Timing Is Everything: Short-Run Population Impacts of Immigration in U.S. Cities

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Abstract

We provide the first analysis of the short-run causal impact of immigrant inflows on native populations at the local labor market level. Using published statistics from the American Community Surveys of 2000-2010, we examine how immigrant inflow shocks to a metropolitan area affect native populations. We find that immigrant inflows are associated with increases in local native populations on an annual basis but that these OLS estimates are generally upward biased. Our IV results are purged of this bias, but we still find that an additional immigrant increases the low skill native population by 0.4 to 0.7 in the concurrent period. To explain this result, we show that immigrant inflows lead to declines in outflows of low skill natives from affected MSAs. This is most pronounced in MSAs from which relocation is arguably more costly, which may disproportionately affect the low skilled. We find short-run responses among high skill natives that are consistent with displacement. The decline in high skilled native populations is driven by high skilled immigrant inflows, and high skilled outflows increase from affected MSAs. We show that these short-run changes are obscured in specifications using longer-run population changes and conclude that the short-run impact of immigrants on native populations differs markedly from their longer-run impact.

JEL: R23, J1, J21, J61

I. Introduction

Research on the economic impacts of immigration in the US stretches back at least three decades, and the great majority of this work relies on US Census data for its empirical analysis.[1] As a result, existing estimates are most appropriately characterized as medium- or long-run impacts of immigration, since they are generally derived from comparing outcomes at ten year intervals. These longer-run relationships are certainly interesting, but they may well differ from the short-run relationships. Specifically, longer-run analysis may obscure short-run impacts if a series of short-run responses restores equilibrium over the longer period.[2] Our paper is the first to examine *short-run* changes in native populations in response to *local* immigrant inflow shocks. To do this, we assemble a panel data set of metropolitan area populations from the annual aggregate statistics of the U.S. Census Bureau's American Community Surveys. Our data consist of repeat observations on native and immigrant populations for a consistent set of 144 metropolitan areas over the eleven year period from 2000 to 2010. Our use of metropolitan area level data further distinguishes our approach from studies that use annual data at the state level to study short run relationships (Barcellos, 2010; Butcher and Card, 1991; Jaeger, 2007).

Although location decisions are typically perceived as lagging local conditions, there are reasons to think that some of immigration's impacts on local native populations and labor market outcomes might take place in the short-run. First, there is evidence that other dimensions of the local economy, like rental housing prices and industrial skill mix, exhibit short-run changes in response to an immigrant inflow shock (Lewis 2005 and Saiz 2003, 2007). Second, the high levels of gross migration in the U.S. (6 to 7% per year according to Greenwood 1997) provide ample scope for a city's potential in- and out-migrants to respond to a short-run shock to local immigrant inflows, thereby affecting both native populations and labor market conditions. A complete understanding of immigration's impacts therefore requires study of its short-run effects, in addition to the longer-run analysis already available in the literature.

[1] Borjas (2001, 2003, and 2006), Borjas, Freeman and Katz (1996), and Card (2001) are prominent examples. The earlier, influential studies of Grossman (1982) and Altonji and Card (1991) also use Census data but focus on cross-sectional associations.
[2] For example, Casey (2011) finds that short-run impacts of black inflows to white neighborhoods on housing prices are significant while the longer run impact of black inflows on neighborhood home prices is zero.

A second contribution of our study is to examine the properties of a commonly used identification strategy and set of estimating equations under conditions when more periods are added to the usual city level panel data sets. We show that a common IV strategy in the immigration literature is not robust to the more detailed panel data controls available in our longer panel. We further show that this is likely due to functional form assumptions in the most common estimating equations, and we propose an alternative set of estimating equations and set of control variables to deal with the problem.

We begin our analysis by estimating correlations between annual changes in native and immigrant populations. We focus on population changes because, after wage impacts, the question of whether immigrants encourage natives to leave an affected local labor market and "arbitrage with their feet" is a central question in the immigration literature. High quality local population variables are also a strength of the ACS in the period we use. We model an immigrant inflow as a single shock and allow responses to that shock to differ across native skill groups.[3] Our OLS results show that observed immigrant inflows are associated with increases in local native populations in the current period. Although these results are descriptive, they show that the correlations between native population changes and immigrant inflows are positive and economically large. We then examine the causal impact of immigrant inflow shocks on native populations using our preferred instrumental variables approach. We show that the OLS correlations are generally upward biased. The causal impact of immigrant inflows on the high skilled and total native populations are smaller than suggested by OLS, and of opposite sign in the case of the high skilled. OLS and IV estimates are indistinguishable for low skill natives. The causal impact of an additional immigrant in the current year is an increase of 0.42 to 0.65 low skill natives while an additional immigrant from the previous year reduces the high skill population by 0.38 to 0.58.

The final contribution of our study is to highlight and examine these differential responses to immigrant inflows across native skill groups. We first show that although our results differ from those in the literature based on longer-period changes, similar results can be obtained by restructuring our data to use

[3] Wozniak (2010) shows that, among new labor force entrants, migration of the more highly educated is more responsive to local demand conditions. She also discusses the literature showing that high skill natives are more geographically mobile on average.

long-period changes rather than the short-run changes that are our focus. Next, we provide evidence of displacement for high skilled natives – a group that is more geographically mobile than the low skilled – that is consistent with the displacement hypothesis examined in detail in Borjas (2006). Specifically, we find that inflows of high skilled immigrants drive the negative impacts of immigrant inflows on the high skilled white population, and we find that immigrant inflows increase total outflows of high skilled natives from affected MSAs. We then show that our results for low skilled native populations are driven by decreases in outflows from affected MSAs. Finally, we find that our main results are attenuated in larger and less geographically isolated cities, but not in "booming" cities. We hypothesize that immigrant inflows provide a weak negative shock that causes outward mobility for the less skilled to decline temporarily, particularly in cities where their isolation or their relative housing prices make relocation to a new market more costly. This suggests that low skill natives are temporarily "trapped" by immigrant inflows. We conclude that the short-run impacts of immigrant inflows differ markedly for both high and low skill workers from effects reported in the literature using longer-run population changes. We further conclude that there are important differences in short-run responses to immigrant inflows across native skill groups and across city types.

II. Empirical Methodology and Estimating Equations

A simple accounting identity relates the net annual change in total population (ΔP) in local market *c* to net annual changes in the local native (ΔN) and foreign born (ΔM) populations:[4]

$$(1) \qquad \Delta P_{ct} = \Delta N_{ct} + \Delta M_{ct}$$

The key question we wish to examine is whether net changes in *N* offset net changes in *M*. That is, do natives move out of an area as immigrants arrive? The displacement theory of native migration adjustment predicts offsetting changes: as immigrants increase the local labor supply in market *c*, they lower wages in *c* relative to other markets. This creates an incentive for natives to move from *c* to higher wage markets, and

[4] Card (2001) derives specifications from the same accounting identity but expresses the components in terms of gross population growth rates.

through this displacement process, wages in *c* rise again. It is important to note that the migration adjustment models motivating previous analyses do not predict perfect displacement. Rather, they predict that as immigrants move in, *some* natives move out or fail to move in, at a rate of less than one-for-one, although we know of no model that makes an explicit prediction about the rate of transfer.

The displacement and wage re-adjustment process is inherently of limited duration. As more natives respond through migration, relative wages return to equilibrium, and the cross-market flows induced by an immigrant supply shock come to an end. If this mechanism is empirically important, we should observe native population changes in an area following immigrant inflows within a short period of time. This raises the question, how much time is enough time to observe these effects? While there is conflicting evidence over the effect of immigrant inflows on native wages, there is evidence that localities begin to adjust to an influx of immigrants on other dimensions within one to five years. Saiz (2003, 2007) finds a large increase in the price of rental housing within one year of a shock to local immigrant population size. Lewis (2005) finds that immigrant inflows affect the skill-intensity of local manufacturing processes within five years of arriving in an area. In light of this evidence, we believe a reasonable starting point for our analysis is to examine the relationship between immigrant inflows and native population changes in an area within a similar 1- to 5-year time frame.

As a first step, we document the relationship between annual changes in native and immigrant populations at the local labor market level controlling for differential native population growth trends across metropolitan areas. Specifically, we estimate the following:

$$\Delta N_{ct} = \beta_0 + \beta_1 \Delta M_{ct} + \Theta_c + \mu_{ct} \qquad (2)$$

The dependent variable is the change in the native population in market *c* between year t and t-1, and the right hand side variable of interest is the change in the immigrant population in *c* over the same period. μ is an i.i.d. error term. M and N are total populations of immigrants and natives, respectively, in city *c*. We discuss these in detail in the next section. The inclusion of the MSA fixed effects, Θ_c, function as metropolitan area-specific time trends since the dependent variable is in changes. Our model is thus an example of the awkwardly-named random trend model for panel data discussed in Wooldridge (2002) and employed by Papke (1994).[5] The MSA-specific effects absorb fixed as well as linearly time-varying differences across MSAs. They therefore account for a number of important but unobserved differences across cities. First, they allow native populations to have different underlying growth trends across MSAs. They also control for smoothly changing MSA characteristics, including a changing industrial structure or age distribution.[6] Finally, the first-differenced specification accounts for fixed differences across cities, like initial population size, which has been shown to be an important driver of both immigrant inflows and native population growth.

We then add a full set of region-year fixed effects, Θ_{rt}, to Equation (2). This is our full model, and the estimating equation becomes the following:

$$\Delta N_{ct} = \alpha_0 + \alpha_1 \Delta M_{ct} + \Theta_c + \Theta_{rt} + +\mu_{ct} \tag{3}$$

Mathematically, the region-year effects are equivalent to year-to-year differences in region-year specific *level* shocks to a region's population. There are a number of reasons one might want to include such controls. First, population levels may fluctuate from year to year for a number of reasons. The region-year effects control for unobserved, non-linear population fluctuations such as those driven by birth rate shocks, national or regional immigrant inflow shocks (from which we abstract to focus on local inflows), and reallocation of the population from one region to another. They also absorb population variation arising from common national or regional changes in ACS sampling or subject response.

