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# ASSESSING INHERENT MODEL BIAS: AN APPLICATION TO NATIVE DISPLACEMENT IN RESPONSE TO IMMIGRATION

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**ABSTRACT**

There is a long-standing debate among academics about the effect of immigration on native internal migration decisions. If immigrants displace natives this may indicate a direct cost of immigration in the form of decreased employment opportunity for native workers. Moreover, displacement would also imply that cross-region analyses of wage effects systematically underestimate the consequences of immigration. The widespread use of such area studies for the US and other countries makes it especially important to know whether a native internal response to immigration truly occurs. This paper introduces a microsimulation methodology to test for inherent bias in regression models that have been used in the literature. We show that some specifications have built biases into their models, thereby casting doubt on the validity of their results. We then provide a brief empirical analysis with a panel of observed US state-by-skill data. Together, our evidence argues against the existence of native displacement. This implies that cross-region analyses of immigration's effect on wages are still informative.

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# 1 Introduction

There is a long-standing debate on whether immigration reduces the employment opportunities of natives. Economic analyses often exploit the wide variation in immigration rates across US states (or cities) and skill groups to identify whether immigration is associated with low native employment growth due to internal migration or job displacement across skill-state (or skill-city) cells. Though this correlation cannot definitively identify the effects of immigration (since causality is unclear and there may be omitted variables bias), researchers often cite such results as *prima facie* evidence for or against the crowding-out theory.

The importance of this issue is not limited to simply understanding the direct question of native displacement and employment opportunities. It also informs the validity of performing cross-regional analyses of the wage effects of immigration (or "area studies"). For example, most of the literature on US immigration across local labor markets finds little impact of immigration on wages.[1] These studies typically argue that mechanisms other than internal migration allow each region to absorb the higher supply of workers.[2] If so, then cross-regional analysis is informative of the impact of immigrants on wages at the national level. In the presence of displacement, however, the wage effects of immigration would dissipate throughout the US – not just in the states receiving large numbers of immigrants. Thus, cross-region wage regressions would miss (or underestimate) the effects of immigration if displacement exists.[3]

In analyzing internal migration, researchers must make numerous methodological decisions. Should the unit of analysis be states, cities, or census tracts? Should regressions include a panel with fixed effects or employ just a single long-term cross section? Which individuals should be included in the sample selection? Should regressions concern the population, labor force, or employees? These all are important questions to answer. This paper focuses on a most basic choice: how to specify the explanatory and dependent variables in the regression model that aims at estimating displacement. While this seems a trivial issue, we will show that some specifications in the literature may have built a bias into the estimates of the displacement coefficient they intended to identify.

We begin with a brief literature review in Section 2. It is far from exhaustive, but we focus on

[1] See Card (2001), Card (2007), Card (2009), Card and Lewis (2007) and Peri and Sparber (2009).

[2] Recent papers have proposed different mechanisms as margins of adjustment to immigration. Lewis (2005) indicates the choice of technique, Ottaviano and Peri (2008) focus on native-immigrant complementarieties and capital adjustment, Peri and Sparber (2009) emphasize changes in relative specialization.

[3] See Longhi, Nijkamp, and Poot (2008) or Hanson (2008) for recent surveys.

studies that have employed cross-regional internal migration regressions at similar levels of aggregation as this will facilitate model comparison. We highlight two seminal works: Card (2001) – which finds no evidence for displacement using US city data – and Borjas (2006) – which argues for large displacement effects at the city-level: roughly 3 natives are displaced for every ten immigrants.

In Section 3 we ask whether the disparate conclusions in these and other studies can be a result of model specification. Our procedure is similar in spirit to Wolf (2001), who advocates using microsimulation to develop appropriate empirical models. We extend this idea by using microsimulation to test for inherent model bias. First we construct hypothetical data using data generating processes that assume, in turn, that the inflow of foreign-born immigrants is negatively correlated, uncorrelated, or positively correlated with the inflow of natives. We then test whether previous empirical models are able to correctly identify the sign and magnitude of the underlying assumed correlation. Unfortunately, empirical model specification is not inconsequential. In particular, Borjas (2006) specifications are biased toward identifying displacement, and this bias grows larger as the variance of native flows rises in proportion to the variance of immigrant flows, independently of their correlation.

This paper does not attempt to replicate the results of prior studies. Differences in sample selection, period of analysis, and other issues would encumber that endeavor while detracting from the main issue – we care to show the importance of model specification in correctly identifying the displacement effect of immigrants on natives. Nonetheless, Section 4 employs a number of alternative empirical specifications to briefly analyze the association between immigration and native migration using observed data from 32 skill-cells and 51 US states (including the District of Columbia) over Census years 1970-2000. Of the models we explore, only the Borjas (2006) specifications reveal a significantly negative correlation. Given the bias uncovered in Section 3, we suspect that this finding for native displacement is spurious, and instead conclude that no evidence for displacement exists.

## 2 Native Displacement in the Existing Literature

A straightforward definition of displacement would ask how many native workers ($N$) respond to the arrival of a single immigrant ($F$) by leaving their region (state or city) of residence $i$.[4] Assuming that the native employment response ($\Delta N$) to an immigrant inflow ($\Delta F$) is linear (at least in first order

[4] This definition could be further refined to account for arrivals of immigrants who share similar skill characteristics or occupations of natives within regions.

approximation), this would imply that the coefficient $\beta$ in Expression (1) would allow us to identify the presence (if $\beta < 0$) and the magnitude (absolute value of $\beta$) of such a phenomenon.

$$\Delta N_{i,t} = \alpha + \beta \cdot \Delta F_{i,t} + u_{i,t} \tag{1}$$

The term $u_{i,t}$ in Equation (1) captures all the determinants of native employment changes in region $i$ and year $t$ other than the response to immigration inflows. If we allow $\phi(i,t)$ to represent the systematic determinants of native employment changes, the final term would reduce to $u_{i,t} = \phi(i,t) + \varepsilon_{it}$, where $\varepsilon_{it}$ is a residual zero-mean random component. By controlling for $\phi(i,t)$, we could directly estimate $\beta$ from a standard regression of (1). In practice, few if any papers actually employ this direct test of displacement. The regression is likely to be confounded by a number of problems, one being that the average and standard deviation of $\Delta N$ and $\Delta F$ are likely to be proportional to the total population in the cell, potentially inducing a spurious positive correlation.

## 2.1 Card (2001) and Card (2007)

Card (2001) and Card (2007) offer a solution by standardizing native and foreign-born changes by population levels. This allows for well behaved residuals (after also controlling for systematic effects). Card (2001) begins with the identity in (2), which relates the flow (between periods $t-1$ and $t$) of native and foreign-born individuals in any observable cell. The variables $N$ and $F$ represent the stock of native and foreign-born workers, while $L = F + N$ is total employment. The superscripts $Est$ and $New$ refer to established and newly-arrived immigrants, respectively.

$$\left(\frac{L_t - L_{t-1}}{L_{t-1}}\right) = \left(\frac{N_t - N_{t-1}}{L_{t-1}}\right) + \left(\frac{F_t^{Est} - F_{t-1}}{L_{t-1}}\right) + \left(\frac{F_t^{New}}{L_{t-1}}\right) \tag{2}$$

Card (2007) instead adopts a more generalized approach by substituting $F_t = F_t^{Est} + F_t^{New}$ to arrive at the quantitatively equivalent identity in (3).

$$\left(\frac{L_t - L_{t-1}}{L_{t-1}}\right) = \left(\frac{N_t - N_{t-1}}{L_{t-1}}\right) + \left(\frac{F_t - F_{t-1}}{L_{t-1}}\right) \tag{3}$$

The key to the empirical estimation in both papers is that the final term (in either identity) may be causally correlated with the other terms. Card (2001) tests whether newly-arrived immigrants displace natives by regressing $\left(\frac{N_t - N_{t-1}}{L_{t-1}}\right)$ on $\left(\frac{F_t^{New}}{L_{t-1}}\right)$ across a single cross-section of 175 US cities and six occupation groups for the year 1990 (with 1985 representing $t-1$). Though this precludes him from exploiting the advantages of a panel dataset, his regressions do include dummy variables for cities and occupation groups.[5] Negative values would imply displacement. Regressions employing various sample selection criteria and instrumental variables techniques, however, find robustly non-negative coefficients ranging from 0.02 to 0.27. Thus, his results argue against a native internal migration response.

