the foreign-born during the sample period if illegal immigrants, who tend to be undercounted in censuses, are disproportionately unskilled.

pattern in the lower panel of Figure 2 is somewhat surprising. However, the aggregate positive correlation between immigrant and native skill could mask a negative causal relationship, particularly at the local market level.

Additionally, given the existence of aggregate labor demand movements, Figure 2 also suggests that differential labor demand trends and shifts across states are a nontrivial possibility. Such differential labor demand, as previously discussed, could confound estimates of the crowd-in and crowd-out parameters. This empirical justification for one of the bias concerns of the model further emphasizes the importance of addressing any such confounding labor demand movements in estimation.

4 Empirical Strategy

4.1 Setup and Selection Issues

The model identifies several empirical decisions to estimate immigrant crowd-in and crowd-out of native college enrollment (see section 2 and Appendix A). These decisions lead to the following general specification to be estimated for state j and year t:

$$\ln\Big(\frac{Native^{CE}}{Native}\Big)_{jt} = \beta\ln\Big(\frac{Immig^{U}}{Immig^{S}}\Big)_{jt} + \alpha\ln(Immig^{CE})_{jt} + \omega_j + \phi_t + \varepsilon_{jt}, \tag{3}$$

where CE is college-enrolled, U is unskilled (i.e., high school education or less), S is skilled (i.e., some college education or more), ω_j and ϕ_t are respectively state and year fixed effects, and ε_{jt} is a mean-zero error.

The dependent variable $\ln\Big(\frac{Native^{CE}}{Native}\Big)_{jt}$ is the log native college enrollment rate for each state-year. Focusing on the native enrollment rate rather than the level addresses concerns from the model of bias due to exogenous shocks in native college demand. Native population growth absent of behavioral changes in college-going would affect enrollment levels but will not alter enrollment rates. On the right-hand side of the equation, $\ln\Big(\frac{Immig^{U}}{Immig^{S}}\Big)_{jt}$ represents relatively unskilled immigrant labor in a state-year, while $\ln(Immig^{CE})_{jt}$ represents college enrollment by immigrant students in a state-year. Given the model's focus on how exogenous immigrant shifts affect native college enrollment, the regressors of interest in the estimating equation are similarly specific to immigrant quantities. Empirically, another advantage of this approach is that it avoids division bias issues (Borjas, 1980) often inherent in the specifications of other displacement studies (e.g., Card, 2005; Hoxby, 1998). Nevertheless, this strategy may prompt worry about the omission of possible scale effects since it is *total* labor supply and not solely immigrant labor supply that affects wages and, consequently, native enrollment. However, such concern is addressed theoretically in Appendix A, as well as addressed empirically in section 5 via alternative specifications.

The dependent and independent variables being specified in logs is consistent with the model and allows the crowding parameters β and α to be interpreted as elasticities. The model predicts $\beta \in [0, \infty)$ (crowd-in) and $\alpha \in [-1, 0]$ (crowd-out) when considering consistent estimates of the parameters. Regarding α, actually, the model's prediction technically holds for the case when native college demand and immigrant college demand are specified identically, which is not the case in equation (3). As discussed earlier, it was useful to specify the dependent variable in equation (3) as a rate in order to address bias concerns. To correct for the impact this has on the meaning of α, I run auxiliary regressions for the main results in order to recover an interpretation of α that is consistent with the model's displacement predictions.

Because serial correlation in native enrollment rates is likely to occur and typically bias OLS standard error estimates downward (Bertrand, Duflo, & Mullainathan, 2004), I cluster standard errors by state to allow for an arbitrary variance-covariance structure within states. All specifications will also be unweighted, so that each state-year cell receives equal weight in estimation.[13]

Immigrants in the sample are neither randomly assigned to states nor randomly assigned to the labor or college market for a given state. Consequently, time-invariant and time-varying market conditions that differ across states and influence native college enrollment rates may also influence the location and college enrollment decisions of immigrants, thus affecting foreign-born labor supply and college demand.[14] To remove any state-level, time-invariant factors, I re-write equation (3) in

[13] An alternative would be to weight observations by the square root of the underlying sample population for each state-year, presumably to decrease the influence of small-sample, high-variance observations. However, a Breusch-Pagan test for heteroskedasticity on such a specification strongly rejects the null hypothesis of homoskedasticity, suggesting that there is a nontrivial group error component to the state-year data and that weighted estimation actually worsens heteroskedasticity rather than eliminates it (Dickens, 1990).

[14] Cadena (2010), for instance, finds evidence that immigrants endogenously select their destination based in part on its labor market conditions.

first differences. The resulting general specification to be estimated is as follows:

$$\Delta\ln\Big(\frac{Native^{CE}}{Native}\Big)_{jt} = \beta\Delta\ln\Big(\frac{Immig^{U}}{Immig^{S}}\Big)_{jt} + \alpha\Delta\ln(Immig^{CE})_{jt} + \Delta\phi_t + \Delta\varepsilon_{jt}, \qquad (4)$$

where the state fixed effect, ω_j, has now been differenced-out.

Estimation of equation (4) by OLS still may not lead to unbiased estimates of β and α if immigrants select which markets to participate in based on time-varying unobservable shocks, inducing a correlation between $\Delta\varepsilon_{jt}$ and both $\Delta\ln\Big(\frac{Immig^{U}}{Immig^{S}}\Big)_{jt}$ and $\Delta\ln(Immig^{CE})_{jt}$. For instance, as discussed in section 2, if unskilled immigrant labor tends to locate in areas that experienced a positive labor demand shock, $\hat{\beta}$ will be biased downward and crowd-in will be underestimated. Similarly, if immigrant students tend to locate in areas where there was a positive college supply shock, $\hat{\alpha}$ will be biased upward and crowd-out will be underestimated. Meanwhile, if immigrants to a *given* location that are on the margin of college enrollment or labor force participation tend to enroll when the area has experienced a negative labor demand shock or positive college supply shock, $\hat{\alpha}$ will again be biased upward. If they tend to join the labor force when the area has experienced a negative college supply shock or positive labor demand shock, $\hat{\beta}$ will again be biased downward.

Although the previous scenarios bias against finding crowd-in or crowd-out, more problematic biases remain a possibility. Immigrant students may opt for markets where a positive labor demand shock occurs because they believe it will improve their post-college employment prospects, biasing $\hat{\alpha}$ downward and overestimating crowd-out. Meanwhile, unskilled immigrant labor, possibly with college-age or younger children, might prefer markets where college supply is expanding, leading to upward-biased $\hat{\beta}$ estimates and overstating crowd-in.[15] If this type of selection is occurring, it may reflect more long-term market selection on the part of immigrants, as both scenarios exhibit forward-looking behavior and longer time horizons.

I attempt two methods to address such market selection by immigrants, beginning first with non-random selection of labor vs. college markets for a given location ("non-spatial selection"). I would like to determine which immigrant inflows contribute to labor supply vs. college demand without using actual labor force participation and enrollment status, which are affected by labor demand and college supply movements. To achieve this, I predict in-sample immigrant college demand using

[15]Higher social returns to college education in areas with larger stocks of skilled labor (e.g., Moretti, 2004) might also induce a positive correlation between college supply and unskilled immigrant labor, with or without young children.

consistent estimates from a logit model of immigrant enrollment using pre-sample data (to be further discussed). These predictions are then utilized to determine how to allocate observed immigrant inflows to either immigrant labor supply or immigrant college demand.

Secondly, I turn to non-random "spatial selection" of local markets by immigrants. To address this, I utilize two-stage least squares (2SLS) estimation that exploits geographic variation in historical immigrant enclaves as instruments. Under certain assumptions (discussed later in detail), these instruments further isolate the exogenous component of immigrant inflows from endogenous flows that are correlated with unobserved movements in labor demand and college supply.[16]

Lastly, measurement error in the immigrant inflows may occur in the census data. Mismeasurement of immigration due to small immigrant inflows or unobserved inflows of undocumented immigrants will both lead to biased crowding estimates. Regarding the former, because immigrants account for less than 10 percent of the population in most of the sample period, small flows are going to be prevalent, particularly in certain states. This results in a higher likelihood of measurement error which, if classical, should lead to attenuation bias in both $\hat{\beta}$ and $\hat{\alpha}$ (Aydemir & Borjas, 2011). Regarding undocumented immigration, if legal and illegal immigrant flows of a given type (i.e., labor, students) are positively correlated, and illegal immigrant inflows cause similar price effects, this would result in an upward bias in $\hat{\beta}$ and a downward bias in $\hat{\alpha}$.[17]

4.2 Predicting Immigrant Student and Labor Inflows

To exogenously determine which immigrants contribute to college demand, I use 1960 census cross-section data on immigrants to run a logit model of college enrollment on individual characteristics as follows, for individual i in state j:

$$Immig_{ij}^{CE} = \vartheta_0 + \vartheta_1 Age_{ij} + \vartheta_2 Age_{ij}^2 + \vartheta_3 Female_{ij} + Race_{ij}' \vartheta_k + Country_{ij}' \vartheta_h + \varepsilon_{ij}, \tag{5}$$

[16] It should be noted that 2SLS alone, if valid, would be sufficient to address both spatial and non-spatial selection. It should therefore purge estimation of any residual, non-spatial endogeneity not already addressed by the logit model of immigrant college demand. However, if both types of selection are reasonably severe, OLS estimates addressing neither type may be uninformative due to large biases, providing support for the current approach to address biases sequentially. Table 1 in section 5 assesses the former approach to the OLS estimates and indeed finds the combined bias to be substantial.

[17] Hanson (2006) discusses evidence that illegal immigrants are already represented to a degree in official household surveys like the U.S. Census, which would tend to diminish this bias. Moreover, because the omitted variables in this case are still immigrant-related, an alternative to classifying this as bias would be to reinterpret the estimated crowding parameters as a reflection of both legal and illegal immigration.

where Age is age in years, $Female$ is a dummy variable for women, and $Race$ and $Country$ are vectors of race/ethnicity and country dummies, respectively.

As shown in Appendix A, if market shocks are not correlated with any of these chosen characteristics, equation (5) will consistently estimate how each of the covariates affects college-enrollment via a change in underlying college demand. Using the coefficient estimates, I predict enrollment out of sample for 1970 to 2000 and designate immigrants during the period into quintiles based on these predicted values. The highest quintile[18] individuals are designated as immigrant students, while the lowest four quintiles are designated as immigrant labor. In the latter case, skill levels are then determined using actual educational attainment information, which is no longer endogenous given that these individuals are predicted to no longer be acquiring human capital.

One caveat with this procedure is that the observed geographic variation of the immigrant covariates from 1970 to 2000 is still subject to confounding market shocks from labor demand and college supply. This implies that this approach would likely, at best, only be able to address non-spatial selection. 2SLS estimation will remain necessary to address spatial selection of immigrants, as well as any residual non-spatial selection not purged in the OLS estimates. By not addressing both types of selection with 2SLS alone, the OLS estimates can thus be more informative than they would be if they did not address either type of selection.

4.3 Instruments

The previous procedure, while addressing endogeneity in immigrants' choice of labor markets vs. college markets, fails to address any endogeneity in immigrants' location choices. To deal with such spatial selection, and purge estimation of any remaining endogeneity from non-spatial selection not already eliminated, I employ 2SLS estimation. The instruments use the historical, 1960 distribution of immigrants in the U.S. to form predictions about the flow of immigrants over the sample period, 1970 to 2000. These instruments are motivated by the idea that existing immigrant networks and enclaves are an important determinant of the location choices of prospective immigrants (Bartel, 1989; Card, 2001; Cortes, 2008; Munshi, 2003). The enclaves, by increasing cultural benefits and

[18] This is a purposely conservative allocation. Observed immigrant enrollment during the sample period has a mean of 5 percent, notably lower than 20 percent. However, the low immigrant enrollment mean may be partly due to inelastic college supply. In the presence of perfectly elastic supply, immigrant college enrollment may have more closely approached 20 percent.

reducing informational and legal costs, increase the net marginal benefit of migration into U.S. local markets for the foreign-born.

For state j and year t, the instruments for the log changes in relatively unskilled immigrant labor and immigrant students take the following form:

$$\sum_h \Big(\frac{Immigrants_{hj,1960}}{Immigrants_{h,1960}}\Big) \times \Delta Immigrant\_Type_{ht}, \tag{6}$$

where h is countries of origin included in the 1960 U.S. Census, $\frac{Immigrants_{hj,1960}}{Immigrants_{h,1960}}$ is the percentage of all immigrants from country h in the 1960 census who were living in state j, and $\Delta Immigrant\_Type_{ht}$ is the difference between year t and year $t-1$ immigrants of a given type from country h. The three $Immigrant\_Type$ stocks utilized are: (1) immigrant students, (2) unskilled immigrant labor, and (3) skilled immigrant labor. All three cases are the "potential" or "predicted" stocks, as determined by the logit model of equation (5), rather than actual stocks. For example, if 15% of Brazilian immigrants (predicted) were living in Massachusetts in 1960, then the instrument would allocate 15% of the total Brazilian student inflow (predicted) between 1980 and 1990 to Massachusetts.

The validity of these instruments and the identification strategy hinges on three assumptions, two of which are related to the two components of the instrument. First, it is assumed that any unobserved, differential market shocks between states j and j' in 1960 that caused immigrants to locate in state j rather than j', are uncorrelated with such relative market shocks from 1970 to 2000. In other words, suppose that in 1960, a labor demand shock occurred in New York that was positive relative to a similar shock in Arizona. As a result, more unskilled immigrants from Russia chose to locate in New York rather than Arizona. Then for the instrument to be valid, it cannot be the case that over the 1970 to 2000 period, all labor demand shocks in New York relative to Arizona were also positive (i.e., labor demand was growing at a faster rate in New York than Arizona). If so, then the 1970 to 2000 allocations of Russian immigrants to New York and Arizona predicted by the instrument would be correlated with the 1970 to 2000 relative labor demand shocks, causing the instrument to be endogenous.

Secondly, instrument validity requires that the total source country immigrant inflows of each type, $\Delta Immigrant\_Type$, are exogenous to such unobserved, relative market shocks between states from 1970 to 2000. For example, suppose that a 1990 labor demand shock in Arizona that was positive relative to a similar shock in New York caused some unskilled Russian immigrants to choose to locate in Arizona rather than New York. For the instrument to be valid, it cannot be the case that such a relative labor demand shock caused some unskilled Russians to immigrate to the U.S. who otherwise would not have, or alternatively dissuaded some unskilled Russians from immigrating, such that the total flow of unskilled Russian immigrants in 1990 was altered by the shock.[19]

Combined, these two assumptions form the instrument exogeneity assumption, or the exclusion restriction. Here, this restriction imposes that the only channel through which the instrument-predicted immigrant inflows affect native enrollment rates is through their impact on the endogenous immigrant inflows - namely, log changes in relatively unskilled immigrant labor and immigrant students. The inclusion of division-year fixed effects in estimation for the nine U.S. Census divisions helps to ensure that the exclusion restriction holds. With the omission of such fixed effects, the restriction would be violated if some divisions' economies were growing, due to labor demand or college supply movements, at differential rates than other divisions since 1960.[20] The division-year effects allow the instrument's restrictions on relative market shocks to apply only within a division (e.g., Arizona and New Mexico) instead of also across divisions (e.g., Arizona and New York).