The region-year effects also address some of the concerns raised by Borjas, Freeman, and Katz (1997), who write that researchers "…will not be able to obtain consistently negative or positive effects [of immigrant inflows on native outcomes] across different censuses unless they can control for the forces that caused the regional wage structure to change so dramatically over time." To the extent that relevant regional wage structure change is at the level of the Census region, our region-year effects do just this. For example,

[5] Wooldridge (2002) points out that this is a misnomer, as there is actually nothing random about the model parameters.
[6] Since we estimate our model over a single decade of data, the possibility that city characteristics like industrial or demographic structure will follow a non-linear pattern is less of a concern.

our region-year effects capture any non-linear changes in economic position of the South and West relative to the Northeast and Midwest. In one of our robustness checks, we substitute state-year effects for the region-year effects to allow even greater disaggregation of these non-linear regional economic shocks. We are able to include them in part because the unique panel nature of our data includes enough variation across space and over time that these can be estimated without absorbing all useful variation.[7] Finally, we also estimate variants of (3) that incorporate the one-period lagged change in immigrant population, either in place of ΔM_{ct} or in addition to it.

The estimation outlined up to this point is largely descriptive, yet it fills an important gap. The literature currently has no correlations of year-to-year native population changes with changes in the foreign born population at the local labor market level. Specifications (2) and (3) provide these correlations and examine their sensitivity to assumptions about underlying trends in native and total population changes at the local level. The specification as written in (3) is also the annual-level analog of most of the existing research on this question. Since previous analyses relied largely on Census data, researchers have typically regressed the change in native populations over a 5- or 10-year period on changes in immigrant populations over the *same* period (e.g. Card, 2001).

To assess causality, we then implement an instrumental variables specification using a modification of instruments used in Card (2001) that was inspired by Bartik (1991). Specifically, we instrument for the change immigrant population in MSA *c* over the period *t* to *t-1* using the following measure of local immigrant population shocks:

(4) $$SPIV_{ct} \equiv \left(\frac{M_{c,2000}}{M_{2000}}\right) \times [(M_t - M_{t-1}) - (M_{ct} - M_{ct-1})]$$

We follow Card and refer to this measure as the supply-push instrumental variable (SPIV).[8] The measure has two components. The term in brackets represents the net change in the immigrant population

[7] However, we note that our results are not sensitive to the use of region-year effects over year effects alone.
[8] This calculation is closely related to others in the labor and urban economics literatures, particularly the Bartik demand instrument or the shift-share instrument. In its use of the share equal to an MSA's immigrant population divided by the national population, it is also related to the location quotient.

in the remainder of the U.S. between *t* and *t-1*, excluding city *c*'s contribution. This purges the measure of changes in *c*'s immigrant population driven by local factors in a manner similar to the way the measure in Bartik (1991) purges local employment changes of supply-driven shifts. Instead, fluctuations in immigrant populations in the rest of the country—which are assumed to be driven by factors exogenous to *c*—drive the SPIV shocks to local immigrant populations. We assume that MSAs with larger shares of the U.S. immigrant population in the prior period are apt to experience larger changes in their local immigrant populations if the national population changes. We therefore weight the term in brackets by the MSA's share of the total US immigrant population in a base period. We use 2000, the first year of our data, as the base.[9] Our SPIV therefore has the following interpretation: it is the net change in an MSA's immigrant population that would arise if the MSA received its year 2000 share of the net change in the U.S. immigrant population, *less the MSA's own contribution to that change*.[10] Note that if our IV strategy fails in the sense that the predicted local immigrant inflows are in fact correlated with unobserved labor demand conditions, then our IV estimates will be biased upwards (as we expect OLS to be) and we will tend not to find evidence of displacement.

A common approach in the literature on immigrant inflows is to express population change in terms of rates after normalizing by some base period population, as in the following:

(5)

$$\frac{\Delta P_{ct}}{P_{ct-1}} = \frac{\Delta M_{ct}}{P_{ct-1}} + \frac{\Delta N_{ct}}{P_{ct-1}}$$

The convention of normalizing population changes derived in part from concerns related to potentially spurious correlation between ΔN and ΔM in a regression with the latter on the right hand side, since city

[9] We assume that the share of immigrants in a city's population in 2000 is uncorrelated with local demand shocks that may drive immigration into c in period t. If such shocks are persistent, our instrument may not be fully exogenous. We examine the sensitivity of our results to this assumption by using immigrant population shares from earlier periods.

[10] An alternative view is that this adjustment may induce correlation between our instrument and ΔM_{ct} since ΔM_{ct} remains a part of the expression for the IV. We show later that the correlation between the instrument and ΔM_{ct} is stronger when this adjustment is *not* made, lending support to our contention that removing a city's own contribution to the total US immigrant inflow is more appropriate than leaving it in the IV expression. In the end, this decision does not substantively affect our results. We show in unreported results (available upon request) that estimates from our preferred, full specification are very similar when an MSA's own contribution to the total immigrant flow is included.

size will drive large changes in both N and M (Peri and Sparber, 2011; Wright, Ellis, and Reibel, 1997).[11] Since city size is highly persistent, the solution suggested by Wright et al is to control directly for these mechanical effects, which are sometimes called scale effects, by including initial city population as a control. This is accommodated by our MSA time trends. Others, including Peri and Sparber and Card (2001, 2007) advocate normalizing population changes by initial population size to further reduce concerns about possible scale effects.

We prefer the specification in (3), which leaves population changes in levels and controls directly for initial population size. This addresses the possibility of scale effects directly by including an appropriate control for the confounding factor – initial city size. The use of levels changes avoids attenuation bias arising from measurement error in immigrant population shares identified in Aydemir and Borjas (2011). Aydemir and Borjas show that this attenuation is particularly severe in models, like ours, that include controls for a wide range of unobserved, fixed factors.

Nevertheless, we take several additional steps to further reduce concerns about the role of scale effects in our estimates. First, we omit the five largest cities from our sample to further mitigate concerns about spurious positive correlation induced by scale effects. As shown in the bottom panel of Table 1, this reduces the standard deviation of metropolitan area population size to be smaller than the mean, something which is not true when the top-five cities are included. We believe this omission has only a modest effect on the generalizability of our results, since immigrants now have sizable representation in many areas outside the major immigrant-receiving states and cities. For example, the state with the largest percentage change in its foreign born population between 1990 and 2000 was North Carolina, a state that had been nearly devoid of immigrants since the Civil War.[12] This is a recent development. Between 1960 and 1990, the US immigrant population became increasingly geographically concentrated (Borjas, Freeman, and Katz, 1997).

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[11] The idea is that immigrants and natives are approximately two pieces of a single pie, that being a city's total population. There will therefore be a mechanical, positive relationship between the two since total population varies widely across cities.

[12] Perry (2003) documents that North Carolina's immigrant population increased by 187% from 1995 to 2000. Haines (1994) shows that states in the Southern US accounted for 5.6% of the white foreign born population in 1860. That number drops to 3.5% by 1910. Over that same time period, the percentage of the white foreign born population in the Northeast grew from 19.3% to 26.2%. Historical waves of immigration were more likely to settle in the Northeast and Midwest over the South.

Since 1990, this trend has reversed itself, and immigrants have become *less* geographically concentrated. In 1990, 37% of the foreign born lived in the five cities with the largest share of the US immigrant population. By 2000, the share in those cities had dropped to 32%, and by 2009 it was only 27%. Our sample therefore still allows us to document the impacts of nearly three quarters of the US immigrant population.

The second step we take is to estimate all our specifications using unweighted MSA level data to further reduce concerns that large cities drive the results. Third, we have examined the assumptions about residuals implicit in the normalized specifications (in the Estimating Equations Appendix) and found that these are not supported by the data. Our use of the levels specification sets our paper apart from others in the literature that cannot directly control for city-specific trends (e.g. Saiz, 2007), and that therefore rely on the correction for unobserved city-level factors that normalized specifications accomplish indirectly. While we cannot rule out the possibility of scale effects entirely, we believe they are limited. Ultimately, since the expected spurious correlation is positive, they work against finding evidence of displacement and therefore will tend to make most of our ultimate results more conservative rather than less.

There are three additional differences between our preferred approach – that is, our IV estimates of Equation (3) – and those in the literature. First, we include a full set of region-year dummies. To our knowledge, no other paper on this question flexibly controls for annual economic shocks at a level below the US. We also remove a metropolitan area's own contribution to immigrant population growth in the US as a whole from our version of the SPIV. Our approach was independently derived, but it is the same as the adjustment made in Smith (2010). Like Smith, we believe this improves on Card's 2001 version of the SPIV. We explicitly exclude a city's contribution to the national change in immigrant populations whereas Card assumes that MSA level factors do not influence the skill composition of incoming immigrant cohorts. Finally, we use a single base period to calculate the shares used as weights in the SPIV. This differs from the approach in Saiz (2007) and others who use the previous data period as the base.

III. Local Population Data from the American Community Survey

Our main data set is a panel of annual published (aggregate) estimates from the American Community Survey (ACS) over the years 2000 to 2010. The ACS has two main advantages over data sets that have been employed in this literature. First it allows for analysis of local labor markets at geographic levels that closely approximate those markets. Second, local populations are recorded annually.

The ACS provides yearly data, whose content is comparable to that of the Census "long form" data, at geographic levels that closely approximate local labor markets, in our case the metropolitan area. Data from the ACS is available in an aggregate summary form as well as in an individual-level microdata form; both forms of the ACS are made publically available beginning in 2000.[13] Ideally we would like to use individual-level microdata to construct our population subtotals as the aggregate statistics produced by the ACS do not include information on all potential subpopulation totals that we may be interested in. The limitation of the microdata is that geographic identifiers at the metropolitan area level do not become available until the 2005 survey year; prior to 2005 the smallest geographic identifier is the state. In order to exploit a longer time series we decide to use the published aggregate statistics from the ACS which allow us to construct data at the metropolitan area level beginning in 2000. Our data set provides us with annual aggregate population estimates at the MSA level for the years 2000-2010. To date the ACS has been used by few researchers, but an example is Chin and Juhn (2010).