The most significant methodological difference between Card (2001) and (2007) is that the former tests the effects of newly-arrived immigrants, whereas the latter's interest is in the effects of foreign-born flows in the aggregate. Table 3 of Card (2007) provides estimation results for regressions of Equation (4) across a single cross-section of US cities ($c$).[6]

$$\left(\frac{L_{c,t} - L_{c,t-1}}{L_{c,t-1}}\right) = \alpha + \beta_{Card} \cdot \left(\frac{F_{c,t} - F_{c,t-1}}{L_{c,t-1}}\right) + \varepsilon_{c,t} \tag{4}$$

Under this specification, displacement occurs if estimated coefficients are less than one.[7] Although the migration analysis is not as thorough as in Card (2001), the results again argue against displacement. Estimated coefficients are near two for OLS regressions and near one for IV specifications. None of the estimates is significantly below one.

## 2.2 Borjas (2006)

Unlike most analyses of internal migration, Borjas (2006) has the distinct quality of being motivated by theory. It begins with a model of labor demand such that native and foreign born workers are perfect substitutes within skill-region groups. Foreign-born arrivals are assumed to be exogenous and constant over time. Wages respond immediately to the increase in labor supply, whereas native labor supply has a lagged response because it is difficult for natives to instantaneously move. Theoretical implications can be found on pages 226-8. Relevant ones for this paper include 1) Internal native migration mitigates wage effects identified through spacial regressions, thereby attesting to the importance of

[5] Estimated coefficients appear in the fourth column of his Table 4.

[6] Since Card (2007) is a single cross-section of cities, but not city-by-occupation cells, dummy variables are not permitted. Regressions do include the log of initial city population as a control.

[7] An equivalent and perhaps more direct approach would replace the dependent variable with $\left(\frac{N_{c,t} - N_{c,t-1}}{L_{c,t-1}}\right)$ and test whether $\beta < 0$.

determining whether an internal migration response occurs; 2) The current stock (and wage) of native workers is determined by preexisting conditions including initial (pre-immigration) native stocks; and 3) Internal migration coefficients are accurately estimated only if regressions control for local labor market conditions.

Borjas's theory offers useful insights for estimating the effects of immigration, particularly in highlighting the need to control for pre-determined conditions and trends. Unfortunately, parameters in the theoretical model cannot be estimated directly. Instead, Borjas imposes a series of assumptions to derive the empirical specification in (5).

$$\ln(N_{ijt}) = \alpha + \beta_{Borjas1} \cdot \left(\frac{F_{ijt}}{N_{ijt} + F_{ijt}}\right) + \gamma \cdot X_{ijt} + s_i + r_j + \tau_t + (s_i \times r_j) + (s_i \times \tau_t) + (r_j \times \tau_t) + \varepsilon_{ijt} \quad (5)$$

Borjas performs this regression across 32 skill groups $j$ (4 education by 8 experience groups), 51 states $i$, and 5 Census years $t$. The terms $s_i$, $r_j$, and $\tau_t$ control for skill, state, and year fixed effects. The three subsequent terms control for all two-way interactions between these effects. Finally, $X_{ijt}$ represents optional controls that include, depending on the specification, the lagged level or growth rate of native employment.

Equation (5) offers a few clear advantages over prior methodologies. First, the full array of fixed effects account for the initial conditions that, according to theory, would bias results if omitted from the model. Second, the fixed effects imply that the coefficient $\beta_{Borjas1}$ is identified by the variations over time within narrowly defined skill-region cells. This should directly identify the effect of immigrants on the group of natives most closely competing with them for jobs. Third, Borjas (2006) uses a long panel, not just a single cross-section.

Closer inspection of the dependent and explanatory variables in (5) reveals a potentially severe limitation, however. It is easy to see that $N_{ijt}$ appears both in the dependent variable $\ln(N_{ijt})$ and in the denominator of the explanatory variable $\frac{F_{ijt}}{N_{ijt}+F_{ijt}}$. Thus, the construction of the dependent and explanatory variables may mechanically force a negative correlation between them even when no displacement relationship between immigrant inflows and native outflows truly exists.

To illustrate this issue, suppose that initial employment levels $N_{ij0}$ and $F_{ij0}$ are predetermined in period $t = 0$. They are fixed and controlled for by fixed effects $s_i \times r_j$. The dependent variable at $t = 1$ will then be $\ln(N_{ij0} + \Delta N_{ij})$ while the explanatory variable will be $\frac{F_{ij0}+\Delta F_{ij}}{F_{ij0}+N_{ij0}+\Delta F_{ij}+\Delta N_{ij}}$. Even if there is zero correlation between the random variables $\Delta F_{ij}$ and $\Delta N_{ij}$ (so that displacement is nonexistent), one would find a negative correlation between $\ln(N_{ij0} + \Delta N_{ij})$ and $\frac{F_{ij0}+\Delta F_{ij}}{F_{ij0}+N_{ij0}+\Delta F_{ij}+\Delta N_{ij}}$ since $\Delta N_{ij}$ appears in the numerator of former and the denominator of the latter. For example, the correlation would be negative and fully driven by the presence of $\Delta N_{ij}$ in the case that $\Delta F_{ij}$ were a constant for all $i, j$.

Borjas (1980) introduces the concept of a "division bias" somewhat reminiscent of this by noting that *measurement error* of $N_{ijt}$ (in this case) would lead to biased coefficient estimates. The problem is more severe in this context, however, as the bias exists because of (and is a function of) the variance of $\Delta N_{ij}$ (which is in large part independent of $\Delta F_{ij}$). As we will see in Section 3.3.1, this bias intensifies with the increase in the standard deviation of $\Delta N_{ijt}$ relative to the standard deviation of $\Delta F_{ijt}$.

Borjas (2006) is aware of the potential for some form of division bias and addresses it by replacing the dependent variable with a measure of net native migration. His resulting alternative specification is computationally similar to Equation (6). The denominator in the dependent variable now includes an average of the native population in the current and previous time periods. Borjas argues that division bias should be mitigated because a measure of current-year native employment appears in the denominator on both sides of the equation.

$$\left(\frac{N_{ij,t} - N_{ij,t-1}}{\left(N_{ij,t} + N_{ij,t-1}\right)/2}\right) = \alpha + \beta_{Borjas2} \cdot \left(\frac{F_{ijt}}{N_{ijt} + F_{ijt}}\right) + \gamma \cdot X_{ijt} + s_i + r_j + \tau_t + (s_i \times r_j) + (s_i \times \tau_t) + (r_j \times \tau_t) + \varepsilon_{ijt} \tag{6}$$

Nonetheless, this specification may also be biased. If we again consider $N_{ij0}$ and $F_{ij0}$ as given and controlled for by the fixed effects, the dependent variable in $t = 1$ will be $\ln\left(\frac{\Delta N_{ij0}}{N_{ij0}+0.5\Delta N_{ij}}\right)$. As before, the explanatory variable will be $\frac{F_{ij0}+\Delta F_{ij}}{F_{ij0}+N_{ij0}+\Delta F_{ij}+\Delta N_{ij}}$. The term $\Delta N_{ij}$ raises the dependent variable while decreasing the explanatory variable. This would induce a negative correlation independently of any true displacement mechanism, as long as the random variable $\Delta N_{ij}$ has a positive variance.