The other necessary assumption for instrument validity and consistent 2SLS estimation is instrument relevance, such that the immigrant flows predicted from the instruments are sufficiently related to the endogenous immigrant flows. Estimation with weakly related instruments could severely bias the crowding coefficients and lead to spuriously significant estimates (Bound, Jaeger, & Baker, 1995). Typically, in the case of one endogenous variable, an F-test on the excluded instruments is used to evaluate such relevance. However, because there are two endogenous variables here and estimation will be made robust to the correlation of errors over time within a state, all 2SLS results will be reported with the Kleibergen-Paap rk statistic to assess instrument relevance (Kleibergen & Paap, 2006).[21] The value of this test statistic will be compared to the Stock and Yogo (2005) weak

[19]This assumption might not hold if immigrants have strong preferences for certain U.S. states. If so, market shocks involving those states may cause individuals to change their immigration plans. However, Boustan (2010) compares results from instruments that use actual migrant flows vs. those that use migrant flows predicted from source area push factors. She finds little difference between the two sets of results, suggesting that this assumption may hold in practice.

[20]Cortes (2008) notes the Sun Belt region as one such example.

[21]An alternative approach with multiple endogenous variables is the Cragg-Donald statistic (Cragg & Donald, 1993).

instrument identification critical values.[22]

4.4 Crowding Parameter Interpretation

Assuming the 2SLS enclave instruments are valid, the econometric interpretation of the crowding parameters $\hat{\beta}$ and $\hat{\alpha}$ still remains. Although the cross-sectional unit is a state, it is an aggregation of individual native and immigrant units at which agent behavior is operating. Because, as discussed in the model (Appendix A), there exists a latent native ability distribution in each state, this can be thought of as determining a state-specific enrollment impact of the two continuous treatments (i.e., the two immigrant inflows). Since different native ability distributions across states j seems probable, it is likely that there are heterogenous impacts of these treatments across states, $\beta_j = \bar{\beta} + \beta_j^*$ and $\alpha_j = \bar{\alpha} + \alpha_j^*$.

With a heterogenous treatment model, parameters estimated by 2SLS are often interpreted as local average treatment effects (LATEs) - namely, marginal effects for those observations induced to treatment by the instrument (Imbens & Angrist, 1994). Here, given continuous rather than binary treatments, the analogous interpretation would be a local average causal response. However, if the exogeneity assumption for a valid instrument in the heterogenous treatment model actually holds,[23] then an average treatment effect (ATE) interpretation of the crowding parameters (or average causal response, in this case) is still valid.[24] The enclave-based "cost" of immigration is known and considered by immigrants, but the native ability-based enrollment "benefit" of the immigrant inflow treatments is known and considered by natives. Therefore, immigrants may not know both the state-specific cost and benefit of immigration.[25] Under this asymmetric information

However, this statistic assumes independent and identically distributed (i.i.d.) errors and so is less appropriate given the error structure here.

[22] Because Stock and Yogo's critical values are constructed assuming i.i.d. errors, they will be used more conservatively in the paper to evaluate the extent of weak instruments.

[23] For example, with heterogeneous treatment effects, the exogeneity assumption relevant for the immigrant student inflow treatment (letting $(Immig^{CE})_{jt} \equiv T_{jt}$, and $\mathbf{Z'}_{jt} \equiv$ the vector of enclave instruments) would be: $E[(\alpha_j^* \Delta T_{jt} + \Delta\varepsilon_{jt})|\Delta\phi_t, \Delta T_{jt}, \Delta\mathbf{Z'}_{jt}] = 0$. In other words, substantively, the assumption is that conditional on the immigrant inflow treatment, the values of the enclave-based instruments are uncorrelated with the state-specific impact of the treatment on native enrollment rates. This contrasts with the weaker exogeneity assumption of a common treatment model: $E[\Delta\varepsilon_{jt}|\Delta\phi_t, \Delta T_{jt}, \Delta\mathbf{Z'}_{jt}] = 0$.

[24] This is of particular interest in this case since there may be non-linear, diminishing effects of the enclave instruments on actual immigrant inflows. This could require the inclusion of quadratic terms as additional instruments, thus making the monotonicity assumption necessary for valid LATE interpretation (Imbens & Angrist, 1994) more questionable, although not necessarily violated.

[25] In other words, for an immigrant inflow "participation" equation, $\Delta T_{jt} \neq \iota_1 \alpha_j^* + \iota_2 \Delta\mathbf{Z'}_{jt} + \Delta\phi_t + \varsigma_{jt}$, but rather $\Delta T_{jt} = \varpi_1 \Delta\mathbf{Z'}_{jt} + \Delta\phi_t + \o_{jt}$. If immigrants did know α_j^*, however, one could then perhaps appeal to their knowledge of the extent of immigrant-native substitutability in production to motivate why the native ability distributions would

assumption, the estimated crowding parameters $\hat{\beta}$ and $\hat{\alpha}$ can be interpreted as marginal effects averaged across all observations rather than just a subset of observations.

5 Main Results

5.1 Immigrant Student and Labor Predictions

Table 1 displays average marginal effects from estimating immigrant college demand in 1960.[26] The full logit model in column (1) shows that being female decreases immigrant enrollment probability on average by 1.3 percentage points relative to being male. Additionally, the probability of enrollment decreases significantly with age, as well as for all of the identified race/ethnicities relative to white non-Hispanic immigrants, although not significantly. The logit model predicts the correct outcome for enrollees at a higher rate than non-enrollees, and also performs better for predictions in-sample rather than out-of-sample, as expected.[27]

Column (2) shows that the linear probability model (LPM) estimated by OLS has qualitatively and often quantitatively similar results to the logit specification, although the age effects are now significantly non-linear and some of the race/ethnicity effects are now significant. However, the indicated measures of model fit are worse for the LPM estimation, other than the model performing somewhat better at predicting enrollees. This is also the case for the logit model with age only in column (3), although not by a large margin. Appendix Table B2 displays average (weighted) characteristics of each quintile in the college demand index, which are qualitatively similar to the estimation results of Table 1, as expected.

There are other potential alternative models to designate immigrant students and labor. One possibility is to not distinguish immigrant inflows, presuming that students and labor have a homogenous effect on native enrollment, contrary to the model's predictions. Alternatively, I can determine an age cutoff using the distribution of enrolled immigrants in 1960. Immigrants of age equal to or below the cutoff age are designated as immigrant students, and immigrants older than

matter to them in their immigration decision.

[26] Appendix Table B1 examines averages of the covariates used in specification (5) for college-enrolled and not-college-enrolled immigrants.

[27] Because, as Appendix Table B1 shows, the unconditional probability of immigrant enrollment in 1960 is very low at 1 percent, this 0.01 value is used as the threshold for evaluation of the logit predictions rather than the standard threshold of 0.5 (Heckman & Smith, 1999).

the age cutoff are designated as immigrant labor. Finally, I can also use the endogenous labor force participation and college enrollment information to designate the immigrant inflows appropriately.

Table 2 displays OLS results from estimation of baseline equation (4) using the above methods to determine the immigrant inflow regressors. Column (1) shows that under the assumption of homogenous immigrant inflows, there is no significant effect of immigration on native college enrollment rates. Column (2), the preferred method, differentiates immigrant inflows. This specification finds support for the predictions of the model as there is both significant crowd-in and crowd-out, with elasticities of 0.26 for $\hat{\beta}$ and -0.14 for $\hat{\alpha}$.

Columns (3) to (5) show that sensible alternative methods yield quantitatively similar results to column (2). However, once endogenous labor and college market information is used in column (6), the coefficient magnitudes are severely diminished. As discussed in section 4, this suggests that non-spatial immigrant selection into the college market is negatively correlated with labor demand shifts or positively correlated with college supply shifts. Conversely, column (6) implies that non-spatial immigrant selection into the labor market is positively correlated with labor demand shifts or negatively correlated with college supply shifts. Thus, non-spatial selection bias in OLS estimation is notably reduced using the preferred method of column (2) relative to column (6).

5.2 Descriptive Statistics

Figures 4a and 4b show that there is substantial geographic variation in the predicted immigrant labor and immigrant student variables over the sample period. Nearly all states saw large decreases (some over 100 percent in magnitude) in the relative labor supply of unskilled immigrant labor, with the exception of Idaho and Kansas, which experienced small increases. Meanwhile, there were widespread increases in immigrant students over the sample period, especially in the Sun Belt region, with the sole exception of Vermont which had a small negative change. Both figures are thus consistent with the upward skill trends shown in Figures 2 and 3.

The precision of the separately estimated coefficients for crowd-in and crowd-out relies on the degree of collinearity between the predicted immigrant labor and student flows. Figure 4c shows that precise identification (at least, for OLS; additional factors matter for 2SLS) does not come from large immigrant flow states such as California, New York, and Florida, but rather from much smaller flow states like Nebraska. This will be explored further in the main estimates.

A caveat of Figures 4a to 4c is that they do not purge the immigrant labor and student flows of macro-level, national variation. They also do not remove variation in the immigrant flows to each state that is time invariant. If such variation reflects unobservables that are also correlated with native college enrollment rates, using it for parameter identification would lead to biased immigrant crowding estimates.

Table 3 shows that, in addition to the statistically significant change that each dependent and independent variable experienced over the sample period, year and state-specific variation in the variables is substantial. For instance, 14% of the variation in native college enrollment rates differs across census years but not across states, while 60% of the variation differs across states but is time-invariant. This leaves 26% of the variation differing within states over time, which generally accounts for one-fifth to one-quarter of the total variation across all variables of interest. As equation (4) notes, because all estimates will account for state and year fixed effects, the identifying variation is only from within states over time.

5.3 Baseline OLS and 2SLS Estimates

Table 4 shows the estimates from the first stage regressions for relatively unskilled immigrant labor and immigrant students. When only levels of the enclave-based instruments are specified as regressors in columns (1) and (3), historical immigrant shares predict relatively small inflows of actual immigrants, with coefficients that are generally not statistically significant. This is reflected in the low F-statistics from tests that the coefficients on the instruments are jointly equal to zero.

Because these instruments reflect differences in the net marginal benefit to immigrants of relocating to the U.S., there may be significant nonlinearities in the impact of historical enclaves on immigrant inflows. In addition to such diminishing returns, nonlinearities may result from a minimum threshold an enclave must reach in size before it has value to a new migrant entrant (i.e., a network externality). Columns (2) and (4) of Table 4 confirm that there are significant nonlinear effects of historical immigrant enclaves on immigrant flows. In each case, both the level and quadratic term for a given covariate are of opposite signs, providing support for diminishing net marginal benefits to the network. The F-statistics are also well above critical values for weak instruments.

Table 5 presents the main OLS and 2SLS estimates. Column (1) is identical to column (2) from Table 2, with one exception. For all specifications, as discussed in section 4, auxiliary regressions are also run where the dependent variables are $\Delta\left(\frac{Native^{CE}}{Native}\right)_{jt}$ and $\Delta\left(\frac{Immig^{CE}}{Native}\right)_{jt}$. The last row of Table 5 reflects the ratio of crowd-out coefficients from those auxiliary specifications, which can be interpreted as the number of natives that disenroll for every immigrant enrollee. This displacement interpretation, not directly discernible from the crowd-out coefficient $\hat{\alpha}$ alone, is more closely aligned with the magnitude prediction for $\hat{\alpha}$ from the model, as displacement should be bounded between -1 and 0.[28]

In the OLS results, there is no statistically significant evidence of crowding once division-year fixed effects or state-specific linear trends are included in columns (2) and (3). In both cases, compared to column (1), the magnitude of both crowding coefficients is also reduced. The crowd-in elasticity decreases from 0.263 to 0.137 with division-year effects and 0.170 with state trends, while the crowd-out elasticity decreases from -0.143 to -0.087 with division-year effects and -0.113 with state trends.

This supports the notion that the division-year fixed effects are accounting for nontrivial bias from immigrant selection of markets across divisions in response to market shocks. The bias is upward on the crowd-in coefficient and downward on the crowd-out coefficient. Immigrant labor is dynamically locating in divisions with growing college prospects (in terms of college supply shifts), while immigrant students are choosing divisions with growing employment opportunities (in terms of labor demand shifts). As discussed in section 4, this may mean that immigrant relocations across divisions are made with longer-term prospects in mind. A similar interpretation holds for the comparison to column (3) except that the immigrant selection is across states rather than divisions, and based on state market trends rather than division shocks.

From the coefficient magnitudes, it appears that immigrant selection is occurring more at the division level than the state level.[29] Additionally, columns (4) and (5) confirm the expectation from Figure 4c that precise OLS identification is not coming from states with large immigrant flows like California. Rather, estimation precision is coming more from states like Idaho with low correlations between the two immigrant inflows.

Turning to 2SLS estimation and comparing column (6) to (1), both crowd-in and crowd-out estimates are larger in magnitude. This supports the idea that, in terms of responses to state-

[28] In the presence of any confounding biases, however, displacement estimates could lie outside of these bounds.

[29] Alternatively, linear trends may not be sufficient for the immigrant selection occurring at the state level, if such selection is a response to state-year shocks.

year shocks, immigrant labor is endogenously locating in states where the labor market for them is improving, downward biasing the OLS estimates compared to 2SLS. Meanwhile, immigrant students are locating in states with expanding college markets, upwarding biasing the OLS estimates relative to 2SLS. The Kleibergen-Paap rk statistic of 36.97 is also comparable to the separate, first stage F-statistics from columns (2) and (4) of Table 4.

Once division-year fixed effects are included to strengthen instrument validity in preferred specification (7) of Table 5, the crowd-out elasticity falls to -0.04 but is no longer statistically significant, while the crowd-in elasticity of 0.33 is also smaller but still significant. In terms of displacement effects for crowd-out, although not significant, I nevertheless estimate a crowd-out ratio of -0.24. This implies that for every four immigrants enrolled in college, one native does not enroll, which falls in a range consistent with the model as well as with other studies.[30]

In column (8), an F test fails to reject that the coefficients on the included state-specific linear trends are jointly zero. Furthermore, unlike the OLS regressions, column (9) shows that the 2SLS results do appear to be nontrivially identified from large immigrant flow states like California. This is not surprising given that these are the states where the historical enclaves would be expected to better predict actual immigrant inflows. However, as in OLS, exclusion of states like Idaho in column (10) tends to inflate the standard errors without significantly affecting the point estimates compared to column (6).

Regarding interpretation of the crowding parameters, the model shows that the level of immigrant inflows plays a role in the estimated effects due to the focus on relatively unskilled immigrant labor as a regressor rather than total labor. Appendix A examines how to separately identify the scale effect from the two immigrant inflow variables, determining that the inclusion of a regressor for skilled immigrant labor inflows should capture this effect. In columns (1), (2), (5), and (6) of Table 6, as in Appendix A, the coefficient on skilled immigrant labor inflows reflecting the scale effect is positive, and statistically significant in columns (1), (2) and (5). However, in preferred column (6) (i.e., 2SLS with division-year fixed effects), the scale effect is now an order of magnitude smaller and no longer significant. The inclusion of three endogenous regressors in column (6) reduces estimate

[30] In her instrumental variables specification, the significant estimates that Hoxby (1998) finds imply a crowd-out ratio ranging from -0.24 to -0.64. Additionally, although not focusing on immigrant-native displacement, Bound and Turner (2007) find in their study of cohort crowding that a 10 percent state-specific increase in the size of the college-age population decreases the fraction attaining a BA degree by 4 percent, an elasticity of -0.4.

precision, resulting in crowd-in and crowd-out estimates that are no longer significant despite similar magnitudes to column (7) of Table 5.