Observations for a given year in our data set are in themselves estimates made by the U.S. Census Bureau using the entire ACS microdata sample in a given year. The ACS provides these population estimates at many different levels of aggregation; our observations will be at the MSAlevel because it is an appropriate approximation for a local labor market. Our metropolitan areas definitions are those defined by the U.S. Office of Management and Budget as of June 30, 1999. Beginning in 2005, the aggregate ACS data uses an

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[13] Aggregate statistics on test sites used by the American Community Survey is available prior to 2000. The American Community Survey began in 1996 with four test sites. Nationally representative data from the ACS became available in 2000. For 2000 and 2001 the summary level data used in the paper comes from the Census 2000 Supplementary Survey, C2SS. This survey was designed to produce state and national estimates as well as estimates for counties with a population of over 250,000 or more. The C2SS is the transition from the ACS test sites from 1996-2000 to the implementation of the first official ACS survey in 2002. For all intents and purposes the C2SS and the ACS are the same (Alexander, 2001).

updated version of metropolitan area definitions. For consistency over time, we developed a crosswalk that translates MSA definitions used in 2005 and beyond into MSA that are consistent with definitions used in earlier years of the ACS. A more complete discussion of the construction of these consistent metropolitan areas over the entire ACS time series can be found in the Data Appendix. Our final dataset contains 144 MSAs that are observed in 2000, observed for at least 8 years during our time span (2000-2010), and exclude the five largest cities as defined in Appendix Table 3. Figure 1 shows their distribution across the US. Our data set has wide geographic coverage. Only states in the inter-mountain West are substantially underrepresented.

Table 1 provides descriptive statistics for the main population variables used in our analysis. The nature of the aggregated ACS data makes presenting statistics for all variables cumbersome, but a more detailed list of the variables in our assembled data can be found in Appendix Table 2. All variables in our data represent population totals for a particular group in a given MSA in a particular year. For example, the maximum value for the population of high skilled, non-Hispanic whites ages 25 and older is 1.73 million; the mean size of that same population is 274,000 for our dataset. Along with not providing data for certain population subgroups of interest, another limitation of the ACS aggregate data is that census confidentiality procedures censor (i.e. leave missing) a number of population totals of interest for particular MSAs in our dataset. This censoring results in missing data for some subpopulations of the foreign born, such as those disaggregated by English language ability. However, there are several different measures of the immigrant population which are available for most MSAs in most years.

From the aggregate ACS statistics we construct three measures of the native population which are used as dependent variables in our analysis. Our measures for the native population in a given MSA include the total number of citizens by birth as well as the total number of non-Hispanic white individuals ages 25 years and older. For the latter group, we are able to disaggregate the population by skill level. We classify populations as high skill or low skill, where the former is all individuals with at least some post-secondary education. One concern about the non-Hispanic white population measure is that the definition encompasses both individuals born in the United States as well as those born in foreign countries; due to limitations in the ACS we are not able to construct measures of non-Hispanic white *citizens* by educational attainment. We are confident however that our measure of the non-Hispanic white population consists of nearly all native individuals; according to the 20010 ACS, about 96% of the non-Hispanic white population was born in the United States. Our preferred measure of the immigrant population is the number of non-citizens by birth, which captures all of the foreign-born population residing in a metropolitan area. For convenience, we refer to this measure as the foreign born population.[14] This population of non-citizens by birth can be decomposed into current non-citizens and naturalized citizens; we will use this decomposition to examine the robustness of our main findings.

Aggregate statistics from the ACS allow us to conduct our main analysis. In order to look at the impact of a net change in the foreign born population on other native outcomes of interest, it is necessary to supplement our main dataset with variables constructed from the individual-level ACS. We construct means at the MSA level for hourly wage and employment for the non-Hispanic white populations (both skill levels). Along with wage and employment data, we construct, by MSA, yearly inflows and outflows of the non-Hispanic white population in order to understand how yearly gross flows of the native population are affected by net changes in the foreign-born population. All of the variables constructed from the individual-level ACS datasets are only available for the years 2005-2010 due to the limitations in identifying MSAs in earlier years. A more detailed discussion of the variables constructed from the ACS microdata can be found in the data appendix.

A drawback to the ACS data is that we cannot examine the composition of the immigrant population by skill. Much of our analysis therefore focuses on impacts of undifferentiated immigrant inflows. We proxy for immigrant skill using information on English language ability in some specifications, to determine whether skill-specific inflows have differential effects on high and low skill natives. In 2005, county level identifiers are released with the public use microdata. We can therefore construct immigrant

[14] In actuality this measure excludes US natives born abroad or at sea.

inflows by skill group for this period. We do not have the first stage power to estimate all our preferred models on this subset of the data alone, but we do perform robustness checks that indicate our skill proxies are working well, particularly for high skilled natives.

Finally, although we have argued that the higher frequency of our data is an advantage, we have considered the possibility that annual data might not be exactly the right level for analysis. In particular, we are sensitive to concerns raised in Baker, Benjamin, and Stanger (1999) that the underlying relationships of interest in the labor market may unfold over a period of years, such that year-to-year correlations are not informative. This is more of a concern in cases where the short run relationships are statistically insignificant, like the minimum wage literature examined by Baker et al. In our case, we adopt their approach to determine whether the relationships we uncover in year-to-year changes are similar when using cyclical variation at somewhat lower frequencies. Specifically, we have repeated our analysis using data filtered to remove variation above and below the 2-4 year window. Using a bandpass filtering method proposed by Corbae, Ouliaris and Phillips (2002), we filter out longer and shorter term cyclical variation and repeat our main analysis using the remaining trend data.[15] Our results using filtered data are qualitatively the same as when we use our unfiltered data. We take this as evidence that our conclusions are not sensitive to using higher frequency annual data as opposed to cycles in the data at the underlying 2-4 year frequency.

IV. Results

A. Correlations from the ACS

We first present correlations between current year net changes in immigrant and native populations estimated from Equation (3). For comparison, we also present results from three alternative specifications. The first is a univariate regression that omits all fixed effects; the second is Equation (2), which omits the region-year fixed effects and includes only the MSA specific trends; and the third is an augmented version of

[15] Using the method from Corbae, Ouliaris, and Phillips (2002) we filter our data using the Couliari filter in Stata. We select a bandwidth of 4 to 8 years for our filter which we feel represents long term cyclical variation in our data (recall our data covers 10 years).

Equation (3) that includes direct controls for local labor demand shocks based on the methodology developed in Bartik (1991).[16] Results are presented in Table 2. The top column heading indicates whether population changes in the regressions are in levels or normalized by initial population in 2000. The second column heading denotes which of the three native population measures *N* is used to construct the dependent variable. The rows of the table report coefficients on ΔM_t from several specifications. We report robust standard errors clustered at the MSA level.

The first row of Table 2 shows that the raw correlations between concurrent annual changes in the foreign born population and our native population measures are all positive and statistically significant. The magnitudes are also economically important. A one-person net increase in the foreign born population is associated with a 0.43 person increase in the high skilled white population, a 0.24 person increase in the low skilled white population, and a 1.3 person increase in the total native born population. The pattern and magnitudes of the correlations in the normalized specifications are very similar. The next two rows show that adding our panel data fixed effects does little to reduce these correlations, particularly for the high and low skilled whites. However, R-squared values increase noticeably with the addition of both the MSA time trends and the region-year fixed effects, indicating that both are important predictors of native population changes. The fourth row shows that these correlations are robust to adding direct controls for local labor demand shocks. In fact, the point estimates become *more* positive. Again, the R-squared terms are higher than in the simpler specification in row 3. This indicates that local demand shocks are predictive of native population changes, but, it is clear that short-run demand shocks are not driving the observed correlations. We therefore continue with Equation 3 as our preferred specification, since limitations to the construction of the demand shock measures prevent us from observing them in all years of our data, as is apparent by comparing samples sizes in the column headed "N" across specifications.

Although we are primarily interested in short-run changes, there are reasons to think that the current year is too short a window for observing native population responses to immigrant inflows. If moving is

[16] See the online appendix on constructing MSA level labor demand shocks for more detail on their construction.

sufficiently costly and information about immigrant inflows is sufficiently slow to diffuse, then some natives may not respond to local immigrant inflows in the concurrent period. Instead, such adjustments may only happen with a lag. We explore the role of one-year lead and one-year lagged immigrant inflows in the final two specifications of Table 2. This allows us to begin to examine how the dynamics of immigrant inflows relate to native population changes. When lead or lagged immigrant inflows are added to the full model, the correlations between current year immigrant and native population changes are little affected. If anything, the positive relationships between current period changes are stronger after the lead or lagged controls are added. These specifications also show that the lead or lagged inflows are sometimes related to current period native population increases, although not as consistently as are the concurrent inflows. Lagged inflows have a stronger relationship with changes in the low skilled white population. Again, the correlation is positive, indicating that lagged immigrant inflows are associated with increases in the low skilled white population at an order of magnitude that is roughly half as large as the correlation between current period inflows and low skilled white population increase. The same is true of the all natives group.

In interpreting the results from the bottom two specifications in Table 2, it is important to consider that the reference period is not uniform across all ACS respondents. Specifically, the ACS is rolled out across locations over a 12-month period. As aresult, MSA populations are measured at intervals of roughly 12 to 24 months, so the concurrent period delta is more correctly interpreted as a change over a 12-24 month period. It is therefore possible that the calendar years involved in the concurrent change for one MSA overlap with the calendar years of the lagged change for another MSA.[17] This prevents us from making a clean distinction between the concurrent and lagged periods in our data. We therefore consider the results from the full model plus the lead or lag to be useful robustness checks, but we use the model regressing native population change on concurrent period immigrant population changes as our preferred specification.