Results for state-level regressions of Borjas's (2006) baseline specification are in Panel II of his Table 3. For the sample including just male employees, he finds a significant coefficient of -0.383. The magnitude drops to -0.218 for a sample with all employees, but it remains significant. These estimates imply that for every ten immigrants arriving in a skill-state cell, between 1.6 and 2.8 natives leave or lose their jobs.[8] Robustness checks using $\left(\frac{N_{ij,t}-N_{ij,t-1}}{(N_{ij,t}+N_{ij,t-1})/2}\right)$ as the dependent variable are in Borjas's

[8] Figures can be calculated by dividing coefficients by $\left(1 + \frac{F_t - F_{BaseYear}}{P_{BaseYear}}\right)^2$, where $\frac{F_t - F_{BaseYear}}{P_{BaseYear}} \approx 0.172$ in the Borjas

Table 4. Coefficients are -0.284 and -0.232 for male and all native employees, respectively. Thus, Borjas maintains that the native internal migration response to immigration is large and significant.

## 2.3 Other Specifications

Card (2001, 2007) and Borjas (2006) – though perhaps the most influential – are not the only papers that have analyzed internal migration. Here we review a few more that have used alternative empirical specifications to estimate displacement.

Cortes's (2006) working paper on immigration and price-levels included the regression in (7) to analyze internal migration among low-education workers across the 25 largest US cities in the 1980, 1990, and 2000 Censuses ($D_c$ and $D_t$ represent city and time fixed effects). She argues that displacement would be implied by negative estimates of $\beta_{Cortes}$, but she finds an OLS figure around 0.20 and an IV value near 0.05. She therefore argues against displacement.

$$\ln\left(F_{c,t} + N_{c,t}\right) = \alpha + \beta_{Cortes1} \cdot \ln\left(F_{c,t}\right) + D_c + D_t + \varepsilon_{c,t} \tag{7}$$

Unfortunately, this model presents potentially serious limitations. First, it is not clear how one should deal with observations in which $F_{c,t}$ (or $L_{c,t}$) is zero, although this does not occur in Cortes's data set. Second, the models might find a positive correlation due to scale effects. Namely, some skill-state groups may be much larger than others, and a positive correlation in the size of native and immigrant employment may lead to positive estimates of $\beta_{Cortes}$. Fixed effects and the measurement of variables in logarithms should mitigate this problem, but it might not solve it altogether.[9] Third and most importantly, note that $F_{c,t}$ appears in both the dependent and explanatory variables. This is likely to build a positive correlation into the model and produce spuriously positive estimates of $\beta_{Cortes}$ when some small displacement does exist. Equation (9) provides an alternative specification that avoids this positive bias by adopting $\ln\left(N_{c,t}\right)$ as the dependent variable.

(2006) data.

[9] Perhaps these limitations encouraged Cortes to respecify her model for the (2008) published version. This alternative, in Equation (8), tests whether the effects of immigration in a city spill-over into larger regions ($r$). The model is close to the working paper version of Card (2005) and implies displacement if $\beta < 1$. Cortes's (2008) point estimates (her Table 4) are often less than one, leading her to concede that there may be "some displacement taking effect," but none of the estimates is significantly different from one.

$$\left(\frac{N_{r,c,t} + F_{c,t}}{L_{c,t}}\right) = \alpha + \beta \cdot \left(\frac{F_{c,t}}{L_{c,t}}\right) + FE_c + FE_{r,t} + \varepsilon_{r,c,t} \tag{8}$$

$$\ln\left(N_{c,t}\right) = \alpha + \beta_{Cortes2} \cdot \ln\left(F_{c,t}\right) + D_c + D_t + \varepsilon_{c,t} \tag{9}$$

Evidence for displacement is provided in Borjas, Freeman, and Katz (1997, page 31) who argue that "To isolate the impact of immigration on the net migration of native workers, one needs a difference-in-difference comparison of how a given state's population grows before and after the immigrant supply shock." This methodology requires the identification of a single date in which such an immigrant supply shock occurred. The authors choose 1970 as the break date, and use cross-state variation to perform the regression in (10). Their estimate of $\beta_{BFK} = -0.756$ is significant and favors displacement.

$$\left(\frac{N_{r,1990} - N_{r,1970}}{P_{r,1970}}\right) \cdot \left(\frac{1}{20}\right) = \alpha + \beta_{BFK} \cdot \left(\left(\frac{F_{r,1990} - F_{r,1970}}{P_{r,1970}}\right) \cdot \left(\frac{1}{20}\right) - \left(\frac{F_{r,1970} - F_{r,1960}}{P_{r,1960}}\right) \cdot \left(\frac{1}{10}\right)\right) + \varepsilon_r \tag{10}$$

Note that this methodology is similar to fixed effects regressions of the employment change of native workers on the inflows of immigrants so that the coefficient is identified on changes of first differences (difference-in-differences). In Section 3 we will adopt specifications of this type that therefore encompass specification (10) above.

Other papers estimating some form of an internal migration equation generally argue against displacement. See Peri (2009), Card and Lewis (2007), Card and DiNardo (2000), and Card (2005) for example.[10] We do not evaluate their methodologies in this paper, however.

# 3 Simulated Data and Resulting Regressions

Observed data can complicate regressions that attempt to identify displacement. This may include, for example, issues such as variation in cell size, the influence of outliers, pre-determined conditions, trends, omitted variables, or other features that may bias estimates and generate spurious results. By creating artificial data, however, we can perform a microsimulation analysis and run regressions that abstract away from these complications in order to evaluate the efficacy (and potential inherent bias) of the regression specifications themselves.

In this section we simulate a world in which we know whether or not displacement exists. We

[10] Peri (2009, page 2) analyzes California relative to the rest of the US. He finds no evidence for displacement, and instead argues that foreign and native born workers within a skill group complement each other to the same extent as workers of different experience levels do. Card and Lewis (2007) estimate the effect of low skilled Mexican immigrants on native employment. Their Table 5 results find an effect of low skilled immigrants on natives between 0 and 0.5 that is rarely significant.

assume the data generating process given by Expression (1). We create several datasets with unique assumed values of $\beta$. Negative values, according to our definition, imply displacement. Positive values imply that immigrants somehow attract natives. After creating our datasets, we then evaluate the regression results given by specifications (4)-(9) to assess whether they identify the correct displacement implications given the assumed data generating process. As we will see, some specifications are inherently biased and identify displacement conclusions inconsistent with the true process in the data.

## 3.1 Data Generating Processes

Following the structure of the state and skill-level data as used in Borjas (2006), we will create a dataset with 8,160 cells representing 5 census years (1960-2000), $t$, 51 states (including the District of Columbia), $i$, and 32 skill groups (4 education groups by 8 experience groups), $j$. We simulate the data but the unconditional moments (average and standard deviation of $\Delta F_{i,j,t}$ and $\Delta N_{i,j,t}$) are chosen to match those in the data.

To construct these moments (as well as the data used in the Section 4 empirical analysis), we use the 1% sample from the 1960 Census, Form 2 State sample in 1970, and the 5% samples from 1980-2000.[11] We include non-group quarter, civilian employees, age 18-64, who record having positive weeks worked, for wages, in identifiable occupations and industries.[12] We identify four education groups – those with less than a high school degree, high school graduates, those with some college experience, and workers with a bachelors degree or more education. For experience groups, we first identify the age a worker was likely to enter the workforce. We assume dropouts entered at age 17, high school graduates at 19, those with some college experience at 21, and college graduates at age 23. We then calculate a person's potential experience as their age minus their age of workforce entry. Individuals are then placed into groups of 1-5 years of experience, 6-10 years, and so on. Those with less than one year of experience are dropped. Next, we sum the number of individuals (by census weights) employed in each year-state-education-experience cell to obtain $F_{i,j,t}$ and $N_{i,j,t}$ and their changes over time.