The remaining columns of Table 6 explore an alternative for capturing the scale effect alluded to in the model: including a regressor for relatively unskilled total labor rather than immigrant labor. However, there are empirical issues with this strategy that make it undesirable, despite its theoretical sensibility. First, if native labor internal migration and location choice is more sensitive to labor market conditions than immigrant labor, relatively unskilled total labor flows will be more severely correlated with labor demand movements. This will downward bias the OLS coefficient on total flows. Columns (3) and (4) suggest that this is the case, as the coefficient on the total labor flow variable is significantly negative. OLS estimates of the impact of total labor flows are therefore uninformative.[31]

Meanwhile, the enclave-based instruments utilized for this paper do not have strong theoretical grounding to have predictive power for natives. The fact that they are not weak in columns (7) and (8), despite the low percentage of immigrants in total labor supply, causes some suspicion that perhaps immigrant enclaves are predictive for native location decisions for reasons correlated with labor demand. This would bias the 2SLS coefficients on total labor supply downward toward OLS, which is what is observed. This makes the previous strategy to separately identify the scale effect preferable. Given the argument that it is not affecting parameter consistency in column (6) but is detrimentally affecting parameter precision, I omit the scale effect from further estimation.

6 Sensitivity Analyses

6.1 Native Response Heterogeneity

The identification of a crowd-in effect and the lack of a significant crowd-out effect are suggestive of college demand that is fairly wage-sensitive and college slots that are flexibly supplied over a decadal time horizon. Table 7 explores heterogeneity in the native enrollment response to examine these hypotheses empirically, running specification (7) of Table 5 on native subgroups. First, there appear to be differential responses by age. The crowd-in effect is identical in magnitude for young

[31] One possibility to address this, however, might be to run a logit model of total college demand, similar to the immigrant demand model in equation (5), to form predicted flows to utilize in the OLS regressions.

natives ages 18-24, with an elasticity of 0.33. However, it is more precisely measured, suggesting that this is the group accounting for the statistical significance of the effect for natives ages 18-44 in Table 5, column (7). While the results are qualitatively similar for 25-34 year-old natives, the crowd-in effect is smaller in magnitude and the crowd-out effect is larger in magnitude, although neither coefficient is significant. Given equations 1 and 2, and if immigrant market price effects are similar across age groups, these results suggest that the college enrollment demand of young natives is more sensitive to changes in the relative unskilled wage and tuition/fees than the demand of older natives. For female natives, both the crowd-in and crowd-out coefficients are slightly larger in magnitude compared to the baseline estimates, although not significantly so. Nevertheless, this is consistent with more elastic enrollment demand for women than men.

Meanwhile, the model predicts that ceteris paribus, as college supply becomes more elastic, the crowd-out effect should decrease in magnitude while the crowd-in effect increases (Appendix A). Because it is expected that college supply is more elastic for public institutions (Bound & Turner, 2007), the theoretical predications can be evaluated by focusing the results on public schools only. Table 7 shows that, consistent with the model, for natives on the margin of public enrollment, crowd-in is larger in magnitude compared to the baseline results while crowd-out is smaller in magnitude. Additionally, given, the decadal nature of the census data and the longer time horizon of the effects being examined here, more elastic college supply at both public and private institutions is likely factoring into the results.

Table 8 examines the extent of an attainment response that is similar to the enrollment response. Qualitatively, the results are indeed similar. However, now the only statistically significant crowd-in response occurs for 25-34 year-olds. This may be due to the fact that attainment, unlike enrollment, is persistent. So in a given year, a significant 25-34 year-old native response may reflect both 25-34 year-olds currently experiencing immigrant inflows into their markets, as well as 18-24 year-olds who experienced *earlier* immigrant inflows. Additionally, Table 8 provides some limited evidence that the marginal natives who are responding to immigration are those who had less than four years of high school education. This could reflect their wages and tuition/fees being most affected by immigrant inflows, or that these natives are the most sensitive to such price changes.

6.2 Assessing Measurement Error in Immigrant Inflows

I turn now toward the assessment of two potential sources of measurement error in the immigrant regressors. As discussed earlier, the prevalence of small immigration inflows will increase the probability of classical measurement error, attenuating crowd-in and crowd-out estimates. To explore the influence of any such error in the results, in columns (3) and (4) of Table 9 I exclude Kansas and Vermont, which have the smallest flows of exogenous immigrant labor and immigrant students over the sample period. Focusing again on the 2SLS estimates, and compared to the baseline estimates reposted in column (2), the crowd-in elasticity increases by 0.05, while the crowd-out elasticity, still not significant, has decreased by 0.01. This suggests that, while measurement error from small flows is indeed attenuating the baseline estimates, it does not appear to be doing so substantially.

Additionally, illegal immigrants may only be partially reflected in the census data and yet could be relatively large inflows in some states, thus likely affecting native enrollment. As previously noted, if legal and illegal immigrant flows of a given type (i.e., labor, students) are positively correlated and cause similar price effects on wages and tuition/fees, then the crowd-in estimate will be upward biased while the crowd-out estimate will be downward biased. To evaluate the extent of such omitted variable bias arising from incorrect measurement of immigrant flows, columns (5) and (6) of Table 9 exclude border states Arizona and New Mexico, the two border states that do not have the largest immigrant inflows.[32] Upon doing so, I observe the expected changes in the crowding coefficients, as the magnitudes of both $\hat{\beta}$ and $\hat{\alpha}$ become reduced. However, the crowd-in result is still significant and remains quite close in magnitude to the column (2) baseline, implying that this source of error in immigrant measurement is not particularly problematic either. The small degree of bias may be due in part to illegal status mitigating the extent of market price effects that undocumented immigrants can exert. This could result from labor employment or college enrollment restrictions. Regardless, as noted earlier, because the omitted variables here are still immigrant-related, any bias could be reinterpreted as part of the parameter of interest, with the crowding elasticities reflecting both legal and illegal immigration.

[32] Remaining border states California and Texas also have the largest immigrant inflows in the country over the sample period. Their exclusion adversely affects the relevance of the enclave instruments to immigrant flows and so they are kept in the sample for this analysis.

7 Implications

7.1 Counterfactual Simulation

Given the preferred crowd-in estimate of 0.330 from Table 7, specification (2), a simple counterfactual simulation can be used to assess the role of crowd-in to the aggregate change in young native mean college enrollment rates observed from 1970 to 2000. The exercise supposes that the immigrant skill mix had stayed constant over the sample period at its 1970 value.[33] This is consistent with a counterfactual increase in relatively unskilled immigrant labor over the sample period of 120.3 percent. Such an inflow of immigrant labor would have led to a 39.7 percent increase in mean enrollment rates of young natives ages 18-24, 18.3 percentage points larger than the observed enrollment rate increase of 21.4 percent during this period.

This is a sizable suggested aggregate effect of crowd-in. However, undercounting of undocumented, unskilled immigrants in the census data (which Table 9 implies might be somewhat of an issue) could be contributing to the large magnitude. Such undercounting would overstate the change in the immigrant skill mix during the sample period, resulting in an overstatement of the aggregate impact of crowd-in.

7.2 Native College Demand Elasticities

Equations 1 and 2 and the formal model in Appendix A illustrate the theoretical link between the crowding parameters estimated in this paper and underlying structural parameters for the relative unskilled wage and college tuition/fee elasticities of native college enrollment demand. It is thus useful to determine what values of these price elasticities, under certain restrictions on the remaining variables in the model, are implied by the crowd-in and crowd-out estimates.

Table 10 summarizes the results for η^N and ϕ^N from such an exercise (further details in Appendix A). Note from the formal model that both parameters enter into college demand negatively. Thus, although the derived elasticities are positive, increases in the relative unskilled wage and college tuition/fees both decrease native college demand, as expected. For all values of ψ, the tuition/fee elasticity of college supply, and θ, the elasticity of substitution between skilled and unskilled labor,

[33]The actual (not predicted) 1970 immigrant (unskilled/skilled) labor force ratio is 2.4, while the actual 2000 immigrant (unskilled/skilled) labor force ratio is 1.1.

natives have fairly wage-sensitive demand for college enrollment, as η^N lies between 5.8 and 8.6. In other words, a 1 percent increase in the relative unskilled wage would decrease the rate of native college enrollment by 5.8 to 8.6 percent. At the mean enrollment rate of 9.2 percent during the sample period for natives 18-44 years old, this would result in a rate decrease of 0.5 to 0.8 percentage points.

For the low and high ψ values, respectively, native college demand ranges from being tuition/fee inelastic with a ϕ^N of 0.7, to being quite elastic with a value of 18.1. Thus, a 1 percent college tuition/fee increase would decrease the native college enrollment rate by 0.7 to 18.1 percent. However, only the 0.7 estimate is derived using a value of ψ that is not purely hypothetical and so is likely more plausible. Once again at the mean enrollment rate of 9.2 percent, this would result in a rate decrease of 0.1 to 1.7 percentage points.

This exercise indicates that for reasonable parameter values, the paper's crowding estimates suggest that native college demand is quite wage-sensitive. It should also be briefly noted that the implied elasticities of immigrant inflows on wages and tuition/fees (not shown) are non-zero but small. For instance, for the first set of values shown in Table 10 for ψ, θ, η^N, and ϕ^N, a 10 percent increase in relatively unskilled immigrant labor reduces relative unskilled wages by about 0.24 percent. Thus, the model and results imply that while immigrants do affect market wages, these effects need not be particularly large to result in the crowding responses observed because of natives' sensitivity to wage changes.

8 Conclusion

This paper estimates how inflows of immigrant students and immigrant labor, by changing the costs and benefits of higher education, affect the postsecondary enrollment of natives. I first construct a dual-market, supply-demand model to form predictions over the effects of immigration on native skill acquisition. Using U.S. Census microdata from 1970 to 2000, I test the predictions of the model by estimating the causal impact of heterogeneous immigrant inflows into local markets on native college enrollment rates in those areas. To isolate the exogenous component of immigrant inflows from endogenous flows that vary with unobserved movements in labor demand and college supply, I use a model of immigrant college demand combined with two-stage least squares estimation that utilizes geographic variation in historical immigrant enclaves.

I find that a 1 percent state-level increase in relatively unskilled immigrant labor raises the rate of native college enrollment in that state by 0.33 percent. Meanwhile, a 1 percent state-level increase in immigrant college students lowers that state's native enrollment rate by 0.04 percent, but this effect is not statistically significant. The lack of a significant crowd-out effect, coupled with the presence of significant crowd-in, is suggestive of fairly wage-sensitive native college demand as well as elastic college supply, particularly at the decadal frequency of the data. This hypothesis is supported empirically. The crowd-in effect is larger and primarily driven by natives ages 18-24, who are likely to have college demand that is more sensitive to returns than older natives. Crowd-in is also larger for natives on the margin of public school enrollment, where college slots are likely to be more elastically supplied.

I also show that the results provide evidence that immigrants do impact market prices like the relative wage. However, these effects need not be large to be consistent with the observed crowding results due to implied native sensitivity to even small market price changes, particularly wage changes.

This paper suggests that education studies on displacement effects of immigrant students on natives, by ignoring immigrant labor inflows, miss an important component of immigration that significantly affects native skill choice. Additionally, over long time horizons and the native college-going population as a whole, I show that displacement effects appear to be small to nonexistent. Further research needs to be done, however, to compare findings in this study with those in existing crowd-out studies. Differences between the two are potentially being driven by differences in market structure (e.g., the elasticity of college supply) in the long-run vs. the short-run, or by differences in examining all college-going natives vs. only disadvantaged natives.

Regarding the implications of this work for labor studies of immigration's effect on natives, by emphasizing a more unified framework between labor and education markets, the paper highlights an endogenous skill acquisition response by natives to immigrant inflows. This contributes to a growing literature on how such general equilibrium responses may play a role in the seemingly rapid absorption of immigrants into local markets, mitigating native wage effects of immigration that the paper suggests are negative but small.

Government policies on immigration that do not take into account how the composition of immigrant inflows is affected may have unanticipated consequences due to the resultant changes in native enrollment that this paper identifies. Moreover, distinguishing the degree to which natives, and individuals more broadly, respond more to changes in the costs or the benefits of higher education also has direct implications for government policy. If the goal of government intervention were to increase college enrollment rates, the paper suggests that labor market policies targeting relative wages may be more efficient in the long-run than education market policies adjusting costs through loans and grants.

In order to definitively make such claims, however, additional investigation is necessary to determine whether the estimated crowding effects are indeed reflective of the entire native population, or only a subset of the native population that is not liquidity-constrained. Related to that, more work on the welfare implications of the immigrant inflows, given this native response, is also of interest and necessary before statements of optimal policy can be made (e.g., Chiswick, 1989, or Eberhard, 2009, who finds positive native welfare implications of immigrant inflows given endogenous native human capital adjustment). Such research will be aided by additional understanding of the price and non-price mechanisms of the native response highlighted in this paper.

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Appendix A1: A Model of Immigration and Native College Enrollment

Assumptions

I present here an algebraic version of the conceptual model in the paper in the spirit of Bound et al. (2004).[34] Several of the model assumptions are already presented in the paper, and so only additional details are now provided.

It is assumed that all input and product markets are competitive. Production of enrollment slots by college institutions maximizing their net benefit of student enrollment is accomplished using constant returns to scale technologies and non-labor inputs (e.g., land, capital),[35] where student tuition/fees are received for each slot.[36] Meanwhile, on the enrollment demand side, natives and immigrants of some latent ability decide whether to enroll in order to acquire skill to maximize their utility, concave in consumption. Consumption itself is a function of either skilled wages net of college tuition/fees or else unskilled wages.[37]

In the labor market, regarding labor supply, all individuals are in the labor force if they are not students acquiring skill.[38] On the labor demand side, with constant returns to scale technologies, firms produce a composite, nontraded good using both skilled and unskilled labor. The restriction to a single sector with a nontraded commodity simplifies the model considerably to focus on areas of interest for this paper, as consumer output demand reduces to individuals maximizing their utility over consumption of the composite good by maximizing their discounted stream of net wages. Additionally, cast in the framework of a basic Heckscher-Ohlin model, the existence of a nontraded commodity allows the wages of both skilled and unskilled workers to be determined locally, to the extent that labor is somewhat immobile across states (Leamer, 1995; Cortes, 2008).

Setup

Let $N \equiv$ natives (as before), $I \equiv$ immigrants, $U \equiv$ unskilled, $S \equiv$ skilled, and $L_k = N_k + I_k$ for $k = U, S$. Also, for any variable x, let $\dot{x} \equiv d\ln x$, the percent change in x.

The higher education market for college enrollment can be described by the following equations:

$$\dot{d}_E = -\phi \dot{f} - \eta \dot{w} + \dot{\mu} \qquad [\textit{College Demand}], \tag{7}$$

$$\dot{s}_E = \psi \dot{f} + \kappa \dot{w} + \dot{\varphi} \qquad [\textit{College Supply}], \tag{8}$$

where $\dot{f}$ is the percent change in tuition/fees, while $\dot{w} = \dot{W}_U - \dot{W}_S$ is the percent change in the relative unskilled wage. Parameters ϕ and η are respectively tuition/fee and wage elasticities of

[34]This version of the model, however, differs in a few ways from theirs, such as an extended modeling of the college market and an incorporation of immigration into both the labor and college markets.

[35]I assume labor is only utilized for production of the output good. Also, as nonprofit institutions, I allow for the possibility that arguments unrelated to profit such as campus diversity may enter into colleges' objective functions.

[36]Because non-labor input costs will remain in the background, they serve as college supply shifters. Additionally, while college slots are likely infinitely or nearly infinitely supplied at any given relative wage, the model does not presuppose this and allows for a more general wage relationship.

[37]Ability affects the psychic costs of schooling and may also affect the wage benefit, thus impacting the sensitivity of college demand to prices.