With that caveat in mind, it is interesting to see that immigrant inflows and native population change are correlated at the concurrent period level. These relationships are not causal, but they underscore the fact

[17] For a more detailed explanation of regarding the survey structure of the ACS please refer to the ACS Design and Methodology document created by the US Census Bureau (2009).

that even within the space of about a year, considerable population change is possible in a metropolitan area. Finding that changes in these populations are correlated at this relatively high frequency motivates us to examine the causality of the annual level relationships.

B. Instrumental Variables First Stage Analysis and Specification Selection

While the correlations in year-to-year population changes for immigrants and natives are new and interesting, they highlight the need for an instrumental variables approach. In particular, if immigrants and natives are attracted to cities because of time-varying unobserved labor demand shocks, this will lead to upward bias in the OLS estimates, even in the full model. We were able to add controls for short-run labor demand shocks, but concerns remain that these may not fully capture demand changes that affect immigrant and native location choices. To assess the causality of the relationships in Table 2, we use our updated version of an instrumental variables approach that has been used widely in the previous literature, called the supply-push IV (SPIV).

As discussed in Section II, both our empirical specification and our construction of the SPIV differ somewhat from the literature. To get a sense of whether and how the changes in our approach might matter for our estimates as compared to those in previous research, we estimate a variety of additional first stage specifications for the SPIV. First, we estimate first stage specifications in which the SPIV *includes* the MSA's own contribution to US immigrant population growth, as has been done in much of the previous research, and compare these estimates to those using our preferred SPIV construction, which excludes the MSA's contribution. Second, we estimate specifications using both the levels change and normalized versions of the population variables. Third, we gradually build up to our preferred specification, which includes both MSA specific time trends and region-year effects. Finally, we estimate our preferred specification on a subset of our data, to examine robustness of the first stage across different time periods and panel lengths.

The results of this analysis are reported in Table 3. Each cell in Table 3 reports the coefficient on the SPIV in a regression with actual immigrant inflows (ΔM_t) on the left hand side. The first stage F-statistic appears below the coefficient, in brackets. The first four rows of the table use the full data panel, and we discuss those estimates first. Comparing results in which the own MSA contribution is included versus excluded, it is obvious that including the contribution generates higher first stage coefficients, particularly in the normalized specifications. This will have two effects. First, it may reduce the IV estimates, which are just the ratio of the reduced form over the first stage. Second, it will tend to generate more statistically significant first stage relationships, since the coefficients of interest are larger because the endogenous immigrant inflow is itself a component of the IV in this case. Because of this second effect, we prefer the SPIV that excludes the MSA's own contribution, as defined in Equation 4.[18]

Comparing across various first stage specifications (down the first four rows), we see that first stage coefficients in the normalized specification are also much more sensitive to the inclusion of the panel controls. Including the MSA time trends raises the coefficient in the normalized specification, while including the region-year effects greatly reduces it. The first stage coefficients in the levels specifications are little affected by the inclusion of either set of controls.[19] Importantly, the first stage in our preferred, full specification is not statistically significant in the normalized specification when the MSA's own contribution to immigrant inflows is excluded (F of 3.8). The first stage of the normalized specification also fails when measures of local demand shocks are included, regardless of whether the MSA's own contribution is included (F of 4.3) or not (F of 1.3). When demand shock measures are added to the full model in the levels change specifications, both F statistics remain above conventionally acceptable levels.

The bottom half of Table 3 examines the sensitivity of our first stage estimates to restrictions to the length and years of the panel. Removing years of data should reduce precision of the estimates, resulting in lower F-statistics. This pattern holds in the levels specification. As we limit the data by starting the panel in 2003, then 2005, 2006, and finally 2008, F-statistics and the first stage coefficient fall almost monotonically. The normalized specification, on the other hand, deviates from the expected patterns. As data years are dropped, the first stage coefficients *rise* and F-statistics are stable or rising. The bottom row of Table 3

[18] In unreported results, we observed that using base period updating to construct the SPIV's led to much larger differences between the included and excluded versions. In several cases the differences were statistically significant.

[19] The F-statistics in both specifications show that the addition of these controls in important for the precision of the relationship between the instrument and the actual inflow.

presents results using only the earliest and latest years of our data for which it is possible to run the full specification. This is a rough approximation to Census data, which is collected at decadal frequencies. Again, the first stage coefficient in the normalized specification is much larger than in the full panel using both the included and excluded versions of the IV. In the levels version, the first stage is smaller than in the full panel and insignificant using the excluded IV.

Each of our adjustments to the literature's previous specifications makes some difference in the first stage relationship between predicted and actual immigrant inflows. We prefer to exclude an MSA's own contribution to US immigrant population growth from the instrument because this contribution is unlikely to be exogenous to local labor demand conditions. However, after excluding this component and removing variation by normalizing all population change variables, the first stage in our full model is no longer sufficiently powerful to justify the use of the IV in standard 2SLS estimation.

Our analysis of the various first stage estimates has led us to prefer the levels change specifications – provided appropriate controls for MSA size are included – for several reasons in addition to those discussed in Section II. First, normalizing removes a good deal of variation from the data and redistributes noise in the remaining variation from large cities to small ones. We suspect this is why the normalized specification cannot support the inclusion of a number of panel data controls that seem important a priori.[20] Second, the behavior of the normalized first stage across the full and restricted versions of the data is counterintuitive. Patterns in the bottom half of Table 3 heighten our concern that normalizing just moves noise in the data to the smaller MSA observations that are more sensitive to it, rather than "correcting" the data for city size differences.[21] The patterns also suggest that the MSA's own contribution to total US inflows becomes a more important driver of the first stage relationship in the normalized specification as data is removed. This is disturbing. The Table 3 results suggest that in settings where panel length is limited, identification in the

[20] We do not think this is because the normalized specification eliminates the need for such controls. Year effects are certainly still important to allow for, even when population variables have been normalized by initial city size.

[21] We have examined this assertion quantitatively. We find that the mean and variance of the normalized population changes are still correlated, only negatively, indicating that cities with smaller mean population changes in percentage terms (of the 2000 base) have more variance in these changes. Also, the variance in normalized population changes is significantly negatively correlated with initial city size. The differential impact of measurement error across city sizes is also the subject of Aydemir and Borjas' (2011) analysis.

normalized specification is largely driven by correlation between a city's own contribution to US immigrant inflows and the immigrant population being predicted.

Because of these concerns, we use the levels change specification with our preferred set of fixed effects as our main model. We do, however, take several steps (beyond the inclusion of MSA time trends to control for initial and subsequent population size) to limit concerns raised earlier in the literature about the use of the levels specification. First, as described above, we omit the five largest cities from our sample.[22] This has little impact on the first stage results, rather than weakening them as might be expected if large population changes in the largest cities were driving the correlations in regressions where population changes entered as levels. As Table 1 shows, this refinement has a large impact on the relationship between the mean and the variance in our data, reducing the standard deviation of mean city size from 1.5 times the mean to a little under the mean.

Second, all of our analysis is unweighted. This again reduces concerns that the changes in the largest cities are disproportionately influencing the results.[23] Finally, we note that our specification includes MSA-specific time trends. We expect that if large cities have large population changes due solely to their size, then the inclusion of these fixed effects will absorb any fixed or linearly time-varying components of the correlation between changes in immigrant and native populations, such as those due to initial city size.

C. Instrumental Variables Results and Robustness Checks

The first three columns of Table 4 present our main IV results. We show results for the same three native populations as in earlier tables. Note that in this table and those that follow, we present F-statistics adjusted for multiple endogenous variables as recommended by Angrist and Pischke (2009, Ch. 4). The first row shows the IV estimates of Equation 4. For low-skilled whites, the IV estimates are very similar to OLS. An increase of one immigrant in the current year leads to a 0.42 increase in the number of low-skilled whites in the current year. By contrast, the IV estimates for high skilled whites and all natives (citizens by birth)

[22] Note that although the largest portions of these MSAs are excluded from our sample, some smaller but separate MSAs in the same areas as the top five are still included. For example, although Los Angeles-Long Beach PMSA is excluded, the Orange County PMSA remains in our data set.
[23] However, Card (2001) notes that weighted estimation is likely to be more efficient in this setting.

differ markedly from OLS in the full model. For all natives, the effect of immigrant inflows is insignificant, as opposed to the greater than one increase in the OLS correlations. For high skilled whites, the point estimate is negative and significant, instead of positive and insignificant as in the OLS. The IV estimates show that immigrant inflows lead to a decline in high skilled white population of about one native for every three additional immigrants.

Results in the bottom two panels show that the IV impacts of concurrent immigrant inflows are robust to instrumenting for the lead and lagged inflows. The IV results in the lead specifications are of further interest because they provide evidence against an alternative explanation for a negative relationship between native wages and immigrant inflows locally. This explanation hypothesizes that immigrants move to areas that natives are already fleeing, perhaps because immigrants are attracted by the low cost of housing or are not dissuaded by the undesirable jobs that remain in such areas.[24] In this case, the predicted sign on lead immigrant inflows is negative. The sign on the lead inflow is negative for low skilled natives, but it is insignificant, so we consider the evidence for this alternative hypothesis weak.

The differences between our IV and OLS estimates in the first three columns of Table 4 make sense given our concerns about possible omitted variables bias in OLS. All of the IV point estimates in Table 4 are smaller than or statistically indistinguishable from their OLS counterparts. If both immigrants and natives respond to MSA-level demand shocks not captured by our fixed effects controls, the OLS estimates would be upward biased. Our IV approach is designed to remove this bias, so we expect the IV estimates to be smaller. Moreover, for high skilled whites, the signs on the IV coefficients for both current and lagged immigrant inflows reverse from OLS. This suggests that our identification strategy purges immigrant inflows of correlation the raw data may have with general local labor supply increases. Finally, the effect of lead immigrant inflows is insignificant in the IV specifications (the lead was a significant predictor of increases in the all citizens group in OLS). This mitigates concerns that serially correlated local demand shocks are retained in the predicted immigrant inflows.