We create simulated data by normalizing initial employment levels in each skill-state cells to 200,000 employees, 6% of which are foreign born (figures are comparable to the average in employment cells in 1960). We then draw hypothetical values of $\Delta F_{i,t}$ from a random normal distribution of mean 1,055

[11] We use IPUMS data from Ruggles et. al. (2005).

[12] Perhaps our most controversial sample selection decision was to include individuals who are currently enrolled in school. Although those people are employed, they may be marginally attached to the labor force. Specific STATA commands used for the sample selection are available upon request.

and standard deviation 2,534 – values that correspond to observed figures after removing observations that lie more than three standard deviations away from the mean. Data for $\Delta N_{i,t}$ comes from the data generating process in (1). We create five separate data series – one each for $\beta = \{-1, -0.5, 0, 0.5, 1\}$. Full displacement occurs when $\beta = -1$. Conversely, $\beta = 1$ implies a 1-for-1 native attraction to immigration. The mean-zero error term $\varepsilon_{i,t}$ is drawn from a normal distribution designed to generate a standard deviation of $\Delta N_{i,t}$ matched by the data (18,104, after removing outliers). The constant $\alpha$ is chosen to ensure that the mean of $\Delta N_{i,t}$ equals 6,443, the value observed in the data (also after removing outliers).

### 3.2 Regression Results for Simulated Data

The initial $N_{i,j,1960}$ and $F_{i,j,1960}$ values, combined with randomly generated $\Delta N_{i,j,t}$ and $\Delta F_{i,j,t}$ terms, allow the creation of $N_{i,j,t}$ and $F_{i,j,t}$ for each simulated year and all the variables necessary for estimating the specifications (4)-(9). Since the data generating process assumed identical initial values across cells, we exclude initial year observations from the regressions. This leaves 6,528 remaining observations, from which we drop all outliers (cells with a dependent or explanatory variable more than three standard deviations from its mean).

Table 1 shows the estimates of the relevant coefficient in each of six specifications. The regressions in Table 1 do not include fixed effects. Results for the alternative specifications are listed in separate columns and are defined in the column headers by the authors who employ the methodology. Headers also show the exact specification of the dependent and explanatory variables. Each row uses a different value of $\beta_{DGP}$ in the data generating process as defined by (1) and reported in the first column of Table 1. The first row ($\beta = -1$) assumes perfect displacement. One native worker leaves his/her state-by-skill cell of employment for every immigrant who enters. Each subsequent row then increases $\beta$ by increments of 0.5 so that the third row assumes no relationship between native and foreign employment changes, and the final row assumes a perfect 1-for-1 native attraction to foreign workers.

The first column tests Card's (2007) methodology, which argues for displacement if $\hat{\beta}_{Card} < 1$. Estimates are consistently correct – they are significantly less than one when the data generating process assumes displacement, near one for $\beta_{DGP}$ values that assume zero-displacement, and greater than one when the data incorporate attraction. The methodology appears to capture displacement appropriately.

The next two columns examine Borjas's (2006) specifications. The first is his baseline model. Unfortunately, $\hat{\beta}_{Borjas1}$ does not correctly identify displacement but instead exhibits a strong negative bias – the model identifies significant false negatives even when the true generating process implies that natives are perfectly attracted to immigrants ($\beta_{DGP} = 1$). We suspect this is a result of the bias discussed in Section 2.2. Large variation of $\Delta N_{i,j,t}$ simultaneously depress the explanatory variable while inflating the response variable, holding $F_{i,j,t}$ and $\Delta F_{i,j,t}$ constant. The alternative Borjas (2006) specification using $\left(\frac{N_{ij,t}-N_{ij,t-1}}{(N_{ij,t}-N_{ij,t-1})/2}\right)$ as the dependent variable mitigates the bias, but it does not fully solve the problem. Column 3 illustrates that this alternative still identifies a negative coefficient $\left(\hat{\beta}_{Borjas2}\right)$ for each data-set, including those simulated with assumed $\beta_{DGP} > 0$.

In contrast, the first Cortes (2006) specification in the next column exhibits a positive bias. Perhaps this too should be unsurprising given that $F$ appears in some form on both sides of the regression equation. The clearer "Cortes (2006) Alternative" specification instead regresses $\ln(N)$ on $\ln(F)$ and tests $\beta_{Cortes2} = 0$. This alternative continues to exhibit a positive bias – probably due to scale effects – though it is less severe.

The final column in Table 1 is a test of our generating process itself. Although the error terms in the data generating process were drawn from a mean-zero distribution, finite sample noise implies that the actual error observations are not mean-zero. Thus, estimation of (1) could result in coefficients that differ from true values. Fortunately, differences driven by finite sample noise are small, and the estimates are similar to the $\beta_{DGP}$ values.

Table 2 performs exactly the same regressions but with fixed effects. This feature should be particularly relevant for Borjas regressions (who argues for the necessity of fixed effects) and the non-dynamic specifications (since change-regressions should already difference-out any cell-specific features). Fixed effects specifications deliver results quite comparable to regressions without fixed effects, however. The Card (2007) specification continues to generate accurate conclusions, while Borjas's (2006) regressions continue to exhibit negative bias. That is, fixed effects do not solve the incorrect displacement identification in the two Borjas (2006) methods.

### 3.3 Exploring the Source of Bias

#### 3.3.1 Relative Standard Deviation

The regressions in Tables 1 and 2 highlight an important limitation – the Borjas (2006) specifications exhibit a large bias in favor of displacement. The regressions in Table 3 help to inform the source of this bias. An important stylized fact about both the observed and simulated data is that the standard deviation of $\Delta N_{ijt}$ is 7.14 times greater than that of $\Delta F_{ijt}$. Section 2 discussed how large variation in $\Delta N_{ijt}$ exacerbates the bias toward negative values built into the Borjas model. Table 3 better explores the importance of variation of $\Delta N_{ijt}$. We now alter the data generating process so that the standard deviation of the simulated $\Delta N_{ijt}$ values equal the observed level (middle row), half of the observed level (top row), and twice the level of the observed figure (bottom row). Each row assumes $\beta_{DGP} = 0$ so that neither displacement nor attraction occurs. The estimated specifications include fixed effects only if the explanatory variables are not differenced.

Two fascinating and important regularities emerge. First, the standard deviation of $\Delta N_{ijt}$ has little effect on the coefficient estimates in columns 1, 4, 5, and 6, though larger standard deviations usually correspond to larger standard errors. The Borjas estimates in Columns 2 and 3, in contrast, are negative and increasing in absolute value as the standard deviation of $\Delta N_{ijt}$ rises (keeping the the standard deviation of $\Delta F_{ijt}$ constant). Even when $\Delta N_{ijt}$ has a small standard deviation, the Borjas method identifies a negative and significant correlation when there should be none. This confirms our intuition that the negative correlation between $\left(\frac{F_{ijt}}{F_{ijt}+N_{ijt}}\right)$ and $\ln(N_{ijt})$ increases with the variance of $\Delta N_{ijt}$ even when the employment changes of natives and immigrants are uncorrelated.

A graphical analysis of the assumed data generating process and the regression results is even more illustrative. We do this by first generating several unique datasets. Each is defined by an assumed value of $\beta \in [-1, 1]$, increasing by units of 0.1, and an assumed multiple of the standard deviation of $\Delta N$ relative to that of $\Delta F$. We represent this multiple by $\lambda \in [0.2, 2]$ and also increase it by units of 0.1. We repeat these steps for ten set random seed generators. This results in 3,990 unique datasets from which we drop the 665 datasets that predict one or more negative values for $N$ or $F$.