[38]Empirically, I focus on working-age, pre-retirement individuals in order to help support this assumption.

college demand, while ψ and κ are respectively tuition/fee and wage elasticities of college supply.[39] Total college demand is a function of both native and immigrant college demand, such that $\dot{d}_E = \pi^N \dot{d}_E^N + \pi^I \dot{d}_E^I$. Note that $\pi^N \in [0,1]$ is the native share of the total population (i.e., the population across the college and labor markets), while $\pi^I = 1 - \pi^N$ is the analogous immigrant share.[40] Combined, this also implies that $\phi = \pi^N \phi^N + \pi^I \phi^I$, $\eta = \pi^N \eta^N + \pi^I \eta^I$, and $\dot{\mu} = \pi^N \dot{\mu}^N + \pi^I \dot{\mu}^I$. Lastly, college demand and college supply shifters are represented by μ and φ, respectively.

The labor market for relatively unskilled labor can be described by the following equations:

$$\dot{d}_L \equiv \dot{L}_U^d - \dot{L}_S^d = -\theta \dot{w} + \dot{\zeta} \qquad [\textit{Labor Demand}], \tag{9}$$

$$\dot{s}_L \equiv \dot{L}_U^s - \dot{L}_S^s = \gamma \dot{w} + \dot{\xi} \qquad [\textit{Labor Supply}], \tag{10}$$

where θ is the elasticity of substitution between skilled and unskilled labor, and γ is the relative labor supply elasticity, representing wage sensitivity of labor supplied both within-state and between states (i.e., the cross-state migration elasticity).[41] Total labor supply is a function of both native and immigrant labor supply, such that $\dot{s}_L = (\dot{N_U^s + I_U^s}) - (\dot{N_S^s + I_S^s}) = (\pi^N \gamma^N + \pi^I \gamma^I)\dot{w} + \pi^N \dot{\xi}^N + \pi^I \dot{\xi}^I$.[42] This implies that $\gamma = \pi^N \gamma^N + \pi^I \gamma^I$ and $\dot{\xi} = \pi^N \dot{\xi}^N + \pi^I \dot{\xi}^I$. Additionally, labor demand and labor supply shifters are represented by ζ and ξ, respectively.

Lastly, as discussed earlier, since enrollment determines skill, there is a functional link between changes in equilibrium enrollment in the college market and shifts in the relative supply of unskilled labor in the labor market. I specify this link as follows:

$$\dot{\xi} = \dot{\nu} - \lambda \dot{d}_E^*, \tag{11}$$

where $\lambda \in [0,1]$ is the share of the endogenous equilibrium change in college-enrolled students, $\dot{d}_E^*$, that remain in the state's labor market as skilled labor, and I have assumed that $\lambda^N = \lambda^I = \lambda$.[43] Meanwhile, $\dot{\nu}$ represents the exogenous component of $\dot{\xi}$ - namely, labor supply shocks that originate in the labor market, unrelated to the college market (e.g., labor immigration).[44]

[39]Although assumed otherwise, it remains a possibility that the college supply function with respect to tuition is actually negatively-sloped, due to a reduction in average costs when colleges expand (Christian, 2004). Empirically, such economies of scale would reduce the magnitude of the crowd-out effects I estimate and allow such effects to even be positive.

[40]For college demand, inclusion of the π population shares follows from a Cobb-Douglas production-style framework for the level of college demand D_E, where $D_E = D_E^{N,\alpha} D_E^{I,(1-\alpha)} \Leftrightarrow \ln D_E = \alpha \ln D_E^N + (1-\alpha)\ln D_E^I$, and α is natives' share in college demand, captured by π^N.

[41]This implies that as labor becomes more mobile, $\gamma \to \infty$. Therefore, perfect labor mobility is a sufficient but not necessary condition for perfectly elastic labor supply, consistent with Bound et al. (2004).

[42]For labor supply, inclusion of the π shares follows from the specification of the level of labor supply, $S_L \equiv \frac{N_U^s + I_U^s}{N_S^s + I_S^s} = (\frac{W_U}{W_S})^{(\pi^N \gamma^N + \pi^I \gamma^I)} e^{(\pi^N \ln \xi^N + \pi^I \ln \xi^I)}$.

[43]This assumption, while not necessary, simplifies the exposition quite a bit. Also note that since equilibrium will impose that $\dot{d}_E^* = \dot{s}_E^*$, the latter could equivalently be substituted into equation (11). Although in this static model, enrollment and attainment are equivalent, in reality λ could also partially represent the fact that the enrolled population will form a subset of the total skilled population.

[44]This is consistent with Fortin (2006), who in her dual-market, supply-demand econometric model, specifies equilibrium college enrollment, relative labor supply, and (inverse) relative labor demand functions at the state-year level, with relative labor supply as a function of past enrollment rates (i.e., homegrown relative labor supplies) and relative in-migration to the state.

Equilibrium

Equations (7)-(10) for demand and supply in the college and labor markets and equation (11) linking equilibrium changes in the college market to labor supply shifts together form an equilibrium in market prices and quantities. All analysis of interest in the paper assumes no confounding labor demand and college supply shifts, so the following equations specify the equilibrium imposing the restriction that $\dot{\zeta} = \dot{\varphi} = 0$:

$$\dot{f}^* = \Delta\dot{\mu} + (\Lambda\Delta\Gamma)\dot{\xi}, \tag{12}$$

$$\dot{w}^* = -\Gamma\dot{\xi}, \tag{13}$$

$$\dot{s}_L^* = (\theta\Gamma)\dot{\xi}, \tag{14}$$

$$\dot{d}_E^* = \frac{(\psi\Delta)\dot{\mu} + (\Omega\Delta\Gamma)\dot{\nu}}{1+\lambda}, \tag{15}$$

where $\Delta = (\frac{1}{\psi+\phi})$, $\Gamma = (\frac{1}{\gamma+\theta})$, $\Lambda = \kappa + \eta$, and $\Omega = \eta\psi - \kappa\phi$. Note again for equations (12)-(14) that $\dot{\xi} = \dot{\nu} - \lambda\dot{d}_E^*$, with $\dot{d}_E^*$ specified in equation (15). Positive shifts in relatively unskilled labor supply, $\dot{\nu}$, decrease relative unskilled wages but increase tuition/fees, while positive shifts in college demand, $\dot{\mu}$, increase both tuition/fees and relative unskilled wages.

Parameters

I am interested in the effect of exogenous shifts in relatively unskilled immigrant labor supply ($\dot{\nu}^I$) and immigrant college enrollment demand ($\dot{\mu}^I$) on equilibrium native college enrollment demanded ($\dot{d}_E^{N*}$). However, I do not observe the shocks $\dot{\nu}^I$ and $\dot{\mu}^I$ directly, but rather observe the equilibrium immigrant quantities $\dot{s}_L^{I*}$ and $\dot{d}_E^{I*}$, where $\dot{s}_L^I \equiv \dot{I}_U^s - \dot{I}_S^s = \gamma^I\dot{w} + \dot{\xi}^I$ and $\dot{d}_E^I = -\phi^I\dot{f} - \eta^I\dot{w} + \dot{\mu}^I$.

Crowd-in

Regarding the effect of an exogenous increase in immigrant labor supply on native college demand, I estimate this parameter under the assumptions of no correlated, exogenous shifts in labor demand ($\dot{\zeta} = 0$), college supply ($\dot{\varphi} = 0$), native and immigrant college demand ($\dot{\mu}^N = \dot{\mu}^I = 0$), and native labor supply ($\dot{\nu}^N = 0$).

It can be derived, given prior assumptions and definitions, that $\dot{\xi} = [\pi^I - (\frac{\lambda}{1+\lambda})(\Omega\Delta\Gamma)\pi^I]\dot{\nu}^I \equiv \Psi\dot{\nu}^I$.[45] Also recall, related to equation (7), that $\dot{d}_E^N = -\phi^N\dot{f} - \eta^N\dot{w} + \dot{\mu}^N$ and $\dot{d}_E^I = -\phi^I\dot{f} - \eta^I\dot{w} + \dot{\mu}^I$. Substituting $\Psi\dot{\nu}^I$ for $\dot{\xi}$ in equilibrium price equations (12) and (13) and manipulating existing formulations, I derive the following equilibrium equations for native college demand $\dot{d}_E^N$ and immigrant labor supply $\dot{s}_L^I$ under the current assumptions:

$$\dot{d}_E^{N*} = [\eta^N\Psi\Gamma - \phi^N\Psi(\Lambda\Delta\Gamma)]\dot{\nu}^I, \tag{16}$$

[45]This follows in part from the fact that, given $\dot{\nu} - \lambda\dot{d}_E^* = \dot{\xi} = \pi^N\dot{\xi}^N + \pi^I\dot{\xi}^I$ from equations (10) and (11), it can be shown that in general $\dot{\nu} = \pi^N\dot{\nu}^N + \pi^I\dot{\nu}^I$.

$$\dot{s}_L^{I*} = \{(\pi^N\gamma^N + \theta)(1 - \lambda[\eta^I\Psi\Gamma - \phi^I\Psi(\Lambda\Delta\Gamma)]) + \lambda\pi^N\gamma^I[\eta^N\Psi\Gamma - \phi^N\Psi(\Lambda\Delta\Gamma)]\}\Gamma\dot{\nu}^I \ . \qquad (17)$$

The implied crowding parameter of interest is thus defined as:

$$\beta = \frac{\dot{d}_E^{N*}/\dot{\nu}^I}{\dot{s}_L^{I*}/\dot{\nu}^I} = \underbrace{\frac{1}{h(.)}}_{-\epsilon_{wL}}\eta^N + \underbrace{\frac{\Lambda\Delta}{h(.)}}_{-\epsilon_{fL}}\phi^N \in [0,\infty), \qquad (18)$$

where $h(.)$ is a complicated function of the structural parameters, while ϵ_{wL} and ϵ_{fL} are elasticities of relative unskilled wages and tuition/fees (respectively) to exogenous inflows of relatively unskilled immigrant labor.[46] The lower bound on β occurs for *any* of several scenarios, including: (a) perfectly elastic labor demand ($\theta \to \infty$), (b) perfectly inelastic college supply ($\psi = \kappa = 0$), (c) very small immigrant population shares ($\pi^I \to 0$), or (d) frictionless mobility across states or highly wage-sensitive within-state labor supply (γ^I or $\gamma^N \to \infty$). The upper bound on β requires the opposite extreme on *all* elements (a)-(d): i.e., perfectly inelastic labor demand, perfectly elastic college supply, very large immigrant population shares, and immobile labor with no labor supply sensitivity to wage changes.

The sign of β shows that relatively unskilled immigrant labor inflows weakly increase (i.e., crowd-in) native college enrollment, and the magnitude of this reduced-form effect is a function of the sensitivity of native college demand to changes in wages and tuition/fees, as well as the sensitivity of those market prices to the immigrant inflows.

Crowd-out

Turning now to the effect of an exogenous increase in immigrant college demand on native college demand, I estimate this parameter under the assumptions of no correlated, exogenous shifts in labor demand ($\dot{\zeta} = 0$), college supply ($\dot{\varphi} = 0$), native and immigrant labor supply ($\dot{\nu}^N = \dot{\nu}^I = 0$), and native college demand ($\dot{\mu}^N = 0$).

It can be determined, given prior assumptions and definitions, that $\dot{\xi} = [-(\frac{\lambda}{1+\lambda})(\psi\Delta)\pi^I]\dot{\mu}^I \equiv \Phi\dot{\mu}^I$. Again recall, related to equation (7), that $\dot{d}_E^N = -\phi^N\dot{f} - \eta^N\dot{w} + \dot{\mu}^N$ and $\dot{d}_E^I = -\phi^I\dot{f} - \eta^I\dot{w} + \dot{\mu}^I$. Substituting $\Phi\dot{\mu}^I$ for $\dot{\xi}$ in equilibrium price equations (12) and (13) and manipulating existing formulations, I derive the following equilibrium equations for native college demand $\dot{d}_E^N$ and immigrant college demand $\dot{d}_E^I$ under the current assumptions:

$$\dot{d}_E^{N*} = \{\eta^N\Phi\Gamma - \phi^N[\Delta + (\Lambda\Delta\Gamma)\Phi]\}\dot{\mu}^I, \qquad (19)$$

$$\dot{d}_E^{I*} = \{1 + (\eta^I\Phi\Gamma - \phi^I[\Delta + (\Lambda\Delta\Gamma)\Phi])\}\dot{\mu}^I, \qquad (20)$$

The implied crowding parameter of interest is thus defined as:

$$\alpha = \frac{\dot{d}_E^{N*}/\dot{\mu}^I}{\dot{d}_E^{I*}/\dot{\mu}^I} = \underbrace{\frac{\Phi\Gamma}{l(.)}}_{-\epsilon_{wE}}\eta^N + \underbrace{\frac{(\Delta + \Lambda\Delta\Gamma\Phi)}{l(.)}}_{-\epsilon_{fE}}\phi^N \in [-1,0], \qquad (21)$$

where $l(.)$ is a complicated function of the structural parameters, while ϵ_{wE} and ϵ_{fE} are elasticities

[46] In other words, $\epsilon_{wL} = \frac{\dot{w}^*/\dot{\nu}^I}{\dot{s}_L^{I*}/\dot{\nu}^I}$ and $\epsilon_{fL} = \frac{\dot{f}^*/\dot{\nu}^I}{\dot{s}_L^{I*}/\dot{\nu}^I}$.

for the sensitivity of relative unskilled wages and tuition/fees (respectively) to exogenous inflows of immigrant students.[47] The upper bound on α occurs when there is perfectly elastic college supply with respect to tuition/fees ($\psi \to \infty$) combined with *any* of several scenarios, including: (a) perfectly elastic labor demand ($\theta \to \infty$), (b) frictionless mobility across states or highly wage-sensitive within-state labor supply (γ^I or $\gamma^N \to \infty$), (c) very small immigrant population shares ($\pi^I \to 0$), or (d) no retention of college students in the state's labor market ($\lambda = 0$). Conversely, the lower bound on α simply requires perfectly inelastic college supply with respect to tuition/fees.

The sign of α shows that immigrant student inflows weakly decrease (i.e., crowd-out) native college enrollment, and the magnitude of this reduced-form effect is once again a function of the sensitivity of native college demand to changes in wages and tuition/fees, as well as the sensitivity of those market prices to the immigrant inflows. The magnitude range of -1 to 0 also aligns with theory and findings of other immigrant-native displacement studies (Hoxby, 1998; Card, 2001; Cortes, 2008).

Implications for Estimation

Although already discussed in the paper, I highlight again the key estimation issues and guidelines, now with reference to the formal model.

First, both coefficients focus on how exogenous, unobserved immigrant shifts affect native college enrollment via observed immigrant quantities for relatively unskilled labor supply and college demand. Thus, the regressors of interest in the estimating equation should also be focused on immigrants. It should be noted that when the focus of the model is, alternatively, how exogenous immigrant shifts affect native college enrollment via observed *total* quantities for relatively unskilled labor supply and college demand, the parameter results are qualitatively similar. When considering total quantities, the noteworthy changes are that: (a) the scale of immigrant inflows (via π^I) no longer factors into the formula for β (crowd-in) (Appendix A2 derives a method to examine the importance of this "scale effect" in the empirical analysis and, unlike equation (18), to separately identify it from β); and (b) the lower bound of α (crowd-out) decreases from -1 to -∞.

Second, compared to the graphical representation, the formal model makes it explicitly clear that the relative magnitudes of the crowd-in and crowd-out parameters are ambiguous, as both $|\beta| > |\alpha|$ and $|\beta| < |\alpha|$ are possible depending on structural parameter values.

Third, changes in several parameters (e.g., increases in labor demand elasticity, θ) will cause *both* β and α to tend toward 0. However, there are exceptions to this. More elastic college supply with respect to tuition/fees, ψ, as well as a lower percentage of a state's college students retained for the labor market, λ, both reduce the magnitude of α, whereas they increase or have an ambiguous effect, respectively, on the magnitude of β.[48]

Fourth, the model motivates the need for independent and dependent variables in the estimating equation that are specified in logs, given that the parameters in equations (18) and (21) are for log changes.