[24] See Jaeger (2000) for evidence on this.

While we these differences provide some reassurance that our IV strategy is working as advertised, we nevertheless perform a number of robustness checks. In unreported results, we verified that the estimates in Table 4 are robust to the inclusion of the labor demand shock control.[25] We also verified that dropping the concurrent period inflow has little effect on estimates on either the lead or the lag terms. It therefore appears that the concurrent period inflow is the most relevant for the changes we observe. The first of our checks that we report appears in the last three columns of Table 4. Here we repeat our IV analysis using only the second half of our data. This reduces concerns about serially correlated local demand shocks that may be related to the share of immigrants going to an MSA in 2000 (which is part of our instrument) driving subsequent increases in both native and immigrant populations. The substantive results are unchanged.[26] We have also conducted a variety of robustness checks on our results. These fall into two categories: changes to the way the SPIV is constructed and other changes to the specification, variables, or sample. The results of these analyses are detailed in the Robustness Check Appendix. In short, we find that our main IV results are robust to the six alternatives we explore, and we therefore have a high degree of confidence in our main results.

Researchers who have looked for native migration responses to immigrant inflows based on net population changes over 5- or 10-year periods typically find that immigrant inflows do not affect metropolitan area native populations. Estimates produced in our analysis, which focus on short-run native migration responses, are not directly comparable to previous studies in the literature. Instead, we modify our data and re-estimate our main model to allow comparison of our results to those from earlier, Census-based studies. We construct a set of long-run net population changes in both native and immigrant populations that is similar to 5-year changes constructed from Census data and re-estimate our main specifications using the long-changes in place of our one-year changes. We again experiment with several specifications to assess the sensitivity of our results to specification choice. The results are in Table 5. We use three sets of long-

[25] This increases our standard errors but tends to make the effects we identify slightly larger in absolute terms.
[26] We have insufficient first stage power to estimate the specification only on the first half of our data, which would allow us to examine whether our overall estimates are affected by the macroeconomic changes occurring in the US economy in the second half of the 2000s.

changes. We first show results from two normalized specifications, as these are the most similar to other estimates in the literature. In particular, Panel A is the same as the main specification estimated in Card (2001) and is similar to that in Borjas (2006). Panel B is our preferred specification, and Panel C is the same as Panel B but omits the MSA time trends to improve first stage power. Overall, the results are quite different from the short-run changes identified in Table 4. For high skill natives, the IV impacts are positive and significant across the specifications, in contrast to negative and significant short-run responses. For low skill natives, the IV impacts are insignificant in Panels A and B and negative in Panel C. Again, this is in contrast to the positive and significant short-run impacts. Although the results are somewhat imprecise, Table 5 suggests to us that our short-run estimates are consistent with the longer-run estimates produced in earlier literature in the sense that using short-run changes (if available) will give our estimates while using longer- run changes will not. Instead, we find longer run changes in our preferred model that we consider to be broadly consistent with those in Card (2001) and Card and Dinardo (2000), although this conclusion is subject to the caveat that the first stage is weak in our data period. The longer-run changes identified in Panel C are – at least for low skill natives – broadly consistent with those in Borjas (2006). As we argued above and has been argued by others (Peri and Sparber 2011), this may indicate that some of the disagreement over longer-run impacts of immigration stem from different empirical specifications. It is not the aim of this paper to settle those disagreements. Instead, we emphasize that our short-run impacts are not artifacts of an unusual data set or data period. Rather, longer run estimates that approximate those in the literature can be obtained in our data subject to specification choice.

V. Mechanisms

We find robust evidence that an MSA's population of low skilled whites increases with immigrant inflow shocks. We also find evidence that the population of high skilled whites declines with these same shocks. These findings are somewhat surprising in light of the displacement model of labor market adjustment following a shock to local labor supply. However, our findings are less surprising in light of theories about how immigrant inflows impact segments of the local economy other than the labor market. Labor market competition is not the only channel through which immigrants affect local markets, and an increase in labor market competition may or may not discourage natives from residing in an MSA if other variables in the economy are not held constant. One channel through which immigrants may influence local economies – aside from direct labor market competition – is through impacts on employers' choice of inputs. For example, Lewis (2003, 2005) and Peri (2009) demonstrate a greater availability of low skilled jobs in immigrant-intensive markets suggesting that immigrant inflows might encourage employers to shift toward less skill-intensive technologies. These economies of scale in low-skill hiring might *attract* low skill natives in a manner consistent with our findings. Alternatively, immigrant inflows may *prevent* low skilled natives from leaving an affected area, thereby increasing native population size. How might this happen? One possibility is that immigrants could reduce out-migration if affected natives do not have sufficient access to credit or savings to move away after experiencing a negative wage, employment, or housing shock.[27]

Roughly, one can summarize these theories as the "attraction" explanation - in which immigrants make an area more appealing for low-skill natives- and the "entrapment" explanation – in which low skill natives are prevented from leaving an area following an immigrant inflow. In this section, we examine the evidence for these mechanisms in order to determine which best explains our findings. We look for clues in four areas. First, we examine whether the skill composition of immigrant inflows affects the native population response. This will tell us whether high skilled or low skilled immigrants are behind the effects found above. We then examine the composition of native responses by decomposing them into changes in inflows and outflows. This can tell us whether the changes we identify in our main results are driven by incumbent natives already in an MSA or by natives coming (or not coming) from other MSAs. Next, we test for differences across different types of MSAs in the size of the native response. Potentially, native

[27] Glaeser, Kahn and Rappaport (2008) suggest that low skill natives live in declining cities because low property values are attractive to them. If immigrants lower property values, this could also keep more natives from leaving. However, evidence in Saiz (2003, 2007) shows that immigrant inflows raise housing costs. If local wages do not increase alongside the inflow, then these inflows make remaining natives worse off.

responses vary with certain MSA characteristics that may provide clues to the mechanism driving our main findings. Finally, we look at the impact of immigrant inflows on native wages and employment.

We first examine the response of high and low skilled whites to immigrant inflow shocks disaggregated by immigrant skill. We divide the immigrant population into two skill groups based on English language ability: those who speak only English or speak it well or very well, and those who speak English not well or not at all.[28] There is evidence that English ability is a reasonable proxy for overall skill among immigrants (Bleakley and Chin 2008). We then re-estimate both OLS and IV versions of the full model from Tables 2 and 4, replacing the general immigrant inflow with the inflow from a specific language ability/skill group.

We report the results in Table 6. The OLS estimates show that, as before, increases in immigrant populations are associated with economically large increases in native populations from both skill groups. The IV results show important differences across the skill groups. The Table 6 results suggest the negative effect of immigrant inflows on the high skilled white population is driven by inflows of high skilled immigrants. The F in this specification is a robust 46.4. High skill immigrants also contribute to the increase in low skill native populations. The IV impacts of low skill immigrants on natives share the same sign as the impacts of high skilled immigrants – negative impacts on high skilled natives and positive impacts on low skill native populations – but neither is significant. However, the F-statistics indicate that we should view the IV results for the low skill immigrant inflows with caution, as the F in these specifications is only 3.5. It appears that our IV strategy is a weak predictor of low skill immigrant inflows in the second half of the 2000. The loss of data due to censoring (since the ACS suppresses reporting of non-native populations by English ability for many MSAs) also contributes to this. From Table 6, we conclude there is strong evidence of displacement effects of high skilled immigrants on high skilled natives, since the first stage for high

[28] Unfortunately, there is no aggregate ACS series for foreign born populations by educational attainment. Evidence from the 2009 ACS microdata suggests using limited English proficiency (LEP) is a good proxy for the high skilled immigrant population greater than 25 years of age. An immigrant is classified as LEP if she reports speaking English not at all or very poorly. Approximately 60% of English proficient immigrants are classified as high skill. Whereas only 16% of low English ability (LEP) immigrants are classified as high skill.

skilled immigrant inflows is strong.[29] Also, high skilled immigrants contribute to the increased populations of low skilled natives that come with immigrant inflows. We are more circumspect about the separate impacts of low skill immigrant inflows, as we do not have strong first stage power for identifying their effects.

We next examine the patterns in gross flows in our MSAs following an immigrant inflow shock. Analysis of the flows shows how the native population impacts of immigration arise. In addition, examining changes in gross flows is important for understanding whether the *sorting* of natives across metropolitan areas in the US is affected by immigration.[30] In Table 7, we report results using the Table 4 full model specification to estimate the impact of immigrant inflows on new dependent variables: gross population flows in and out of an MSA, total inflows, and total outflows. The top panel uses gross flows as the dependent variable. The IV results show significant differences between high skill whites and low skill whites. An additional immigrant in the current year increases the gross flow of high skilled whites by 0.87. In contrast, an additional immigrant reduces the gross flow of low skilled whites in an MSA by 0.56. As with our earlier estimates, OLS and IV estimates differ markedly in Table 7. However, in contrast to the case of net population changes, there is no theoretical reason to suppose that the coefficients on *flows* are upward biased when estimated via OLS. The OLS estimates of the relationship between flows of high skilled whites and immigrant inflows are insignificant and much smaller in magnitude than the positive impacts estimated by IV. OLS estimates for the low skilled are generally of the same sign as the IV estimates but again much smaller in magnitude.

The next two panels examine the impact of immigrant inflows on the two components of the gross flow: total inflows to and outflows from an MSA. Again, the results differ across skill groups. For both native skill groups, we find that the impact of immigrants on gross flows is accounted for almost entirely by

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[29] We find the same impact of high skill immigrants on high skill natives when we use direct measures of immigrant inflows by skill group, constructed from the microdata for 2006-2010. However, because the IV strategy performs even more poorly for low skill immigrants in this subset of the data, we prefer the estimates in Table 6 which trades a proxy for skill for longer panel length.