Figure 1 displays four scatter-plots. The top two evaluate the Card (2007) methodology, and the bottom two illustrate the baseline Borjas (2006) specification. The horizontal axis in the left two graphs represents the $\beta$ value assumed by the data generating process, while the horizontal axis in the right two charts represents the assumed multiple of the observed relative standard deviation. Recall that $\beta = 0$ implies zero displacement and $\lambda = 1$ represents the observed relative standard deviation value of 7.14. Each dot in the scatter-plot then represents the unique coefficient estimate for the relevant specification determined by $\beta$, $\lambda$, and the random seed generator.

At a minium, a methodology for examining displacement should deliver coefficient estimates that increase in the assumed $\beta$ value. Better methodologies would exhibit small variation in the estimates for a given $\beta$. Moreover, estimates should be insensitive to assumptions regarding the relative standard deviation of $\Delta N$. The two top panels of Figure 1 clearly demonstrate that the Card (2007) methodology meets these criteria. The top-left figure shows that as $\beta_{DGP}$ varies, estimates of $\beta_{Card}$ cluster around $(1 + \beta_{DGP})$. This implies that displacement conclusions in Card ($\beta_{Card} < 1$) are usually associated with displacement in the data ($\beta_{DGP} < 0$). The top-right figure also shows that the estimates of $\widehat{\beta}_{Card}$ are centered around one for $\beta_{DGP} = 0$ no matter what value is taken by the standard deviation of $\Delta N$. The corresponding graphs for Borjas (2006), in contrast, show that $\widehat{\beta}_{Borjas1}$ is almost always negative even when $\beta_{DGP} > 0$. When the relative standard deviation of $\Delta N$ rises, the estimates of $\widehat{\beta}_{Borjas1}$ are more likely to be negative in sign, larger in magnitude, and increasingly precise.

#### 3.3.2 Number of Cells

A secondary issue might involve the size and number of cells. The advantage of small cells is that it minimizes heterogeneity within cells when using real data. The disadvantage is that it reduces the number of available observations while potentially increasing the risk of heavy influence from single outliers. We explore the consequences of cell size by employing an alternative data generating process that reduces the number of skill groups from 32 to just 2 ("high" and "low" education groups, for example). We create data similar to the procedure described above, except that we increase in initial cell size to 2,000,000, and we change the sampling procedure to match the appropriate moments in the observed data. Using these smaller cells, the observed mean and standard deviation of $\Delta N$ are (104,863; 192,159), while the corresponding values for $\Delta F$ are (16,747; 32,378).

Table 4 presents results analogous to those in Tables 1 and 2, using fixed effects when appropriate. Table 5 examines the consequences of varying the standard deviation of $\Delta N$ in this smaller sample with larger size cells. Both tables support the prior conclusions. Most regressions correctly identify the correlation between immigration and internal native migration, but the Borjas specifications exhibit a negative bias that grows as the standard deviation of $\Delta N$ increases.[13]

## 4 Empirical Results Using Observed Data

Wolf (2001, page 317) argues that if "microsimulation output produces a finding that is sharply at odds with known [i.e., simulated] facts, then... one must return to the model, prepared to respecify it." Section 3 identified inherent biases in several models that have been employed by economists to assess the displacement effects of immigration. Of course, these biases would have been unknown to analysts, thus preventing them from respecifying their models if necessary. In this section, we assess how each of the previously-described model specifications performs when using observed – rather than simulated – data. We neither advocate nor produce exact replication of prior work, as the analyses substantially differ along a number of dimensions (e.g., sample selection, the time period of analysis, the definition of cells used in the regressions, etc.). However, the use of observed data within the methodological framework of past studies should still be informative about the differences in displacement conclusions that have emerged in the literature.

Table 6 presents the results for these regressions. The data represents a panel of 51 "state" by 32 skill-group cells in each of four Census years (1970-2000) for a total of 6528 observations. Standard errors are clustered at the skill-state level since actual data may be correlated within cells over time. The estimates reported in the two rows of Table 6 are distinguished solely by whether or not the regressions include fixed effects. None of the specifications employ instrumental variables to control for endogeneity, so one should be cautious in ascribing a causal role in correlative relationships. These regressions simply reveal the correlation in the data, with and without controlling for an array of fixed effects.

In the absence of fixed effects, Borjas regressions argue for displacement, while all other specifications suggest a positive relationship between immigration and native employment. The inclusion of fixed effects reduces the magnitudes of each coefficient. This supports the larger point in Borjas (2006) – regressions exploring native internal migration should account for initial conditions and trends. Otherwise results will be biased. It is important to add, however, that only Borjas's baseline specification continues to find a significantly negative relationship between immigration and native

[13] Note that the standard deviation of $\Delta N$ is seven times larger than that of $\Delta F$ when using the less-aggregated state-skill cells, and is six times larger when using more-aggregated cells. This similarity in relative variation might be one reason why the Borjas magnitudes in Tables 3 and 5 are similar.

internal migration once fixed effects are included. The other specifications either identify attraction or neither displacement nor attraction. Given the inherent negative bias uncovered in the Borjas' specifications, we believe that there is no evidence for a true displacement effect. The correlation evidence, at least *prima facie*, does not support displacement.

In choosing a preferred specification, we might be inclined to advocate something like Card's (2007) methodology – Equation (4) – but with the following modification: Replace the dependent variable $\left(\frac{L_t - L_{t-1}}{L_{t-1}}\right)$ with $\left(\frac{N_t - N_{t-1}}{L_{t-1}}\right)$. First, this would lead to coefficient estimates that are exactly one less than the Card (2007) estimates provided in this (and his) paper and would provide a more direct test of displacement. That is, the coefficient would translate directly into the number of native employees who respond to one extra immigrant worker in the group. Second, the model would not be affected by cell size, nor it would force any artificial correlation between the dependent and explanatory variables. Third, it is even more demanding than (5) in controlling for pre-determined trends of native employment growth since it expresses the variables in differences, not levels, and still controls for an array of fixed effects. The identifying variation therefore comes from deviations of *growth rates* from skill-state specific trends. Finally, the regression can employ observations in which $N$ or $F$ equal zero, unlike natural log specifications. Such a specification (including all fixed effects and using the US state-skill data) would generate a significant coefficient of 1.361 and suggest a strong attraction between immigrants and natives.

## 5 Conclusions

The debate on the labor market effects of immigration is important from an academic and policy point of view. It is essential that we have a good understanding of the potential crowding-out of native workers that immigrants might cause. Analysis of the correlation between immigrant and native employment within skill-state groups over time might be able to provide or deny support to the crowding out theory. Should displacement exist, then not only would immigration decrease native employment opportunities, but cross-region analyses of the wage effects of immigration would be invalid. In particular, the negative wage consequences of immigration would be much more severe than the small effects found by area studies if displacement occurs. As recent papers find different answers to this question using similar data but different empirical methodologies, this paper aims at explaining where these differences come from.

We generated several artificial datasets and then used them to explore whether different regression specifications are able to robustly and correctly identify the native displacement consequences of immigration. Some models (notably Card 2007) performed well and correctly uncovered negative relationships when displacement was assumed in the data generating process, while also identifying a positive relationship when native attraction to immigration was assumed. Borjas (2006) specifications, however, exhibited a strong bias toward displacement. This is likely due to an inherent and mechanical bias created by including a measure of native employment in the denominator of the explanatory variable and in the numerator of the dependent variable. Further simulations support this conclusion by showing that the bias becomes larger as the standard deviation of native employment changes grows in relation to the standard deviation of immigration flows.