Fifth, given that it is always assumed that there are no exogenous increases in native college enrollment ($\dot{\mu}^N = 0$), it is necessary to account for native demographic shocks that would otherwise affect their college demand. This can be accomplished by examining log changes in enrollment rates rather than enrollment levels.

Finally, appropriate estimation is necessary to ensure that other assumptions about the lack of confounding market shifts - e.g., in labor demand ($\dot{\zeta} = 0$) and college supply ($\dot{\varphi} = 0$) - actually hold.

[47] In other words, $\epsilon_{wE} = \frac{\dot{w}^*/\dot{\mu}^I}{\dot{d}_E^{I*}/\dot{\mu}^I}$ and $\epsilon_{fE} = \frac{\dot{f}^*/\dot{\mu}^I}{\dot{d}_E^{I*}/\dot{\mu}^I}$.

[48] Additionally, although absent from this static model, in reality the different time horizons for the crowd-in and crowd-out effects due to the lag between college enrollment and labor market entry could also open a role for native expectations and uncertainty to explain differences in the coefficient magnitudes.

To accomplish this, I utilize a procedure to estimate immigrant college demand, as well as use 2SLS estimation, various fixed effects,[49] and an estimating equation specified in first differences.

[49]This includes those at the state level, since effects in the model are theorized for given labor and higher education markets of a fixed size. The empirical analog of this assumption is thus to estimate effects over time within states, while also accounting for any native demographic shocks, as already discussed.

Appendix A2: Latent Variable Model of Immigrant College Demand

For any immigrant i, let

$y_i^* \equiv$ college demand (latent),

$y_i \equiv$ college-enrolled (observed), where

$$y_i^* = \mathbf{x'}_i \boldsymbol{\vartheta} + \varepsilon_i,$$

and

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases}.$$

$\mathbf{x'}_i$ is a vector of individual characteristics (e.g., age - see section 4 for details), ε_i is the mean-zero error term, and y_i^* can be thought of as the difference between an individual's marginal value of college enrollment and equilibrium tuition/fees. Further allowing for differential observations and innovations by state j yields

$$y_{ij}^* = \mathbf{x'}_{ij} \boldsymbol{\vartheta} + \varepsilon_{ij},$$

where

$$\varepsilon_{ij} = \delta_{ij} + \underbrace{\omega_j + \varphi_j}_{market\ shocks}.$$

$\omega_j = -\zeta_j$ is a *negative* labor demand shock, φ_j is a *positive* college supply shock, and δ_{ij} is the idiosyncratic component of the composite error.

Further using the notation of Appendix A1, y_{ij}^* is related to a parameterization of $\dot{d}_E^I = -\phi^I \dot{f} - \eta^I \dot{w} + \dot{\mu}^I$. The composite error is intended to capture the effects of market price changes, $\dot{f}$ and $\dot{w}$, on immigrant enrollment demand, while the covariates and coefficients are meant to capture the effects of exogenous shifts, $\dot{\mu}^I$.

Given that the population of interest is immigrants and *not* the foreign-born, non-random sample selection of immigrants into U.S. states is not problematic.[50] Consistent estimation of the $\boldsymbol{\vartheta}$'s $\Leftrightarrow E(x_{ij}\varepsilon_{ij}) = 0$.[51]

[50] Demand for immigration into particular states can similarly be thought of as a latent variable, m_{ij}^*, where only binary m_{ij} (immigration into state j) is observed, and $m_{ij}^* = \mathbf{x'}_{ij} \boldsymbol{\varrho} + \tau_{ij}$. If τ_{ij} is a composite error that is similarly a function of shocks ω_j and φ_j, then correlation $\rho_{\varepsilon\tau} \neq 0$, and sample selection bias prevents consistent estimation of the $\boldsymbol{\varrho}$'s for the foreign-born population via OLS without further corrections. Note that labor demand or college supply shocks having an influence on immigration demand is a sufficient but not necessary condition for $\rho_{\varepsilon\tau} \neq 0$ and the existence of sample selection bias.

[51] A violation of this exogeneity condition would occur, for instance, if New York universities added 10,000 additional enrollment seats specifically for non-traditional college students ages 25 and older.

Appendix A3: Scale Effect in Impact of Immigration

As shown in the model, because one of the regressors in the main empirical specifications is Δln[Immigrants (unskilled / skilled), labor] rather than Δln[Total (unskilled / skilled), labor], the level/scale of immigrant (labor) inflows also affects native college enrollment. Because this effect operates primarily through relative wages (which may then, in turn, impact tuition prices through induced changes in native college demand), I can focus solely on this mechanism.

I return to the relative unskilled wage function from the model, now in levels rather than log changes and with slightly more generic notation g for the wage function, for simplicity:

$$w = g(S_L, D_L) \text{ , where } \frac{\partial g}{\partial S_L} \geq 0 \text{ , } \frac{\partial g}{\partial D_L} \leq 0 \text{ .}$$

Note that S_L and D_L are the relative supply and demand for unskilled (u) labor, respectively. The magnitudes of the above comparative statics, respectively, are inversely related to the relative labor supply and relative labor demand elasticities, γ and θ. For natives N and immigrants I, recall

$$L_k = N_k + I_k, \quad k = \{u, s\} \text{ ,}$$

$$S_L^I = I_u / I_s \text{ ,}$$

where s is skilled.[52] Want to solve for the sign of $\frac{\partial w}{\partial S_L^I}$:

$$\frac{\partial w}{\partial S_L^I} = \frac{\partial g}{\partial S_L} \frac{\partial S_L}{\partial S_L^I}.$$

Note that

$$S_L \equiv \frac{L_u}{L_s} = \frac{N_u + I_u}{N_s + I_s} = \frac{(N_u/I_s) + (I_u/I_s)}{(N_s/I_s) + 1} = \frac{(N_u/I_s)}{(N_s/I_s) + 1} + \frac{S_L^I}{(N_s/I_s) + 1}.$$

$$\Longrightarrow \frac{\partial S_L}{\partial S_L^I} = 0 + \frac{1}{(N_s/I_s) + 1} = \frac{I_s}{N_s + I_s} = \frac{I_s}{L_s} \in [0, 1] \Longleftrightarrow \frac{\partial w}{\partial S_L^I} \geq 0 \text{ ,}$$

which is consistent with the model.

Call $\chi_s^I = \frac{I_s}{L_s} \equiv$ skilled immigrant share of total skilled labor. Thus, if χ_s^I (or a proxy, specified instead in logs) were included in a regression to account for the scale effect, the expected coefficient sign would be weakly positive. However, in the denominator of χ_s^I, N_s is endogenous, as it is related to the outcome of interest. Still, χ_s^I can at least be approximated in regressions with I_s to account for the scale effect. In this case, the expected coefficient sign is still weakly positive, since

$$\frac{\partial \chi_s^I}{\partial I_s} = \frac{1}{N_s + I_s} \left[1 - \frac{I_s}{N_s + I_s}\right] \geq 0.$$

[52] Unlike the model, because all quantities here are quantities supplied, superscripts indicating such are suppressed.

Appendix A4: Parameters for Native College Demand Elasticities

As discussed in the paper and Table 10, several assumptions were necessary to derive the native college demand elasticities, described here in detail. Equations (18) and (21) of the model more fully describe the nonlinear system of two equations to be solved for the two unknown college demand elasticities, η^N and ϕ^N. Because no closed-form solution to the nonlinear system exists, a numerical solution is determined. There are eleven free parameters from the model whose values need to be assigned: $\eta^I, \phi^I, \beta, \alpha, \pi^N, \gamma^N, \gamma^I, \kappa, \lambda, \psi$, and θ.

Immigrant College Demand Elasticities
I make a simplifying assumption that there are no differences in the price sensitivities of native and immigrant college demand, so that $\eta^I = \eta^N$ and $\phi^I = \phi^N$. While this is admittedly restrictive, it may be the case that the distributions of natives vs. immigrants across states do not differ systematically with regard to these parameters. More functionally, this assumption allows the exercise to continue without having to further specify immigrant behavior in the model.

Crowding Elasticities
I use the crowding estimates $\hat{\beta}$ and $\hat{\alpha}$ from Table 5, column 7 for β and α, respectively. For $\hat{\alpha}$, I utilize the adjusted, crowd-out ratio estimate in place of the coefficient estimate since the former is more closely aligned with the model, as previously discussed.

Native Population Share
For π^N, the native share of the total population, I use the native share of the 18-64 population from 1970 to 2000 in the census data.

Labor Supply Elasticities
The relative labor supply elasticities for natives and immigrants, γ^N and γ^I respectively, cannot however be similarly observed directly from the census data. To proxy for these variables, I assume that the wage sensitivity of labor supply within-state is the same for natives and immigrants, focusing instead on the wage sensitivity of labor supply between states (i.e., the cross-state migration elasticity) and how it differs for the skilled and unskilled. Separately for natives and immigrants, ages 18 to 64 from 1970 to 2000, I calculate the proportion of unskilled individuals who migrated across states in the five years prior to being surveyed, *relative* to the proportion of skilled individuals who migrated across states in the five years prior to being surveyed. I use these ratios as the proxies for γ^N and γ^I.[53]

Wage Elasticity of College Supply
To fix κ, I assume that college supply is completely wage inelastic.

Retention of College Students in Local Labor Market
I obtain from Bound et al. (2004) a value for λ, the share of the endogenous equilibrium change in college-enrolled students that remain in the state's labor market as skilled labor.

Tuition/Fee Elasticity of College Supply
Multiple values are assigned for ψ, the tuition/fee elasticity of college supply, in order to observe

[53]Individual observations are weighted using census person weights. For immigrants, the ratio is calculated using only immigrants who have lived in the U.S. for more than five years. Only information on prior country of residence, rather than cross-state migration activity, is reported in the census for more recent immigrants.

how the price elasticities of native college demand change in response. The initial value of ψ is calculated to be inversely related to an estimate from Bound and Turner (2007) for the elasticity of college enrollment with respect to cohort size.[54] The alternate value of ψ is simply assumed to be larger and more elastic. Recall the model predicts, ceteris paribus, that as college supply becomes more elastic, the crowd-in effect increases in magnitude while the crowd-out effect decreases in magnitude. Thus, as ψ increases, in order to observe given values of β and α, natives must be increasingly less wage-sensitive and increasingly more tuition/fee-sensitive. Therefore η^N should decrease in magnitude and ϕ^N should increase in magnitude.

Elasticity of Substitution

Multiple values are also assigned for θ, the elasticity of substitution between skilled and unskilled labor, in order to observe how the price elasticities of native college demand change in response. The two chosen values of θ come from Katz and Murphy (1992) and Card and Lemieux (2001), although it should be noted that their definition of skilled and unskilled differs somewhat from this paper's definition.[55] Recall here the model predicts, ceteris paribus, that as relative labor demand becomes more elastic, both the crowd-in and crowd-out effects decrease in magnitude. Thus, as θ increases, in order to observe given values of β and α, natives must be increasingly more wage- and tuition/fee-sensitive. Therefore both η^N and ϕ^N should increase in magnitude.

[54]Specifically, I assume $\psi = \frac{x}{1-x}$, where $x \in [0, 1]$ is the Bound and Turner (2007) estimate, equal to 0.79. This ensures $\psi \in [0, \infty)$ and positively correlated to x.

[55]For this exercise, I opt for the Card and Lemieux (2001) estimate from their males-only sample rather than their estimate from the sample pooling men and women. While the latter is more comparable to this paper's sample, the former differs from Katz and Murphy (1992) more starkly and so is more illustrative.

Appendix B: Additional Analyses

Table B1: Immigrant Covariate Averages in 1960, by College Enrollment Status

	All	College-Enrolled [CE]	Not College-Enrolled [NCE]	Δ_{CE-NCE}
	(1)	(2)	(3)	(4)
Age	46.84	22.92	47.10	-24.181
	(12.74)	(4.05)	(12.55)	(0.167)***
Female	0.53	0.33	0.53	-0.201
	(0.50)	(0.47)	(0.50)	(0.019)***
White non-Hispanic	0.84	0.71	0.84	-0.138
	(0.36)	(0.46)	(0.36)	(0.018)***
Black non-Hispanic	0.01	0.04	0.01	0.023
	(0.11)	(0.19)	(0.11)	(0.007)***
Asian non-Hispanic	0.03	0.09	0.03	0.053
	(0.18)	(0.28)	(0.18)	(0.011)***
Hispanic	0.11	0.13	0.11	0.028
	(0.31)	(0.34)	(0.31)	(0.013)**
Other	0.003	0.037	0.003	0.034
	(0.05)	(0.19)	(0.05)	(0.007)***
Sample probabilities	1.00	0.01	0.99	
Observations	59,084	648	58,436	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Columns (1)-(3) contain covariate means and standard deviations (in parentheses) from the U.S. Census in 1960. Column (4) contains differences in means for enrolled and not-enrolled immigrants and their significance levels, with heteroskedasticity-robust standard errors in parentheses.

Table B2: College Demand Index 1970-2000, Quintiles

	Lowest (1)	2nd (2)	3rd (3)	4th (4)	Highest (5)
Age (mean)	57.1	45.5	36.9	29.6	23.6
Female (%)	0.59	0.55	0.54	0.52	0.35
Black non-Hispanic (%)	0.04	0.06	0.06	0.06	0.08
Asian non-Hispanic (%)	0.15	0.20	0.21	0.20	0.27
Hispanic (%)	0.30	0.38	0.46	0.50	0.39
Other (excl. white non-Hispanic) (%)	0.01	0.02	0.02	0.02	0.03
Source country A1	Mexico	Mexico	Mexico	Mexico	Mexico
(country % in quintile)	0.16	0.22	0.30	0.34	0.18
Source country A2	Canada	Canada	Philippines	Philippines	Philippines
(country % in quintile)	0.07	0.05	0.05	0.04	0.05
Source country A3	Italy	Philippines	Cuba	Vietnam	India
(country % in quintile)	0.07	0.04	0.03	0.03	0.05
Source country B1	Estonia	North Korea	Kiribati	Turks & Caicos	UAE
(quintile % in country)	0.49	0.34	0.31	0.50	0.88
Source country B2	Lithuania	Botswana	Anguilla	Gambia	Oman
(quintile % in country)	0.47	0.33	0.29	0.39	0.84
Source country B3	Madeira	British Vir.	Guadeloupe	Zambia	Qatar
(quintile % in country)	0.46	0.32	0.29	0.36	0.79
Observations (actual)	442,034	458,244	471,055	454,028	464,563

Notes: U.S. Census 1970-2000 and author's calculations. See text for details on the construction of the college demand index. Individual observations utilized for descriptive statistics above are weighted using census person weights. Source country B rankings are based on weighted proportions for countries with at least 10 immigrants (actual, not weighted) over 1970-2000.