[30] Saiz (2007) makes a similar point in his analysis of the impact of immigrant inflows on housing prices, noting that immigrants can affect housing prices with no net change in the native population if immigrants affect the composition of the native population either within or across skill groups.

changes in outflows. Therefore the increase in low skill native populations following an immigrant inflow seems to be explained by short-run declines in outflows of these natives.[31] For high skill natives, the declines in their local populations seem to be explained by increased outflows from affected cities.

The flows analysis shows very different routes to the net impacts observed in our main results across high and low skill workers. Increased outflows of high skilled natives are consistent with the negative net population impacts observed for this group. However, the declining outflows of low skilled natives – while consistent with the observed net impacts – remain puzzling. To try to understand this result, we divide our sample along various MSA characteristics. Perhaps the low skill native population responses differ across MSAs in a way that might shed light on the mechanisms driving the short-run increases in their populations. Our sample size is limited in the period for which we can construct population flows from the microdata. Therefore any analysis that relies on interactions with the immigrant inflow variable (with city characteristics, in this case) is very imprecise. Instead of examining how our results in the flows analysis of Table 7 differ with city characteristics, we go back to the specifications and sample for our main results in Table 4. We interact the immigrant inflow variable with various city characteristics to see how our main results vary across city types. Since our Table 4 results map well to the Table 7 results, we feel this is a reasonable approach to understanding both the net and gross population impacts.

Table 8 contains the first set of these results. Here, we examine whether our main IV results differ across MSAs that are geographically isolated versus those that are not. We use two different distances to define geographic isolation: having no other MSA in the sample within 50 miles and no other MSA within 75 miles.[32] The middle panels of Table 1 show that isolated and non-isolated MSAs differ along other dimensions. The isolated MSAs are smaller on average, although they are not uniformly small (the max sizes are similar in the two groups). The foreign born also tend to constitute a smaller share of the population in

[31] It is possible that this discourages immigrant inflows in subsequent periods, since Cadena (2010) finds large negative effects of increases in local native labor supply on immigrant inflows.
[32] Our data contain only a subsample of all MSAs in the United States. It is possible, therefore, that we may misclassify an MSA as isolated if its nearby MSA is not in our data. We think this type of misclassification is unlikely to be severe, since most MSAs added to the ACS after 2004 tended to be sub-units of very large urbanized areas with many MSAs nearby.

isolated MSAs, although it is clear that many of the isolated cities still have substantial immigrant populations as the mean share is roughly 9%. Isolated cities are more likely to be found in the South (excluding Florida), Midwest, and inter-mountain West. Non-isolated cities are more likely to be in Florida, the Northeast, or on the West Coast. We interact the immigrant inflow in our main IV specification with a dummy variable for having another MSA within 50 (or 75) miles. We instrument for the additional interaction term accordingly.

We present the results using the 50-mile cutoff in Panel (i). Using this definition, both instruments have acceptably high F-statistics. (See the table notes for details.) We find differences across isolated and non-isolated MSAs, particularly for the groups of low skill whites and all natives. The estimates in Panel (i) show that the increases in the low skill white and all native populations following immigrant inflows are muted in non-isolated MSAs, with immigrant inflows increasing the low skill native population by less and decreasing the high skill population by less than in isolated MSAs. This suggests that isolated MSAs are the ones driving most of the population changes we find following immigrant inflow shocks in our main IV specifications. Panel (ii) shows that the differences in the impact of immigrant inflows on low skill whites across isolated and non-isolated MSAs are even larger using the 75-mile cutoff.[33]

In Table 9, we perform a similar analysis decomposing our sample across cities classified as "declining" versus not, where declining is defined as being below a fixed percentile cutoff for native population growth in the five years immediately preceding our data period. As with the geographic isolation measure, we use two cutoffs: below median growth and bottom quartile growth. The results are shown in Table 9. The analysis indicates that our main results are not sensitive to whether the affected MSA is declining or not. As in Table 8, the main effects of immigrant inflows in Table 9 are similar in sign, magnitude, and significance to those in Table 4. However, the interactions with declining city indicate that these impacts are the same or larger in magnitude in declining cities, whereas results in Table 8 show that our main results are attenuated in isolated cities. We repeated the same exercise allowing the impact of

[33] In unreported estimates, we show that these results are robust to using state-year effects in place of region-year effects, to account for some of the geographic clustering of the two types of cities.

immigrant inflows to differ along city size lines. The results are very similar to those in Table 8. In other words, the short-run impacts of immigrant inflows on native populations are attenuated in both larger and less isolated MSAs.[34]

Lastly, we examine the impacts of our immigrant inflow shocks on the labor market outcomes of natives. Unfortunately, the ACS data in these years is not ideal for examining labor market outcomes. As with the gross flows, we lose half our sample years since we need to use the public microdata to construct individual wages. Furthermore, for several of the remaining years, hours of work are only available in binned form, which adds significant measurement error to our wage measure. See the data appendix for more details.

Nevertheless, we construct wages and employment measures for individuals in our sample MSAs to the best of our ability and create cell averages to mirror those in the aggregate data. We report our estimates of the wage and employment impacts of immigrants in Table 10, using the change in cell average wages or cell employment as our dependent variables in our preferred specifications. To be consistent with a local CRTS production function, we use normalized versions of the immigrant inflow shocks.[35] Again, we show both OLS and IV estimates but focus our discussion on the IV estimates. We find weak evidence of negative wage impacts of immigrant inflows on low skill native wages. Ultimately, however, estimates are very noisy and we cannot reject that the effects of immigrant inflows on wages and employment is zero for both groups.

VI. Conclusions and Implications

For roughly thirty years, economists have debated the impact of immigration on native labor market outcomes. This paper brings a useful new dataset to bear on these questions: annual population data on

[34] In unreported results, we show that this is not solely due to a correlation between isolation and city size. The impact of immigrants on low skill natives in isolated cities is similar across large and small MSAs (defined as above or below median in terms of 2000 population), and similar to those reported in Table 7. For high skilled natives, the Table 7 difference between isolated and non-isolated MSAs also appears within the group of large cities, but not in small ones.

[35] Our results are not sensitive to using the levels measure of immigrant inflows, although it complicates the interpretation of the coefficients. Also note that for the subset of years on which we estimate the wage equations, we have acceptable first stage power, as shown in the bottom panel of Table 3.

more than 140 metropolitan areas from the aggregate statistics of the American Community Survey for the period 2000-2010. Ours is the first paper to examine the impact of immigration on short-run population changes and labor market outcomes at the local labor market level.

This new perspective provides a number of important insights. First, we show that a common combination of instrumental variables and estimating equations in the previous literature is not robust to the inclusion of the richer panel data controls made possible by annual metropolitan area level data. This raises questions about earlier conclusions based on this empirical combination. Second, we show that immigrant inflows to a metropolitan area are strongly positively correlated with native population increases at annual frequencies. Specifically, populations of all natives, low skill whites, and high skill whites all increase substantially alongside or in the year following an immigrant inflow. Third, using an improved instrumental variables technique and more robust empirical specifications than in previous studies, we show that the OLS correlations are generally upward biased. The causal impact of immigrant inflows on the high skilled native population is weakly negative, with our main estimates of the net decline ranging over -0.3 to -0.6 high skill natives for each additional immigrant. The arrival of an additional immigrant leads to an increase of 0.4 to 0.65 low skill natives in the same year, which is similar to the OLS relationship.

The fact that we still estimate a positive effect of immigrant inflows on low skilled native populations after instrumenting is initially puzzling and contradicts the displacement hypothesis of the labor economics literature. However, we do not conclude that spatial displacement is not important. We find direct evidence in favor of the displacement hypothesis for high skilled whites, a group that is more geographically mobile than low skilled whites. Specifically, we find that inflows of high skilled immigrants drive the negative impacts of immigrant inflows more generally on the high skilled white population, and we find that immigrant inflow shocks significantly increase total outflows of high skilled natives from affected MSAs. In the case of high skilled natives, we conclude that displacement by high skilled immigrants is quantitatively important and occurs in the short-run. In this sense, our findings for this group are consistent with findings in Borjas (2006). Borjas' study uses decadal Census data and therefore his estimates reflect longer-run adjustments, but as in the case of high skilled natives in our paper, he finds significant displacement of natives alongside inflows of immigrants in the same skill group.[36]

The story for low skilled natives is quite different. We show that our results for low skilled native populations are driven by decreased outflows from affected MSAs rather than increased inflows of natives from other areas. We further show that our main results are attenuated in larger and less geographically isolated MSAs, but not in "booming" MSAs, defined as those with population growth in the upper quartiles. Finally, we find no evidence that labor market outcomes improve for low skill natives in the short run as a result of an immigrant inflow. Together, these results suggest to us that low skill natives are temporarily "trapped" by immigrant inflows. We hypothesize that immigrant inflows provide a negative short-run shock that causes outward mobility for the less skilled to decline temporarily. The impact is largest in cities that are more costly to move from – specifically, isolated cities, which entail a longer distance move to reach a new labor market, and smaller cities, which have lower housing costs than large ones and therefore entail a negative housing price shock for outmigrants. These costs may disproportionately affect low skill natives.

It is important to remember that our estimates are short-run impacts. We show that our results are consistent with other analyses of the impact of immigrant inflows on local population change in the sense that by using longer-period changes in our data, we obtain estimates similar to those in other studies using longer-run changes in earlier decades. Our findings show very different short-run relationships, suggesting that data at longer intervals obscure important dynamics in the native location adjustment process. Although our short-run impacts for high skilled natives are similar to those Borjas (2006) finds for all skill groups in the longer-run, our short-run findings for low skill natives differ from his findings. In sum, our short-run findings do not match any of the available studies on the longer-run impacts of immigrants on population adjustment.[37] Future research should explore these short-run adjustment processes in more detail, as soon as adequate data are available for the analysis.

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[36] Peri and Sparber (2011) have demonstrated that the analysis in Borjas (2006) may suffer from division bias that favors finding displacement. Our specification was chosen to avoid this bias.

[37] Including older studies by Filer (1992), Frey (1995), and Borjas, Freeman and Katz (1997).