Regressions that use real data fail to uncover a significant relationship between immigration and native migration, and instead mostly estimate no displacement and no attraction. The exceptions, however, are Borjas (2006) specifications that systematically find displacement. Though we cannot interpret the effects as causal, we believe that inherent bias in the Borjas specifications, coupled with the consistency of results across alternative models, combine to provide no evidence in favor of displacement. Our results therefore preserve the validity of other cross-region empirical analyses of the effects of immigration.

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**Table 1:**
**Empirical Models for Identifying Internal Migration Response**
*Estimates Using Simulated Data for Skill-Region-Time Cells*

| **Data Generating Process** | *Empirical Model:* | **Card (2007)** | **Borjas (2006) Baseline** | **Borjas (2006) Alternative** | **Cortes (2006)** | **Cortes (2006) Alternative** | **Equation (1) in Text** |
|---|---|---|---|---|---|---|---|
| ***ΔN*** | *Dependent Variable:* | ***Δ(N+F)/(lag N+F)*** | ***ln(N)*** | ***(ΔN) / (Avg N)*** | ***ln(N+F)*** | ***ln(N)*** | ***ΔN*** |
| ***ΔF*** | *Explanatory Variable:* | ***(ΔF) / (lag N+F)*** | ***F / (N+F)*** | ***F / (N+F)*** | ***ln(F)*** | ***ln(F)*** | ***ΔF*** |
| $\beta_{DGP}$ | *Displacement if :* | $\beta_{Card} < 1$ | $\beta_{Borjas1} < 0$ | $\beta_{Borjas2} < 0$ | $\beta_{Cortes1} < 0$ | $\beta_{Cortes2} < 0$ | $\beta < 0$ |
| **-1** | *Coefficient on* | -0.056 | -3.626 | -1.572 | 0.029 | -0.035 | -1.005 |
| **(Displacement)** | *Explanatory* | (0.089) | (0.079)*** | (0.053)*** | (0.006)*** | (0.006)*** | (0.088)*** |
| **-0.5** | *Variable:* | 0.430 | -3.415 | -1.479 | 0.058 | -0.005 | -0.505 |
| **(Displacement)** | *(Standard Error)* | (0.089)*** | (0.083)*** | (0.055)*** | (0.006)*** | (0.006) | (0.089)*** |
| **0** | | 0.902 | -3.168 | -1.382 | 0.087 | 0.026 | -0.030 |
| **(No effect)** | | (0.090)*** | (0.087)*** | (0.056)*** | (0.006)*** | (0.006)*** | (0.089) |
| **0.5** | | 1.376 | -2.884 | -1.261 | 0.116 | 0.057 | 0.458 |
| **(Attraction)** | | (0.089)*** | (0.091)*** | (0.058)*** | (0.006)*** | (0.006)*** | (0.089)*** |
| **1** | | 1.854 | -2.554 | -1.140 | 0.144 | 0.088 | 0.949 |
| **(Attraction)** | | (0.089)*** | (0.095)*** | (0.061)*** | (0.006)*** | (0.006)*** | (0.088)*** |
| | *Obs (Min)* | 6475 | 6432 | 6434 | 6426 | 6422 | 6500 |
| | *Obs (Max)* | 6481 | 6438 | 6445 | 6433 | 6426 | 6503 |
| | *Fixed Effects* | No | No | No | No | No | No |

**Note:** Results from regressions employing data generated from the process described in Equation (1) of the text. The values of $\beta_{DGP}$ = {-1, -0.5, 0, 0.5, 1} used are reported in the first column. Immigrants are said to displace natives if $\beta_{DGP}$ <0, and attract natives if $\beta_{DGP}$ >0. Each column uses a different empirical model for identifying displacement, identified in the first three rows of the column. Each cell represents a coefficient estimate from the regression specification of the column's methodology when the $\beta_{DGP}$ value in the corresponding row is used in the data generating process (DGP). The final column, as a check, uses the DGP's regression specification. Units of observations are skill-state cells. There are 32 skill levels, 51 regions and 4 years.
***Significant at 1%; **Significant at 5%; *Significant at 10%

**Table 2:**
**Empirical Models for Identifying Internal Migration Response, Adding Fixed Effects**
*Estimates Using Simulated Data for Skill-Region-Time Cells*

| Data Generating Process | *Empirical Model:* | Card (2007) | Borjas (2006) Baseline | Borjas (2006) Alternative | Cortes (2006) | Cortes (2006) Alternative | Equation (1) in Text |
|---|---|---|---|---|---|---|---|
| $\Delta N$ | *Dependent Variable:* | $\Delta$(N+F)/(lag N+F) | ln(N) | ($\Delta$N) / (Avg N) | ln(N+F) | ln(N) | $\Delta N$ |
| $\Delta F$ | *Explanatory Variable:* | ($\Delta$F) / (lag N+F) | F / (N+F) | F / (N+F) | ln(F) | ln(F) | $\Delta F$ |
| $\beta_{DGP}$ | *Displacement if :* | $\beta_{Card} < 1$ | $\beta_{Borjas1} < 0$ | $\beta_{Borjas2} < 0$ | $\beta_{Cortes1} < 0$ | $\beta_{Cortes2} < 0$ | $\beta < 0$ |
| **-1** | *Coefficient on* | 0.151 | -3.746 | -2.214 | -0.015 | -0.082 | -0.906 |
| **(Displacement)** | *Explanatory* | (0.105) | (0.082)*** | (0.109)*** | (0.007)** | (0.007)*** | (0.103)*** |
| **-0.5** | *Variable:* | 0.638 | -3.525 | -2.044 | 0.016 | -0.050 | -0.402 |
| **(Displacement)** | *(Standard Error)* | (0.106)*** | (0.087)*** | (0.112)*** | (0.007)** | (0.007)*** | (0.104)*** |
| **0** | | 1.111 | -3.266 | -1.865 | 0.047 | -0.017 | 0.064 |
| **(No effect)** | | (0.106)*** | (0.092)*** | (0.116)*** | (0.007)*** | (0.007)** | (0.104) |
| **0.5** | | 1.594 | -2.982 | -1.657 | 0.078 | 0.016 | 0.550 |
| **(Attraction)** | | (0.106)*** | (0.098)*** | (0.121)*** | (0.007)*** | (0.007)** | (0.104)*** |
| **1** | | 2.081 | -2.640 | -1.431 | 0.108 | 0.050 | 1.037 |
| **(Attraction)** | | (0.105)*** | (0.103)*** | (0.125)*** | (0.007)*** | (0.007)*** | (0.103)*** |
| | *Obs (Min)* | 6475 | 6432 | 6434 | 6426 | 6422 | 6500 |
| | *Obs (Max)* | 6481 | 6438 | 6445 | 6433 | 6426 | 6503 |
| | *Fixed Effects* | Year*Skill Year*Region Skill*Region | Year*Skill Year*Region Skill*Region | Year*Skill Year*Region Skill*Region | Year*Skill Year*Region Skill*Region | Year*Skill Year*Region Skill*Region | Year*Skill Year*Region Skill*Region |

**Note:** All Variables, specifications and definitions are as in Table 1. Year by Skill, Year by region and Skill by region effects are included in all regressions.
***Significant at 1%; **Significant at 5%; *Significant at 10%