Table 1: Estimating Immigrant College Demand in 1960, Marginal Effects

Dependent Variable:	College-Enrolled (0/1)		
	Logit [MLE] (1)	LPM [OLS] (2)	Logit [MLE] (3)
Age	0.001	-0.013	-0.003
	(0.001)	(0.000)***	(0.000)***
Age^2	-0.000	0.000	
	(0.000)***	(0.000)***	
Female	-0.013	-0.011	
	(0.001)***	(0.001)***	
Black non-Hispanic	-0.001	-0.003	
	(0.004)	(0.006)	
Asian non-Hispanic	-0.002	-0.013	
	(0.003)	(0.005)**	
Hispanic	-0.008	-0.014	
	(0.005)	(0.005)***	
Other (excl. white non-Hispanic)	-0.001	0.031	
	(0.004)	(0.008)***	
Constant	0.002	0.320	0.037
	(0.013)	(0.005)***	(0.002)***
Source country fixed effects	Yes	Yes	No
Observations	58,578	59,084	59,084
Log likelihood	-1917.33		-2265.20
(Pseudo) R^2	0.46	0.10	0.37
% Correct, enrolled=1 (1960)	0.94	0.99	0.95
% Correct, enrolled=0 (1960)	0.88	0.67	0.85
% Correct, enrolled=1 (1970-2000)	0.69	0.84	0.73
% Correct, enrolled=0 (1970-2000)	0.73	0.47	0.68

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: All specifications are estimated in 1960 using U.S. Census data and weight individual observations using census person weights. Specifications (1) and (2) also include source country dummies (not reported). "White Non-Hispanic" is the omitted racial category. Average marginal effects are reported for all specifications, and for the logistic models are calculated at the sample average rate of college enrollment in 1960, $\hat{\beta} * \bar{y} * (1 - \bar{y})$. "% Correct" is the proportion of accurate in-sample (1960) or out-of-sample (1970-2000) predictions for enrolled or not-enrolled individuals. An individual is predicted to be enrolled if $\hat{y} > \bar{y}$, and not enrolled if $\hat{y} \leq \bar{y}$. Standard errors in parentheses.

Table 2: Comparing Immigrant Differentiation Methods: Baseline (OLS)

Dependent Variable:	Δln[Native College Enrollment as fraction of Native Population]					
	Homog.	Full Spec, Logit	Full Spec, LPM	Age Only, Logit	CDF(Age)	LF & Enroll
	(1)	(2)	(3)	(4)	(5)	(6)
Δln[Immigrants, Total]	0.054					
	(0.044)					
Δln[Immigrants (unskilled / skilled), labor]		0.263	0.248	0.290	0.304	0.097
		(0.090)***	(0.096)**	(0.096)***	(0.093)***	(0.033)***
Δln[Immigrants, students]		-0.143	-0.114	-0.138	-0.139	0.050
		(0.065)**	(0.064)*	(0.056)**	(0.055)**	(0.045)
R^2	0.47	0.54	0.53	0.55	0.55	0.52
Observations	150	150	150	150	150	149

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Native enrollment and population is for ages 18-44. All specifications include Δ(year) fixed effects. Specification (1) uses homogenous, rather than heterogeneous, immigrant inflows as a regressor. Specifications (2)-(4) determine labor and students immigrants from first-step procedures, as noted, to predict immigrant college demand (see Table 1). Specification (5) determines labor and students immigrants using an age cutoff (students if age ≤ 28, labor otherwise; cutoff is age where ∼90% of immigrants are enrolled) from the cumulative distribution function of age for college-enrolled immigrants in 1960. Specification (6) uses endogenous information on actual labor force participation and college enrollment to define labor and student immigrants, respectively. Standard errors clustered at the state level are in parentheses.

Table 3: Descriptive Statistics for Immigrant Inflows and Native Outcomes

	All Years (1970-2000)							Analysis of Variance		
	Mean	Median	Min	Max	Mean_{1970}	Mean_{2000}	$\Delta_{2000-1970}$	Year	State	Within
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Immigrants (unskilled / skilled), labor	1.830	1.465	0.500	8.128	3.129	1.254	-1.875	0.48	0.30	0.22
	(1.131)				(1.320)	(0.550)	(0.192)***			
Immigrants, students (millions)	0.054	0.014	0.000	1.242	0.021	0.095	0.074	0.04	0.76	0.20
	(0.144)				(0.042)	(0.200)	(0.023)***			
Native college enroll. / native population	0.092	0.093	0.046	0.165	0.089	0.099	0.010	0.14	0.60	0.26
	(0.018)				(0.021)	(0.014)	(0.002)***			
Native population (millions)	1.671	1.163	0.110	9.458	1.304	1.851	0.547	0.02	0.96	0.02
	(1.677)				(1.369)	(1.774)	(0.088)***			
Native college enroll. / native pop., 18-24	0.237	0.234	0.107	0.390	0.229	0.278	0.049	0.27	0.51	0.22
	(0.048)				(0.050)	(0.039)	(0.005)***			
Native college enroll. / native pop., 25-34	0.048	0.047	0.010	0.094	0.021	0.055	0.023	0.37	0.46	0.17
	(0.015)				(0.012)	(0.013)	(0.001)***			
Native female col. enroll. / native pop.	0.093	0.094	0.030	0.158	0.073	0.107	0.034	0.38	0.38	0.24
	(0.021)				(0.018)	(0.016)	(0.002)***			
Native public col. enroll. / native pop.	0.072	0.072	0.034	0.123	0.062	0.078	0.015	0.20	0.55	0.25
	(0.017)				(0.020)	(0.014)	(0.002)***			
Some college natives / native population	0.297	0.301	0.153	0.455	0.221	0.357	0.136	0.59	0.36	0.04
	(0.068)				(0.048)	(0.037)	(0.004)***			
4 years col.+ natives / native population	0.174	0.171	0.064	0.338	0.111	0.215	0.104	0.56	0.37	0.07
	(0.055)				(0.022)	(0.047)	(0.005)***			
4 years HS natives / native population	0.355	0.353	0.262	0.455	0.364	0.332	-0.032	0.13	0.60	0.28
	(0.042)				(0.041)	(0.039)	(0.007)***			
< 4 years HS natives / native population	0.174	0.143	0.054	0.470	0.304	0.096	-0.208	0.72	0.23	0.05
	(0.097)				(0.076)	(0.027)	(0.008)***			
Observations	200	200	200	200	50	50		200	200	200

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Native population is ages 18-44 unless otherwise noted. Descriptive statistics shown for predicted, not actual, immigrant students and labor. Columns (1), (5) and (6) contain variable means and standard deviations (in parentheses), while columns (2)-(4) contain other descriptive statistics, all from the U.S. Census years noted. Column (7) contains differences in means for 2000 and 1970 variables and their significance levels, with standard errors clustered at the state level in parentheses. Columns (8)-(10) analyze the relative sources of variation for each variable.

Table 4: First Stage Results (OLS)

Dependent Variable:	Δln[Immigrants (unskilled / skilled), labor]		Δln[Immigrants, students]	
	(1)	(2)	(3)	(4)
[(1960 immigrant share)$\times$ Δ(immigrants, labor, unskilled)]	0.022 (0.018)	0.164 (0.048)***	0.011 (0.028)	0.263 (0.063)***
[(1960 immigrant share)$\times$ Δ(immigrants, labor, skilled)]	-0.097 (0.046)**	-0.250 (0.101)**	-0.091 (0.065)	0.042 (0.162)
[(1960 immigrant share)$\times$ Δ(immigrants, students)]	0.062 (0.065)	-0.128 (0.105)	0.072 (0.147)	-0.514 (0.200)**
[(1960 immigrant share)$\times$ Δ(immigrants, labor, unskilled)]^2		-0.012 (0.003)***		-0.020 (0.004)***
[(1960 immigrant share)$\times$ Δ(immigrants, labor, skilled)]^2		0.022 (0.013)*		-0.026 (0.021)
[(1960 immigrant share)$\times$ Δ(immigrants, students)]^2		0.068 (0.022)***		0.165 (0.044)***
R^2	0.50	0.53	0.45	0.51
Observations	150	150	150	150
F test: instruments=0	1.62	37.57	2.14	49.76
Prob > F	0.20	0.00	0.11	0.00

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Regressors are constructed from individual-level 1960 U.S. Census data and aggregated to the state-year level. All immigrant inflows are predicted, not actual, as described in text (section 4). For source country h, state j, and year t, the general form of the regressor is $\sum_h \left(\frac{Immigrants_{hj,1960}}{Immigrants_{h,1960}}\right) \times \Delta\Big(Immigrant\_Type\Big)_{ht}$. The $Immigrant\_Type$ stocks utilized are: (1) unskilled immigrant labor, (2) skilled immigrant labor, and (3) immigrant students. All specifications include Δ(year) fixed effects. All coefficients and standard errors are multiplied by 100,000. Reported coefficients are thus the marginal effects of increases in the predicted (via 1960 historical shares) flows of 100,000 immigrants on the flows of immigrant labor and students, as specified by the dependent variable. Standard errors clustered at the state level are in parentheses.

Table 5: Impact of Immigration on Native College Enrollment

Dependent Variable:	Δln[Native College Enrollment as fraction of Native Population]									
	OLS	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δln[Immigrants (unskilled / skilled), labor]	0.263	0.137	0.170	0.262	0.263	0.416	0.330	0.620	0.229	0.433
	(0.090)***	(0.105)	(0.168)	(0.090)***	(0.101)**	(0.147)***	(0.179)*	(0.568)	(0.095)**	(0.167)**
Δln[Immigrants, students]	-0.143	-0.087	-0.113	-0.149	-0.141	-0.237	-0.039	-0.096	-0.170	-0.238
	(0.065)**	(0.069)	(0.102)	(0.067)**	(0.069)**	(0.129)*	(0.090)	(0.258)	(0.127)	(0.132)*
Δ(Division $\times$ year) fixed effects	No	Yes	No	No	No	No	Yes	No	No	No
Δ(State-specific linear trends)	No	No	Yes	No	No	No	No	Yes	No	No
Excluding CA, FL, NY	No	No	No	Yes	No	No	No	No	Yes	No
Excluding ID, NE, NC	No	No	No	No	Yes	No	No	No	No	Yes
R^2	0.54	0.77	0.80	0.53	0.54					
Observations	150	150	150	141	141	150	150	150	141	141
Kleibergen-Paap rk (H_0: rank(r)=0)						36.97	23.49	84.34	9.91	37.14
Crowd-out ratio ($\frac{Ntv}{Img}$)	-13.128	-4.035	-13.974	-14.437	-11.687	-6.724	-0.243	-1.535	-67.616	-6.578

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Native enrollment and population is for ages 18-44. All immigrant inflows are predicted, not actual, as described in text (section 4). Instruments in specifications (6)-(10) are level and quadratic of $\sum_h \left(\frac{Immigrants_{hj,1960}}{Immigrants_{h,1960}}\right) \times \Delta\Big(Immigrant\_Type\Big)_{ht}$, for source country h, state j, and year t. The $Immigrant\_Type$ stocks utilized are: (1) unskilled immigrant labor, (2) skilled immigrant labor, and (3) immigrant students. All specifications include Δ(year) fixed effects. Divisions are nine U.S. Census divisions. F-statistic version of the Kleibergen-Paap rk statistic for weak identification, which is robust to a clustered error structure, is reported. Standard errors clustered at the state level are in parentheses. Crowd-out ratio is the estimated number of natives displaced from college enrollment by every immigrant enrolled. To determine this, two separate regressions are run that vary the specification noted by replacing the dependent variable Δln[Native College Enrollment as fraction of Native Population] with: (a) Δ[Native College Enrollment as fraction of Native Population]; and (b) Δ[Immigrant College Enrollment as fraction of Native Population]. The crowd-out ratio is calculated as the ratio of Δln[Immigrants, students] coefficients from those specifications [i.e., (a)/(b)].

Table 6: Scale Effect in Impact of Immigration

Dependent Variable:	Δln[Native College Enrollment as fraction of Native Population]							
	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δln[Immigrants (unskilled / skilled), labor]	0.289	0.171			0.382	0.341		
	(0.084)***	(0.099)*			(0.156)**	(0.330)		
Δln[Immigrants, students]	-0.233	-0.167	-0.067	-0.048	-0.339	-0.049	-0.051	0.087
	(0.068)***	(0.070)**	(0.053)	(0.051)	(0.161)**	(0.252)	(0.070)	(0.062)
Δln[Immigrants, skilled labor]	0.191	0.183			0.272	0.013		
	(0.082)**	(0.068)**			(0.136)*	(0.297)		
Δln[Total (unskilled / skilled), labor]			-0.372	-0.327			-0.382	-0.187
			(0.143)**	(0.137)**			(0.231)	(0.190)
Δ(Division × year) fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.56	0.78	0.50	0.77				
Observations	150	150	150	150	150	150	150	150
Kleibergen-Paap *rk* (H_0: rank(r)=0)					47.18	456.47	46.04	42.72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Native enrollment and population is for ages 18-44. All immigrant inflows are predicted, not actual, as described in text (section 4). Δln[Immigrants, skilled labor] added as an additional endogenous variable in specifications (1)-(2) and (5)-(6), while Δln[Total (unskilled/skilled), labor] replaces Δln[Immigrants (unskilled/skilled), labor] as an endogenous variable in specifications (3)-(4) and (7)-(8). Δln[Total (unskilled/skilled), labor] is composed of predicted immigrant labor inflows and native population ages 45-64. Instruments in specifications (5)-(8) are level and quadratic of $\sum_h \left(\frac{Immigrants_{hj,1960}}{Immigrants_{h,1960}}\right) \times \Delta\Big(Immigrant\_Type\Big)_{ht}$, for source country h, state j, and year t. The $Immigrant\_Type$ stocks utilized are: (1) unskilled immigrant labor, (2) skilled immigrant labor, and (3) immigrant students. All specifications include Δ(year) fixed effects. Divisions are nine U.S. Census divisions. F-statistic version of the Kleibergen-Paap rk statistic for weak identification, which is robust to a clustered error structure, is reported. Standard errors clustered at the state level are in parentheses.

Table 7: Heterogeneity in Native Education Response to Immigration

Dependent Variable:	Δln[Native College Enrollment as fraction of Native Population]			
	OLS		2SLS	
	Immig. Labor	*Immig. Students*	*Immig. Labor*	*Immig. Students*
Natives 18-24 Years Old	(1)	(1)	(2)	(2)
	0.166	-0.070	0.330	0.001
	(0.120)	(0.075)	(0.149)**	(0.078)
R^2	0.74			
Observations	150		150	
Natives 25-34 Years Old	(3)	(3)	(4)	(4)
	0.160	-0.254	0.271	-0.141
	(0.108)	(0.069)***	(0.223)	(0.118)
R^2	0.71			
Observations	150		150	
Female Natives	(5)	(5)	(6)	(6)
	0.172	-0.134	0.336	-0.058
	(0.133)	(0.091)	(0.170)*	(0.134)
R^2	0.73			
Observations	150		150	
Natives, Public Colleges	(7)	(7)	(8)	(8)
	0.144	-0.122	0.356	-0.037
	(0.107)	(0.078)	(0.188)*	(0.105)
R^2	0.81			
Observations	150		150	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Native enrollment and population differs across specifications as noted in table and is for ages 18-44 unless otherwise stated. All immigrant inflows are predicted, not actual, as described in text (section 4). Instruments in specifications (2), (4), (6), (8), (10), and (12) are level and quadratic of $\sum_h \left(\frac{Immigrants_{hj,1960}}{Immigrants_{h,1960}}\right) \times \Delta\Big(Immigrant\_Type\Big)_{ht}$, for source country h, state j, and year t. The $Immigrant\_Type$ stocks utilized are: (1) unskilled immigrant labor, (2) skilled immigrant labor, and (3) immigrant students. All specifications include Δ(year) and Δ(division × year) fixed effects, where divisions are nine U.S. Census divisions. Standard errors clustered at the state level are in parentheses.