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Table 1. Statistics from the MSA-Level ACS Data

Variable	N	Mean	Std. Dev.	Min	Max
Estimating Sample: MSAs observed in ACS 2000 omitting 5 largest					
Citizens by birth	1584	847.86	739.96	107.42	4763.33
Not a citizen by birth	1584	134.15	212.79	3.14	1302.21
… current non-citizen	1584	77.52	124.43	0.89	846.32
Abroad 1 year ago	1557	6.91	9.15	0.00	67.29
High skilled non-Hispanic whites†	1584	274.11	254.03	19.59	1726.89
Low skilled non-Hispanic whites†	1584	167.37	137.33	10.61	852.10
Years in data set	1584	11.00	0.00	11.00	11.00
Population Size in 2000	1584	906.36	800.56	252.15	4105.45
Rank by Population in 2000	1584	77.81	42.01	6.00	151.00
Subsample: MSAs where next MSA <= 50 miles (non-isolated)					
Citizens by birth	770	944.0	806.4	107.4	4104.1
Not a citizen by birth	770	204.1	267.2	3.21	1302.2
Total population in 2000	770	1060.1	901.9	262.0	4105.4
Subsample: MSAs where next MSA > 50 miles (isolated)					
Citizens by birth	792	750.4	657.2	215.3	4763.3
Not a citizen by birth	792	65.7	106.8	3.1	728.4
Total population in 2000	792	754.5	657.7	252.1	4036.6
Total MSA Population Size in 2000					
All MSAs observed in 2000	1639	1116.8	1429.6	252.1	9344.1
… 5 largest MSAs excluded	1584	906.4	800.6	252.1	4105.4
… 10 largest MSAs excluded	1529	808.8	620.0	252.1	4105.4
… 25 largest MSAs excluded	1364	634.7	367.0	252.1	1652.9

Notes: Data collected by the authors from the U.S. Census Bureau's American FactFinder. Data are published MSA-level statistics from the 2000-2010 American Community Surveys. Restricted to MSAs with eight or more years of annual observations. Appendix 1 and Appendix 2 detail the included MSAs and additional MSA-level population totals in the data. † indicates that this population total was constructed by the authors from ACS provided totals.

Table 2. OLS models of change in native population vs. change in immigrant population

Population specification:	**Levels change**			**Normalized change**			**N**
Native population N_t:	**High skill NH whites**	**Low skill NH whites**	**All citizens by birth**	**Low skill NH whites**	**High skill NH whites**	**All citizens by birth**	
No Controls							1440
ΔM_t	0.43	0.24	1.27	0.32	0.23	0.75	
	(0.15)***	(0.09)**	(0.43)***	(0.08)***	(0.06)***	(0.41)*	
R-sq	0.15	0.07	0.16	0.06	0.04	0.05	
MSA Time Trend Only							1440
ΔM_t	0.40	0.32	0.97	0.32	0.23	0.62	
	(0.16)**	(0.12)**	(0.55)*	(0.09)	(0.06)***	(0.43)***	
R-sq	0.25	0.15	0.25	0.16	0.09	0.17	
Full Model (MSA Trend + Region-Year Effects)							1440
ΔM_t	0.44	0.30	0.97	0.35	0.19	0.59	
	(0.16)***	(0.11)**	(0.56)*	(0.08)***	(0.06)***	(0.46)	
R-sq	0.32	0.26	0.30	0.23	0.19	0.22	
Full Model plus Direct Controls for Labor Demand Shocks							1152
ΔM_t	0.50	0.34	1.19	0.39	0.24	0.81	
	(0.19)**	(0.13)**	(0.64)*	(0.09)***	(0.07)***	(0.51)	
R-sq	0.39	0.30	0.36	0.26	0.23	0.26	
Full Model plus Lag							1296
ΔM_t	0.50	0.37	1.32	0.40	0.25	0.92	
	(0.18)**	(0.13)**	(0.60)**	(0.10)***	(0.07)***	(0.49)*	
ΔM_{t-1}	0.06	0.18	0.64	0.06	0.07	0.40	
	(0.06)	(0.06)**	(0.25)**	(0.04)	(0.04)*	(0.09)***	
R-sq	0.34	0.30	0.34	0.25	0.22	0.25	
Full Model plus Lead							1296
ΔM_{t+1}	0.03	0.06	0.33	0.09	0.07	0.48	
	(0.04)	(0.03)**	(0.07)***	(0.03)**	(0.03)**	(0.11)***	
ΔM_t	0.46	0.33	1.08	0.39	0.23	0.79	
	(0.18)**	(0.13)**	(0.61)*	(0.09)***	(0.07)***	(0.52)	
R-sq	0.38	0.27	0.34	0.24	0.21	0.25	

Notes: Data collected by the authors from the MSA-level population estimates of the American Community Surveys, 2000-2010. Immigrant population M is all non-citizens by birth. Region-year effects are the set of year interactions with the four main geographic regions of the US. Normalized levels change divides all population levels change variables by MSA population in 2000. Robust standard errors clustered at the MSA level reported in brackets. * indicates significance at the 10% level; ** 5%; *** 1%.

Table 3. Single Equation First Stage Estimates: Predicting MSA Level Changes in Non-Citizens

Population change specification:	Levels Change		Normalized levels change	
MSA's own contribution to US immigrant change:	**Excluded**	**Included**	**Excluded**	**Included**
ANNUAL PANEL 2001-2010				
No Controls	0.88 [29.5]	0.90 [31.2]	0.72 [35.7]	0.76 [44.4]
MSA Time Trends Only	0.88 [36.0]	0.96 [39.7]	0.95 [30.8]	1.04 [41.2]
Region-Year FEs Only	0.87 [25.2]	0.89 [26.7]	0.57 [25.4]	0.63 [32.8]
Full Model	0.80 [22.8]	0.91 [26.1]	0.52 [3.8]	0.77 [9.6]
Full Model plus local demand	0.82 [11.2]	0.92 [13.0]	0.31 [1.3]	0.55 [4.3]
PARTIAL PANEL				
2003-2010	0.82 [28.7]	0.92 [31.1]	0.58 [4.4]	0.80 [11.1]
2005-2010	0.79 [19.0]	0.86 [21.4]	0.61 [4.6]	0.78 [9.9]
2006-2010	0.73 [20.8]	0.75 [23.3]	0.85 [13.0]	0.90 [14.7]
2008-2010	0.60 [3.1]	0.64 [4.0]	1.32 [7.75]	1.38 [8.9]
2001-2005	1.03 [4.0]	1.41 [6.5]	-0.27 [0.16]	0.53 [0.84]
2001 & 2010 Only	0.41 [0.05]	1.40 [0.67]	1.24 [0.07]	3.74 [0.55]

Notes: Data collected by the authors from the MSA-level population estimates of the American Community Surveys, 2000-2010. Cells report coefficients from a regression of the change in the current non-citizens population on predicted change plus included controls. The first stage F-statistic is in brackets. "Excluded" specifications remove an MSA's own change in immigrant population from the US increase over the period used to form the prediction, as in Equation (4). "Included" specifications do not. Normalized levels change divides levels change in immigrant and native populations by total MSA population in 2000. Region-year FE specifications include full set of year and region (4) x year fixed effects. Standard errors clustered on MSA are unreported.

Table 4. Instrumental Variables Estimates

Data Years:	Full Panel			2005-2010 Only		
Dependent variable:	**High skill NH Whites**	**Low skill NH Whites**	**Citizens by birth**	**High skill NH Whites**	**Low skill NH Whites**	**Citizens by birth**
Full Model						
	-0.38 (0.12)***	0.42 (0.15)***	0.47 (0.40)	-0.58 (0.20)***	0.65 (0.18)***	0.56 (0.50)
		F=22.8			*F*=19.0	
Full Model plus Lag						
ΔM_t	-0.32 (0.14)**	0.34 (0.18)*	0.37 (0.43)	-0.56 (0.20)***	0.50 (0.18)***	0.29 (0.44)
ΔM_{t-1}	-0.12 ((0.16)	0.26 (0.11)**	0.15 (0.24)	-0.03 (0.16)	0.22 (0.12)*	0.42 (0.29)
	F on ΔM_t =39.5, F on ΔM_{t-1}= 17.9			F on ΔM_t =,28.1 F on ΔM_{t-1}= 12.5		
Full Model plus Lead						
ΔM_{t+1}	0.25 (0.25)	-0.19 (0.13)	0.08 (0.54)	0.47 (0.39)	-0.29 (0.25)	-0.25 (0.89)
ΔM_t	-0.14 (0.15)	0.54 (0.17)***	1.06 (0.49)**	-0.20 (0.24)	0.87 (0.21)***	1.44 (0.68)**
	F on ΔM_{t+1} = 39.5, F on ΔM_t= 17.9			F on ΔM_{t+1} = 16.8, F on ΔM_t= 12.1		

Notes: Data collected by the authors from the MSA-level population estimates of the American Community Surveys, 2000-2010. Endogenous variable is levels change in non-citizens by birth. Cells report coefficients from a 2SLS estimation of the impact of the change in the current non-citizens population on listed native populations. Instrument is the "excluded" version of the levels change in Table 3. All specifications include the full set of year and region (4) x year fixed effects. N is 1440 in full model specification using full panel. Robust standard errors clustered on MSA in parentheses. Angrist-Pischke F's reported for models with more than one endogenous variable. * indicates significance at the 10% level; ** 5%; *** 1%.