**Table 3:**

**Sensitivity of Estimated Displacement to the Standard Deviation of Native Employment Growth**

*Estimates Using Simulated Data for Skill-Region-Time Cells*

| **Data Generating Process** | *Empirical Model:* | **Card (2007)** | **Borjas (2006) Baseline** | **Borjas (2006) Alternative** | **Cortes (2006)** | **Cortes (2006) Alternative** | **Equation (1) in Text** |
|---|---|---|---|---|---|---|---|
| $\Delta N$ | *Dependent Variable:* | $\Delta$(N+F)/(lag N+F) | ln(N) | ($\Delta$N) / (Avg N) | ln(N+F) | ln(N) | $\Delta N$ |
| $\Delta F$ | *Explanatory Variable:* | ($\Delta$F) / (lag N+F) | F / (N+F) | F / (N+F) | ln(F) | ln(F) | $\Delta F$ |
| | *Displacement if :* | $\beta_{Card} < 1$ | $\beta_{Borjas1} < 0$ | $\beta_{Borjas2} < 0$ | $\beta_{Cortes1} < 0$ | $\beta_{Cortes2} < 0$ | $\beta < 0$ |
| $\beta_{DGP}$=0 (Small σ[ΔN]) | *Coefficient on Explanatory Variable: (Standard Error)* | 0.953<br>(0.045)*** | -1.056<br>(0.055)*** | -0.584<br>(0.065)*** | 0.054<br>(0.003)*** | -0.007<br>(0.004)** | -0.015<br>(0.045) |
| $\beta_{DGP}$=0 (Observed σ[ΔN]) | | 0.902<br>(0.090)*** | -3.266<br>(0.092)*** | -1.865<br>(0.116)*** | 0.047<br>(0.007)*** | -0.017<br>(0.007)** | -0.030<br>(0.089) |
| $\beta_{DGP}$=0 (large σ[ΔN]) | | 0.870<br>(0.134)*** | -5.646<br>(0.107)*** | -3.219<br>(0.149)*** | 0.038<br>(0.010)*** | -0.027<br>(0.011)** | -0.045<br>(0.134) |
| | *Obs (Min)* | 6458 | 6417 | 6412 | 6414 | 6407 | 6500 |
| | *Obs (Max)* | 6489 | 6474 | 6481 | 6446 | 6442 | 6500 |
| | *Fixed Effects* | No | Year*Skill<br>Year*Region<br>Skill*Region | Year*Skill<br>Year*Region<br>Skill*Region | Year*Skill<br>Year*Region<br>Skill*Region | Year*Skill<br>Year*Region<br>Skill*Region | No |

**Note:** Variables, specifications and definitions in the Empirical Models are as in Table 1. The data generating process, described in the first column maintains the value of $\beta_{DGP}$=0 while it modifies the standard deviation of the native employment changes, σ[ΔN] in each of the three rows. The middle row assumes $\sigma_{\Delta N}/\sigma_{\Delta F}$ equals its observed value (7.14), the top row assumes it equal to 3.57 (half of the observed value), and the bottom row assumes it equal to 14.28 (twice the observed value) Standard Errors in parentheses. ***Significant at 1%; **Significant at 5%; *Significant at 10%

**Table 4:**
**Sensitivity of Estimated Displacement to the Number of Cells**
*Estimates Using Simulated Data for Skill-Region-Time Cells*

| **Data Generating Process** | *Empirical Model:* | **Card (2007)** | **Borjas (2006) Baseline** | **Borjas (2006) Alternative** | **Cortes (2006)** | **Cortes (2006) Alternative** | **Equation (1) in Text** |
|---|---|---|---|---|---|---|---|
| ***ΔN*** | *Dependent Variable:* | ***Δ(N+F)/(lag N+F)*** | ***ln(N)*** | ***(ΔN) / (Avg N)*** | ***ln(N+F)*** | ***ln(N)*** | ***ΔN*** |
| ***ΔF*** | *Explanatory Variable:* | ***(ΔF) / (lag N+F)*** | ***F / (N+F)*** | ***F / (N+F)*** | ***ln(F)*** | ***ln(F)*** | ***ΔF*** |
| $\beta_{DGP}$ | *Displacement if :* | $\beta_{Card} < 1$ | $\beta_{Borjas1} < 0$ | $\beta_{Borjas2} < 0$ | $\beta_{Cortes1} < 0$ | $\beta_{Cortes2} < 0$ | $\beta < 0$ |
| **-1** | *Coefficient on* | 0.060 | -3.873 | -1.670 | -0.053 | -0.118 | -1.038 |
| **(Displacement)** | *Explanatory* | (0.284) | (0.443)*** | (0.564)*** | (0.038) | (0.041)*** | (0.285)*** |
| **-0.5** | *Variable:* | 0.546 | -3.698 | -1.515 | -0.027 | -0.088 | -0.539 |
| **(Displacement)** | *(Standard Error)* | (0.287)* | (0.473)*** | (0.588)** | (0.039) | (0.042)** | (0.289)* |
| **0** | | 1.031 | -3.566 | -1.337 | -0.003 | -0.061 | -0.161 |
| **(No effect)** | | (0.289)*** | (0.499)*** | (0.612)** | (0.040) | (0.042) | (0.294) |
| **0.5** | | 1.514 | -3.425 | -1.136 | 0.026 | -0.034 | 0.339 |
| **(Attraction)** | | (0.288)*** | (0.519)*** | (0.631)* | (0.040) | (0.043) | (0.293) |
| **1** | | 1.997 | -3.120 | -0.900 | 0.055 | -0.003 | 0.841 |
| **(Attraction)** | | (0.285)*** | (0.548)*** | (0.656) | (0.040) | (0.042) | (0.290)*** |
| | *Obs (Min)* | 406 | 406 | 405 | 400 | 400 | 405 |
| | *Obs (Max)* | 406 | 408 | 406 | 402 | 402 | 407 |
| | *Fixed Effects* | No | Year*Skill<br>Year*Region<br>Skill*Region | Year*Skill<br>Year*Region<br>Skill*Region | Year*Skill<br>Year*Region<br>Skill*Region | Year*Skill<br>Year*Region<br>Skill*Region | No |

**Note:** All Variables, specifications and definitions are as in Table 1. Skill groups are only 2 (rather than 32) in each region-year.
***Significant at 1%; **Significant at 5%; *Significant at 10%

**Table 5:**

**Sensitivity of Estimated Displacement to the Standard Deviation of Native Employment Growth with Fewer Cells**

*Estimates Using Simulated Data for Skill-Region-Time Cells*

| **Data Generating Process** | *Empirical Model:* | **Card (2007)** | **Borjas (2006) Baseline** | **Borjas (2006) Alternative** | **Cortes (2006)** | **Cortes (2006) Alternative** | **Equation (1) in Text** |
|---|---|---|---|---|---|---|---|
| $\Delta N$ | *Dependent Variable:* | $\Delta(N+F)/(lag\ N+F)$ | $ln(N)$ | $(\Delta N) / (Avg\ N)$ | $ln(N+F)$ | $ln(N)$ | $\Delta N$ |
| $\Delta F$ | *Explanatory Variable:* | $(\Delta F) / (lag\ N+F)$ | $F / (N+F)$ | $F / (N+F)$ | $ln(F)$ | $ln(F)$ | $\Delta F$ |
| | *Displacement if :* | $\beta_{Card} < 1$ | $\beta_{Borjas1} < 0$ | $\beta_{Borjas2} < 0$ | $\beta_{Cortes1} < 0$ | $\beta_{Cortes2} < 0$ | $\beta < 0$ |
| $\beta_{DGP}=0$ | *Coefficient on Explanatory Variable: (Standard Error)* | 0.988 | -1.030 | -0.151 | 0.024 | -0.030 | -0.081 |
| (Small σ[ΔN]) | | (0.144)*** | (0.298)*** | (0.332) | (0.020) | (0.021) | (0.147) |
| $\beta_{DGP}=0$ | | 1.031 | -3.566 | -1.337 | -0.003 | -0.061 | -0.161 |
| (Observed σ[ΔN]) | | (0.289)*** | (0.499)*** | (0.612)** | (0.040) | (0.042) | (0.294) |
| $\beta_{DGP}=0$ | | 1.018 | -6.078 | -2.729 | -0.043 | -0.108 | -0.242 |
| (large σ[ΔN]) | | (0.432)** | (0.541)*** | (0.806)*** | (0.059) | (0.064)* | (0.441) |
| | *Obs (Min)* | 405 | 405 | 404 | 399 | 399 | 407 |
| | *Obs (Max)* | 406 | 408 | 408 | 401 | 402 | 407 |
| | *Fixed Effects* | No | Year*Skill<br>Year*Region<br>Skill*Region | Year*Skill<br>Year*Region<br>Skill*Region | Year*Skill<br>Year*Region<br>Skill*Region | Year*Skill<br>Year*Region<br>Skill*Region | No |