Table 8: Impact of Immigration on Native Educational Attainment

Dependent Variable:	Δln[Native Educational Attainment as fraction of Native Population]							
	Some College		4 Years College +		4 Years HS		Less than 4 Years HS	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Natives 18-44 Years Old	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δln[Immigrants (unskilled / skilled), labor]	0.036	0.201	0.043	0.066	-0.024	0.161	0.019	-0.009
	(0.027)	(0.129)	(0.055)	(0.119)	(0.041)	(0.087)*	(0.046)	(0.175)
Δln[Immigrants, students]	-0.011	-0.077	0.014	-0.005	-0.008	-0.085	-0.038	-0.004
	(0.024)	(0.065)	(0.031)	(0.072)	(0.024)	(0.046)*	(0.024)	(0.095)
R^2	0.77		0.88		0.65		0.86	
Observations	150	150	150	150	150	150	150	150
Natives 18-24 Years Old	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Δln[Immigrants (unskilled / skilled), labor]	0.066	0.236	0.100	0.287	-0.113	-0.064	0.064	-0.306
	(0.044)	(0.146)	(0.081)	(0.315)	(0.064)*	(0.120)	(0.045)	(0.249)
Δln[Immigrants, students]	-0.021	-0.042	0.017	0.125	0.071	0.005	-0.099	0.081
	(0.030)	(0.070)	(0.049)	(0.121)	(0.032)**	(0.057)	(0.024)***	(0.135)
R^2	0.67		0.53		0.71		0.52	
Observations	150	150	150	150	150	150	150	150
Natives 25-34 Years Old	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Δln[Immigrants (unskilled / skilled), labor]	0.037	0.310	0.001	0.105	0.019	0.216	-0.006	-0.116
	(0.043)	(0.173)*	(0.038)	(0.113)	(0.047)	(0.096)**	(0.070)	(0.208)
Δln[Immigrants, students]	-0.030	-0.122	0.069	0.047	-0.024	-0.134	-0.067	-0.067
	(0.024)	(0.099)	(0.037)*	(0.046)	(0.028)	(0.068)*	(0.045)	(0.145)
R^2	0.86		0.92		0.68		0.77	
Observations	150	150	150	150	150	150	150	150

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Native attainment and population differs across specifications for ages noted in table. All immigrant inflows are predicted, not actual, as described in text (section 4). Instruments in 2SLS specifications are level and quadratic of $\sum_h \left(\frac{Immigrants_{hj,1960}}{Immigrants_{h,1960}}\right) \times \Delta\Big(Immigrant\_Type\Big)_{ht}$, for source country h, state j, and year t. The $Immigrant\_Type$ stocks utilized are: (1) unskilled immigrant labor, (2) skilled immigrant labor, and (3) immigrant students. All specifications include Δ(year) and Δ(division × year) fixed effects, where divisions are nine U.S. Census divisions. Standard errors clustered at the state level are in parentheses.

Table 9: Influence of Measurement Error in Impact of Immigration

Dependent Variable:	Δln[Native College Enrollment as fraction of Native Population]					
	OLS (1)	2SLS (2)	OLS (3)	2SLS (4)	OLS (5)	2SLS (6)
Δln[Immigrants (unskilled / skilled), labor]	0.166 (0.120)	0.330 (0.149)**	0.181 (0.124)	0.377 (0.159)**	0.159 (0.126)	0.312 (0.153)**
Δln[Immigrants, students]	-0.070 (0.075)	0.001 (0.078)	-0.082 (0.077)	-0.012 (0.080)	-0.057 (0.074)	0.028 (0.075)
Excluding KS, VT (small flows)	No	No	Yes	Yes	No	No
Excluding AZ, NM (border)	No	No	No	No	Yes	Yes
R^2	0.74		0.74		0.75	
Observations	150	150	144	144	144	144
Kleibergen-Paap rk (H_0: rank(r)=0)		23.49		27.19		28.14

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Native enrollment and population is for ages 18-24. All immigrant inflows are predicted, not actual, as described in text (section 4). Instruments in specifications (2) and (4) are level and quadratic of $\sum_h \left(\frac{Immigrants_{hj,1960}}{Immigrants_{h,1960}}\right) \times \Delta\Big(Immigrant\_Type\Big)_{ht}$, for source country h, state j, and year t. The $Immigrant\_Type$ stocks utilized are: (1) unskilled immigrant labor, (2) skilled immigrant labor, and (3) immigrant students. F-statistic version of the Kleibergen-Paap rk statistic for weak identification, which is robust to a clustered error structure, is reported. All specifications include Δ(year) and Δ(division $\times$ year) fixed effects, where divisions are nine U.S. Census divisions. Standard errors clustered at the state level are in parentheses.

Table 10: Implied Wage and Tuition/Fee Elasticities of Native College Enrollment Demand

Parameter	Value				Source
π^N	0.90				U.S. Census and author's calculation
γ^N	0.85				Author's calculation
γ^I	0.90				Author's calculation
κ	0				Assumed
λ	0.30				Bound et al. (2004)
β	0.330				Table 5, column 7
α	-0.243				Table 5, column 7
ψ	3.7		100		Bound & Turner (2007) and author's calc.; Assumed
θ	1.4	2.5	1.4	2.5	Katz & Murphy (1992); Card & Lemieux (2001)
η^N	5.770	8.584	5.769	8.582	Equations 16-21, numerical solution
ϕ^N	0.669	0.669	18.081	18.093	Equations 16-21, numerical solution

Notes: To obtain the numerical solutions for η^N and ϕ^N, it is assumed that $\eta^N = \eta^I$ and that $\phi^N = \phi^I$. While all values of η^N and ϕ^N above are positive, note that both parameters enter negatively into college demand (see Appendix A). Thus, increases in the relative unskilled wage and college tuition/fees both decrease native college demand. π^N is the native share of the population. γ^N and γ^I are the relative labor supply elasticities for natives and immigrants, respectively. κ is the wage elasticity of college supply, while λ is the share of the endogenous equilibrium change in college-enrolled students that remain in the state's labor market as skilled labor. β and α are estimates of crowd-in and crowd-out, respectively, where α here is the adjusted crowd-out ratio estimate. Finally, ψ is the tuition/fee elasticity of college supply, while θ is the elasticity of substitution between skilled and unskilled labor. See text for further details on parameters, model, and author's calculations.

Figure 1a: Inflow of Relatively Unskilled Immigrant Labor

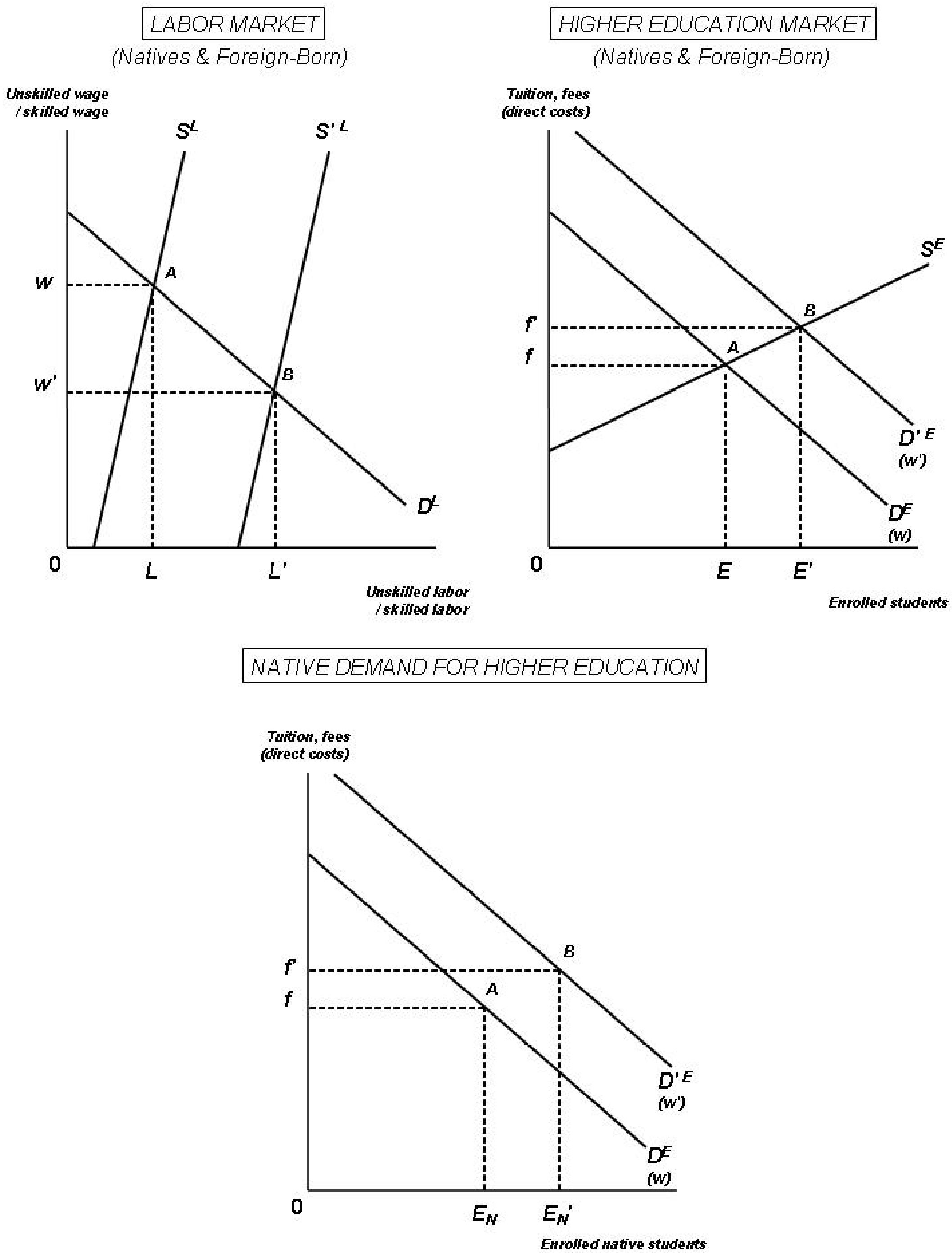


Figure 1b: Inflow of Immigrant Students

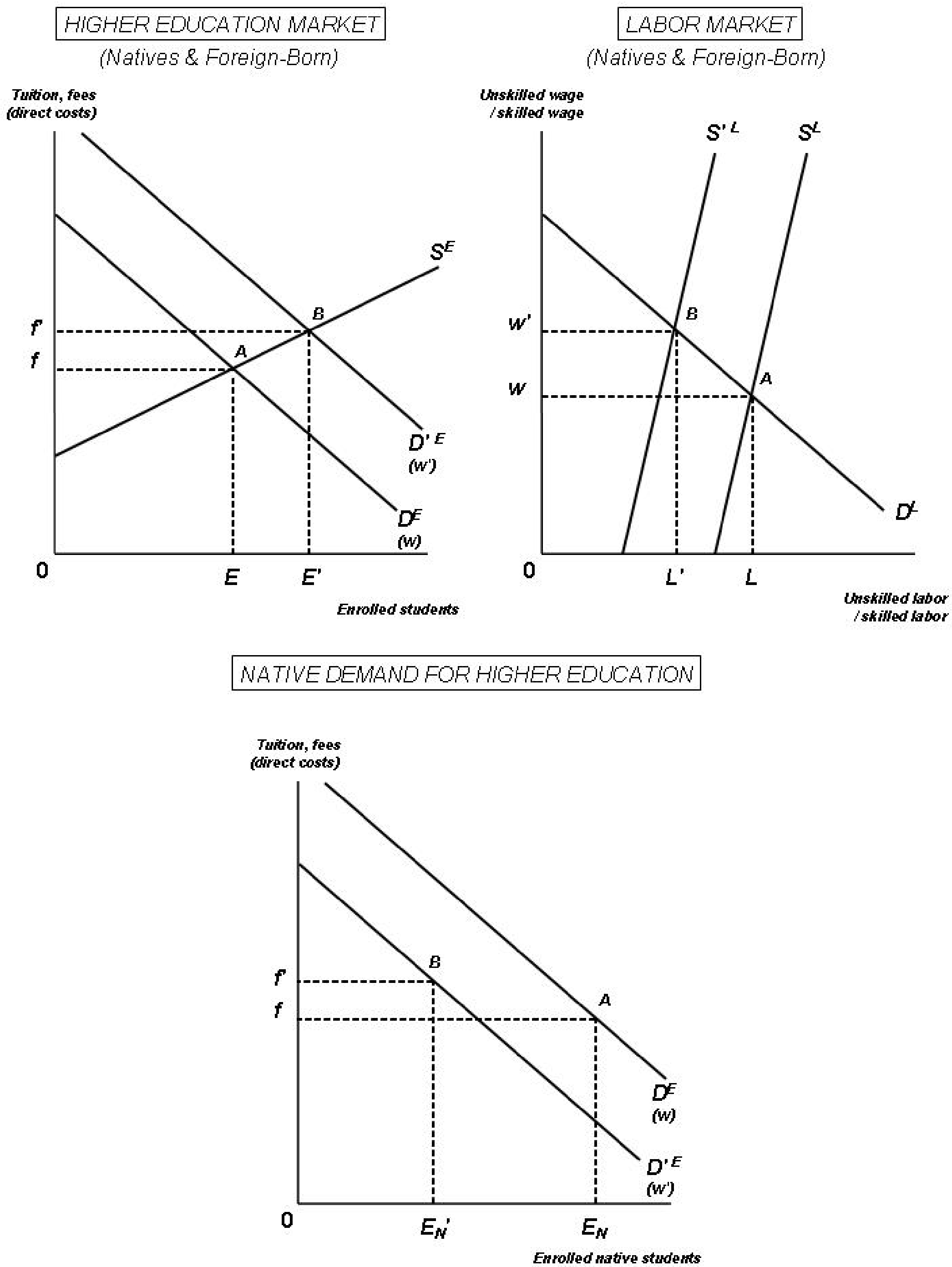
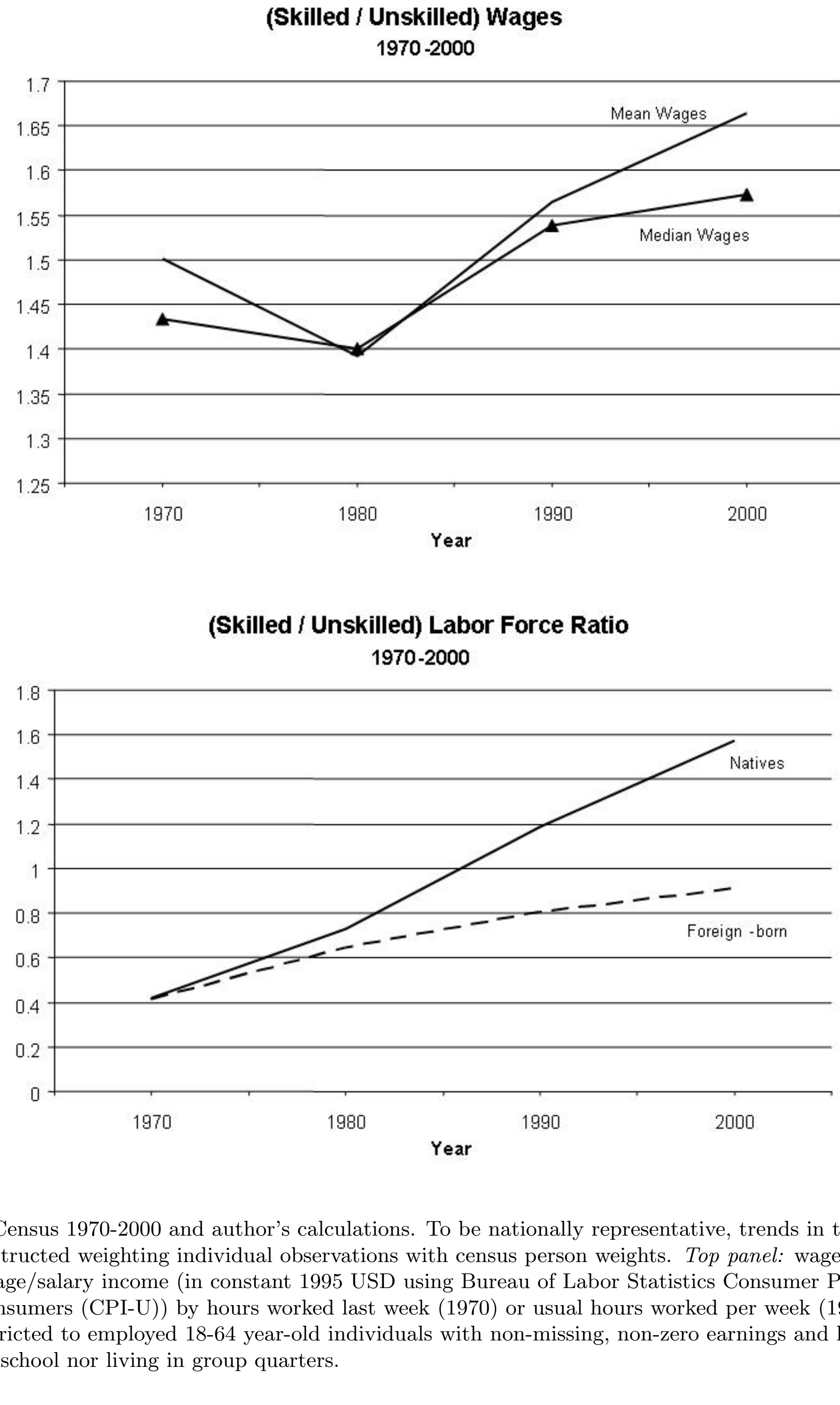
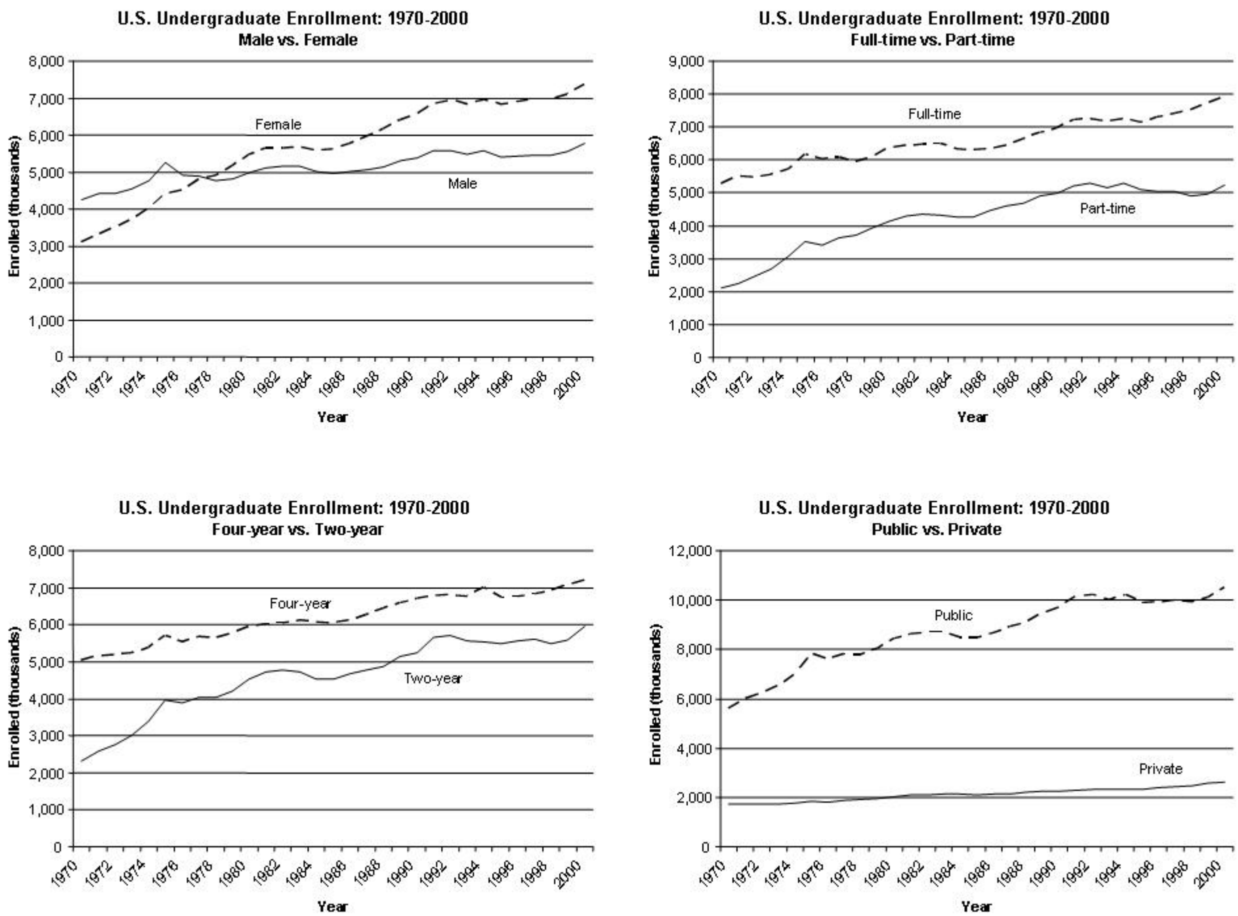


Figure 2: Relative Skilled Wage and Relative Supply of Skill



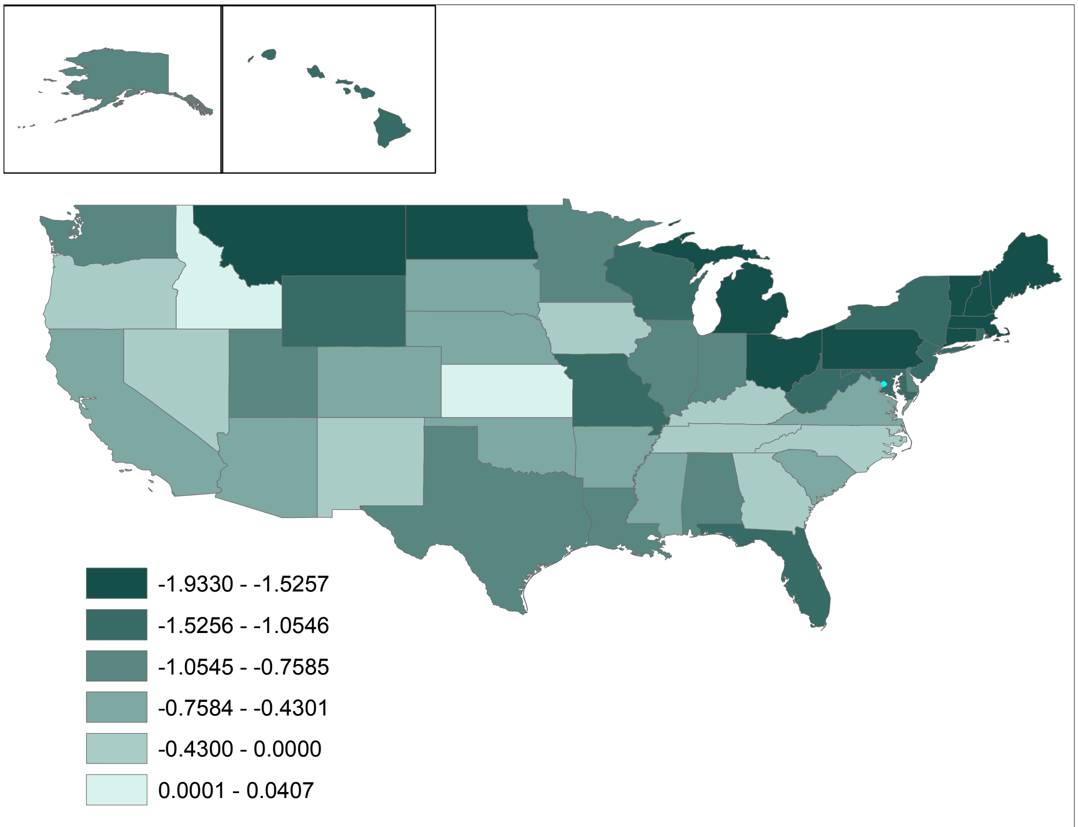
Source: U.S. Census 1970-2000 and author's calculations. To be nationally representative, trends in top and bottom panel are constructed weighting individual observations with census person weights. *Top panel:* wages are estimated by dividing wage/salary income (in constant 1995 USD using Bureau of Labor Statistics Consumer Price Index for All Urban Consumers (CPI-U)) by hours worked last week (1970) or usual hours worked per week (1980-2000). Sample is restricted to employed 18-64 year-old individuals with non-missing, non-zero earnings and hours, and who are neither in school nor living in group quarters.

Figure 3: Trends in U.S. College Enrollment by Group



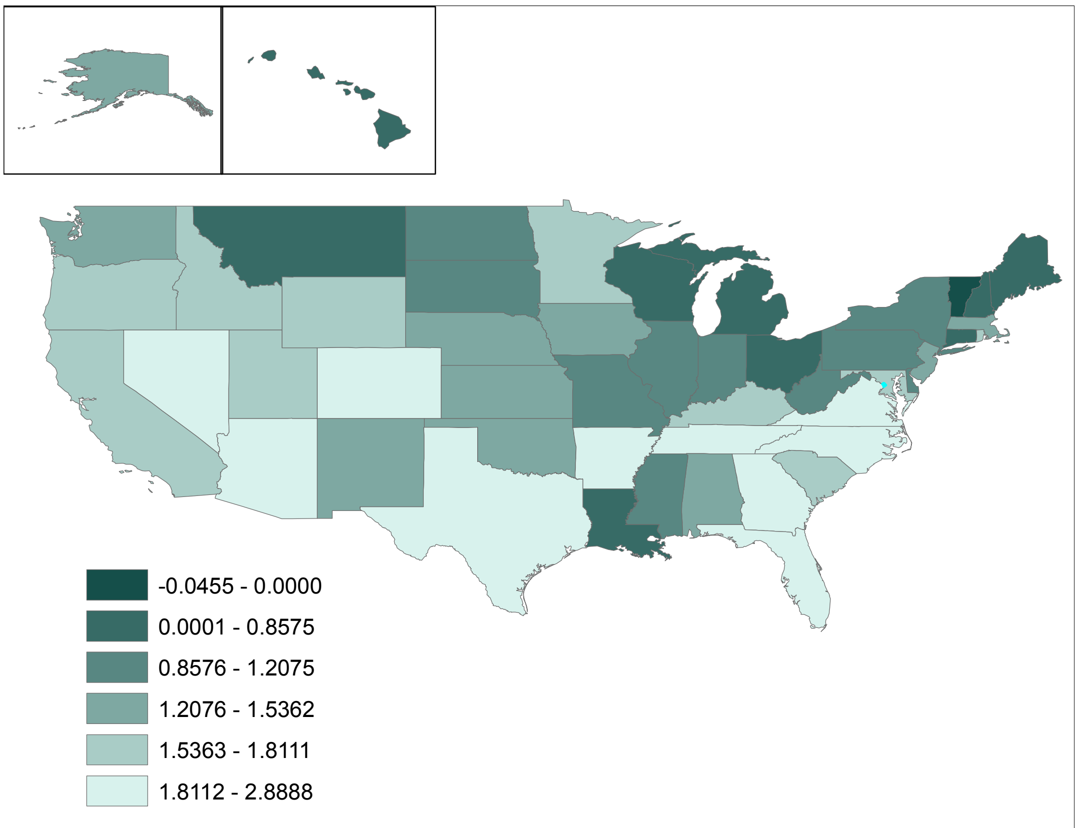
Source: U.S. Department of Education, National Center for Education Statistics (NCES), *Digest of Education Statistics, 2007.*

Figure 4a: Geographic Variation of Predicted Immigrant Inflows 1970-2000, Δln[Immigrants (unskilled / skilled), labor]



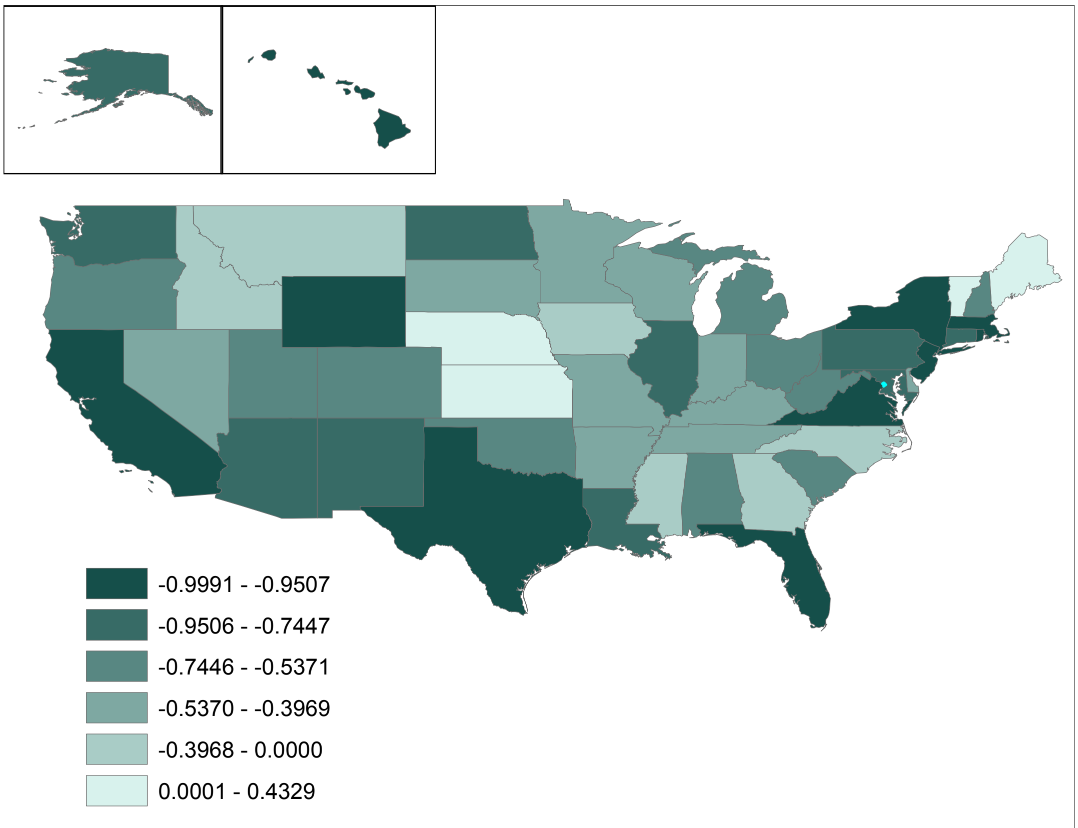
Source: U.S. Census 1970-2000 and author's calculations. Immigrant inflows are predicted, not actual, as described in text (section 4). Differences shown for each state are between 2000 and 1970 values of the variable (i.e. $\Delta \equiv \Delta_{2000-1970}$).

Figure 4b: Geographic Variation of Predicted Immigrant Inflows 1970-2000, Δln[Immigrants, students]



Source: U.S. Census 1970-2000 and author's calculations. Immigrant inflows are predicted, not actual, as described in text (section 4). Differences shown for each state are between 2000 and 1970 values of the variable (i.e. $\Delta \equiv \Delta_{2000-1970}$).

Figure 4c: Geographic Variation of Predicted Immigrant Inflows 1970-2000, $\rho_{\mathbf{labor,students}}$



Source: U.S. Census 1970-2000 and author's calculations. Immigrant inflows are predicted, not actual, as described in text (section 4). Correlations shown for each state, $\rho_{labor,students}$, are between ln[Immigrants (unskilled/skilled), labor] and ln[Immigrants, students], over all years 1970-2000.