**Note:** All Variables, specifications and definitions are as in Table 3. Skill groups are only 2 (rather than 32) in each region-year.
Standard Errors in parentheses. ***Significant at 1%; **Significant at 5%; *Significant at 10%

**Table 6:**

**Empirical Models Estimates of Internal Migration Response**

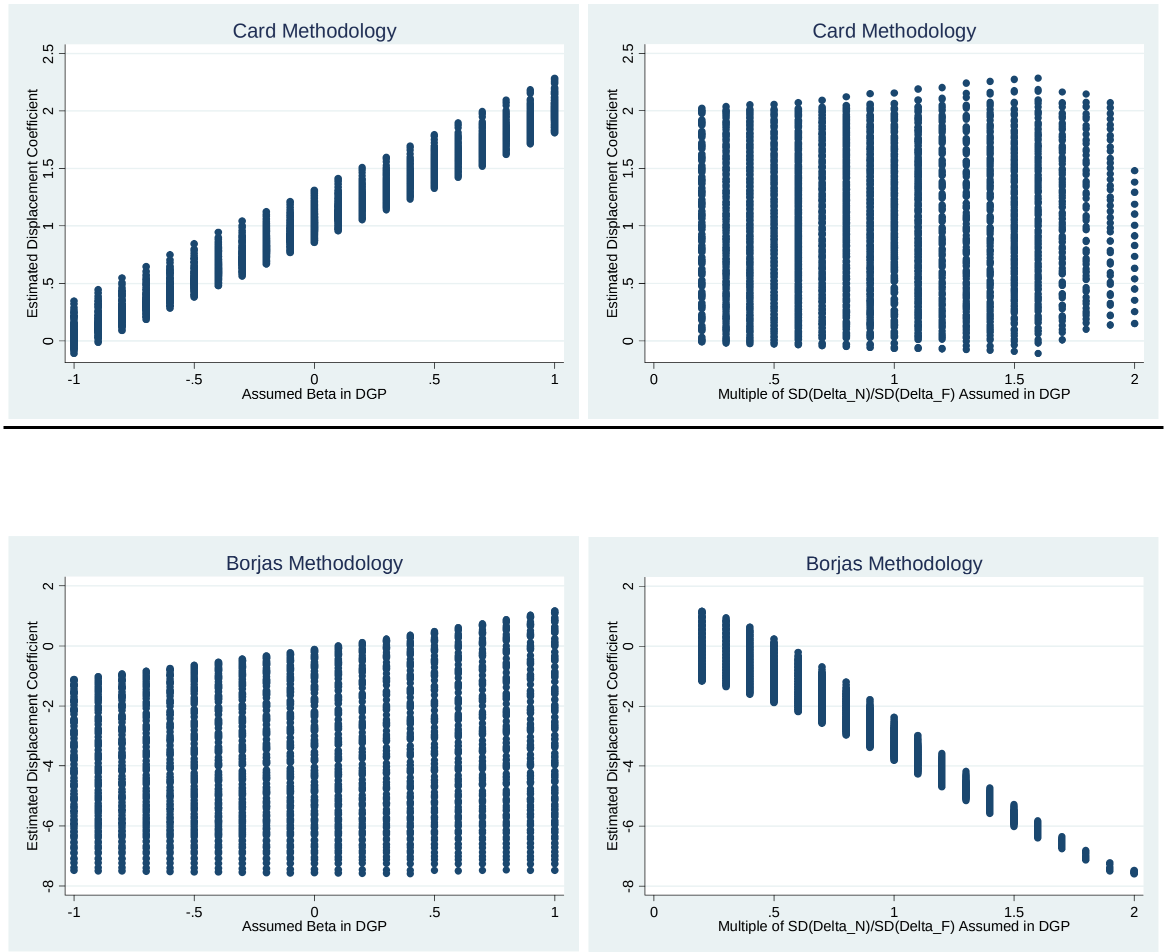
*Estimates Using Observed Data for 32 Skills in 51 US States in Years 1970, 1980, 1990 and 2000*

| *Empirical Model:* | | **Card (2007)** | **Borjas (2006) Baseline** | **Borjas (2006) Alternative** | **Cortes (2006)** | **Cortes (2006) Alternative** | **Equation (1) in Text** |
|---|---|---|---|---|---|---|---|
| *Dependent Variable:* | | $\Delta$(N+F)/(lag N+F) | ln(N) | ($\Delta$N) / (Avg N) | ln(N+F) | ln(N) | $\Delta$N |
| *Explanatory Variable:* | | ($\Delta$F) / (lag N+F) | F / (N+F) | F / (N+F) | ln(F) | ln(F) | $\Delta$F |
| *Displacement if :* | | $\beta_{Card} < 1$ | $\beta_{Borjas1} < 0$ | $\beta_{Borjas2} < 0$ | $\beta_{Cortes1} < 0$ | $\beta_{Cortes2} < 0$ | $\beta < 0$ |
| *Coefficient on Explanatory Variable: (Standard Error)* | *No Fixed Effects* | 3.288 | -0.551 | -1.692 | 0.425 | 0.396 | 1.397 |
| | | (0.527)*** | (0.277)** | (0.054)*** | (0.009)*** | (0.009)*** | (0.234)*** |
| | *Full Fixed Effects* | 2.361 | -0.406 | -0.363 | 0.022 | 0.009 | 1.166 |
| | | (0.871)*** | (0.093)*** | (0.090)*** | (0.004)*** | (0.004)** | (0.436)*** |
| *Observations* | | 6528 | 6528 | 6528 | 6528 | 6528 | 6528 |

**Note:** OLS results from regressions employing observed decennial data from 1970-2000, 51 states, and 32 education*experience skill-cells. Each column represents a different methodology for identifying displacement and is identified by the column header. Regression in the top column present results without fixed effects. Regressions in the second row present results with year, skill, region, year*skill, year*region, and skill*region fixed effects. Cells represent unique coefficient estimates given by the regression specification of the column's methodology and the exclusion/inclusion of fixed effects as indicated by rows.

Standard Errors in parentheses are cluster-robust at the skill-state level. ***Significant at 1%; **Significant at 5%; *Significant at 10%

**Figure 1: Regression Coefficients for Card (2007) and Borjas (2006) Methodologies for Various Assumed Data Generating Processes**




**Note:** Each point in the figures above represents a displacement regression coefficient identified by the stated regression methodology resulting from unique datasets created by the data generating process (DGP) in Equation (1). These datasets are distinguished by distinct random seed generators, assumed values of the true displacement coefficient ($\beta_{DGP}$), and multiples ($\lambda$) of the relative standard deviation of shocks to natives and shocks to immigrants ($\sigma_{\Delta N}/\sigma_{\Delta F}$). In particular, we adopt values of $\beta_{DGP} \in [-1, 1]$, increasing in increments of 0.1; values of $\lambda \in [0.2, 2]$, also increasing in increments of 0.1; and repeat the process for ten random seed generators. This results in a potential of 3,990 datasets, coefficient estimates, and points on the figures above. An assumed $\beta_{DGP} = 0$ in the DGP corresponds to no displacement. The observed $\sigma_{\Delta N}/\sigma_{\Delta F}$ value in the data (7.14) corresponds to the multiple value ($\lambda$) of 1. Unbiased regression methodologies should identify coefficient estimates that are increasing in $\beta_{DGP}$ and unrelated to $\lambda$.