Table 5. IV Analysis using Five Year Population Changes

Variable specifications		OLS Results		IV Results			
Native population	**Immigrant population**	**High Skill NH Whites**	**Low Skill NH Whites**	**High Skill NH Whites**	**Low Skill NH Whites**	**F-statistic**	**Included fixed effects**
A. Normalized specification							
$\left(\frac{N_t}{N_{t-1}}\right)$	$\left(\frac{M_t}{M_{t-1}}\right)$	0.42 (0.07)***	0.31 (0.05)***	0.52 (0.08)***	0.39 (0.06)***	2.84	MSA + Year
B. Levels change – Full model							
ΔN_t	ΔM_t	0.45 (0.23)*	0.21 (0.13)	0.57 (0.29)**	0.33 (0.22)	1.89	MSA + Year
C. Levels change – MSA time trends omitted							
ΔN_t	ΔM_t	0.42 (0.15)***	0.08 (0.04)**	0.19 (0.11)*	-0.09 (0.05)*	43.6	Year

Notes: Data consists of population totals for 1995, 2000, 2005, and 2010. Population totals for 1995 and 2000 are constructed using the 2000 US Decennial Census (5% PUMS). 2005 and 2010 data from the main ACS dataset. IV estimation in Panel A uses the "excluded" instrument normalized by the total population in an MSA five years previous (t-1) with base immigrant shares constructed from the 1990 US Census. IV estimation in Panels B and C use the "excluded" levels specification. N equals 423 observations for each regression in al the panels. (141 MSAs). Standard errors are clustered at the MSA level. * indicates significance at the 10% level; ** 5%; *** 1%.

Table 6. High skilled versus low skilled immigrant inflow shocks, 2000-2010 ACS

Dependent variable population:	High Skilled NHW		Low Skilled NHW	
	OLS	IV	OLS	IV
Measure of ΔM_t:				
$\Delta High\ English\ Skills_t$	0.38 (0.16)**	-0.83 (0.29)***	0.24 (0.13)*	0.59 (0.27)**
$\Delta Low\ English\ Skills_t$	0.26 (0.19)	-0.34 (0.25)	0.25 (0.13)*	0.95 (0.67)

Notes: Data collected by the authors from the MSA-level population estimates of the American Community Surveys, 2000-2010. Each cell is an estimate from a separate regression. High English Skills immigrants report speaking English well, verywell, or being native speakers. N is 1264 when the High English Skills immigrant population is the measure of ΔM_t and the first stage F is 46.4 Low English Skills report speaking English not well or not at all. N is 1192 when the Low English Skills immigrant population is the measure of ΔM_t and the first stage F is 3.5. Robust standard errors clustered on MSA in parentheses. * indicates significance at the 10% level; ** 5%; *** 1%.

Table 7. IV estimates of annual immigrant inflows on MSA-level population flows

	OLS		IV	
	i. Gross Flows			
Dependent variable population:	**HSW**	**LSW**	**HSW**	**LSW**
ΔM_t	-0.10 (0.12)	-0.12 (0.10)	0.87 (0.27)***	-0.56 (0.19)***
	ii. Inflows			
Dependent variable population:	**HSW**	**LSW**	**HSW**	**LSW**
ΔM_t	0.02 (0.01)**	0.01 (0.01)	0.05 (0.03)*	0.02 (0.01)
	iii. Outflows			
Dependent variable population:	**HSW**	**LSW**	**HSW**	**LSW**
ΔM_t	-0.12 (0.13)	-0.13 (0.10)	0.82 (0.26)***	-0.58 (0.19)***

Notes: Data collected by authors are MSA-level averages constructed from the publicly available microdata samples from the American Community Survey, 2005-2010. Instrumental Variables estimates are from a 2SLS estimation of the impact of the change in the current non-citizens populations on listed native populations. Instrument is the "excluded" version of the levels change in Table 4. First stage F-statistic is 20.75. The mean of the change in current non-citizens by birth is 3691. All specifications include a full set of year and region (4) x year fixed effects. N is 720 in all specifications. Robust standard errors are clustered on MSA in parentheses. * indicates significance at 10% level; ** 5%; *** 1%.

Table 8. Main IV specifications with interactions for a nearby MSA

Dependent variable population:	HSW	LSW	All Citizens
Panel (i): Isolated MSAs ≡ no other sample MSA within 50 miles (51% of MSAs)			
ΔM_t	-0.69	0.78	0.85
	(0.22)***	(0.37)**	(0.71)
ΔM_t * Next MSA <= 50 miles	0.34	-0.38	-0.40
	(0.24)	(0.35)	(0.72)
Panel (ii): Isolated MSAs ≡ no other sample MSA within 75 miles (27% of MSAs)			
ΔM_t	-0.70	1.61	2.74
	(0.33)**	(0.36)***	(0.68)***
ΔM_t * Next MSA <= 75 miles	0.33	-1.22	-2.32
	(0.33)	(0.36)***	(0.66)***

Notes: Data collected by the authors from the MSA-level population estimates of the American Community Surveys, 2000-2010. Model is identical to "full model" from Table 4, with the inclusion of the MSA distance interaction terms. Instrument set includes interaction of SPIV with the MSA distance dummy. N is 1440 in all regressions. In Panel (i), Angrist-Pischke F-statistics are above 19 on both endogenous variables. In Panel (ii), Angrist-Pischke F-statistics are above 17 on both endogenous variables. Robust standard errors clustered on MSA in parentheses. * indicates significance at the 10% level; ** 5%; *** 1%.

Table 9. Main IV specifications with interactions for declining city status

Dependent variable population:	HSW	LSW	All Citizens
Panel (i): Declining MSAs ≡ Population growth over 1995-2000 below median			
ΔM_t	-0.29	0.33	0.09
	(0.11)***	(0.16)**	(0.42)
ΔM_t * Declining MSA	-0.15	0.17	0.70
	(0.19)	(0.19)	(0.59)
Panel (ii): Declining MSAs ≡ Population growth over 1995-2000 below 25th percentile			
ΔM_t	-0.35	0.40	0.35
	(0.08)***	(0.13)***	(0.30)
ΔM_t * Declining MSA	-0.19	0.13	0.73
	(0.50)	(0.42)	(1.27)

Notes: Data collected by the authors from the MSA-level population estimates of the American Community Surveys, 2000-2010. Model is identical to "full model" from Table 4, with the inclusion of the MSA declining citizen pop interaction terms. Instrument set includes interaction of SPIV with the MSA declining population dummy. N is 1440 in all regressions. Angrist-Pischke F-statistics are above 11 on both endogenous variables (11.57 on the change in non-citizens by birth and 19.82 on the interaction). Robust standard errors clustered on MSA in parentheses. * indicates significance at the 10% level; ** 5%; *** 1%.

Table 10. Effects of annual immigrant inflows on wages and employment

i. Log wages				
Specification:	**OLS**		**IV**	
Dependent variable = Δ Log wages of…	**High Skill NH Whites**	**Low skill NH Whites**	**High Skill NH Whites**	**Low Skill NH Whites**
ΔM_t	0.05 (0.29)	-0.23 (0.19)	1.10 (1.44)	-0.03 (0.73)
Mean of dependent var.	-0.012	-0.007	-0.012	-0.007

ii. Employment				
Specification:	**OLS**		**IV**	
Dependent variable = Δ Employment of…	**High Skill NH Whites**	**Low skill NH Whites**	**High Skill NH Whites**	**Low Skill NH Whites**
ΔM_t	-0.10 (0.07)	-0.006 (0.06)	-0.25 (0.26)	0.31 (0.31)
Mean of dependent var.	-0.006	-0.008	-0.006	-0.008

Notes: Data collected by authors are MSA-level averages constructed from the publicly available microdata samples from the American Community Survey, 2005-2010. Wages are in real 1999 dollars (deflated by CPI-U). Wages are calculated by dividing wage and self-employment income by the total number of hours worked in the previous year (usual hours worked per week*total number of weeks worked last year). Wages under $2 and over $90 are dropped from this analysis. Employment status is derived from the “empstat” question via IPUMS-USA. Instrumental Variables estimates are from a 2SLS estimation of the impact of the normalized change in the current non-citizens populations on listed native populations. Instrument is the “excluded” version of the normalized change in Table 3. First stage F-statistic is 12.96. The mean of the normalized change in current non-citizens by birth is 0.004. All specifications include a full set of year and region (4) x year fixed effects. N is 720 in all specifications. Robust standard errors are clustered on MSA in parentheses. * indicates significance at 10% level; ** 5%; *** 1%.

Data Appendix

Aggregate American Community Survey Data Construction

Our data source is constructed using aggregate annual estimates from the American Community Survey (ACS) downloaded via American Factfinder.[38] The dataset consists of 11 years worth of aggregate data for 151 metropolitan areas collected at an annual frequency spanning the years 2000 to 20010.[39] The data are assembled using the "detailed tables" option for each individual year of the ACS; a list and description of the variables used in this analysis is available in Appendix Table 2. Data for metropolitan statistical areas for the years 2000 and 2001 are taken from the Census Supplementary Surveys for those respective years (extracted via American Factfinder). These two surveys represent the precursor to the complete American Community Survey, which is fully implemented beginning with the 2002 American Community Survey.[40] The American Community Survey provides aggregate statistics for geographic areas with populations greater than 250,000 individuals and for some selected areas with populations greater than 65,000 individuals for survey years 2000-2004. Beginning in 2005, the ACS greatly expands its coverage to include most areas with populations greater than 65,000 individuals; this expanded coverage allows for the construction of aggregate statistics for smaller MSAs and for many counties across the country.

Along with the vast expansion in coverage, the ACS updated its geographical definitions for what constitutes a metropolitan area beginning with its 2005 survey. The metropolitan area definitions used by the ACS for the years 2000-2004 are based on the U.S. Office of Management and Budget definitions as of June 30, 1999. Surveys beginning in 2005 and beyond area based off of definitions established in November of 2004. There are many differences between the two sets of definitions for metropolitan areas.[41] In order to construct consistent definitions of metropolitan areas for the entire time series (2000 to 2009), we manipulate the November 2004 definitions to match earlier geographic definitions used during the first five years of our time series (2000-2004). The differences between metropolitan areas among the two sets of definitions lie in the inclusion (or exclusion) of specific counties. Due to the lack of coverage at the county level for the earlier years of the ACS, it is only possible to reverse-engineer the definitions used in more recent years of the ACS (2005 and onward) to match older definitions (2000 to 2004). This reverse-engineering is made possible due to the extensive increase in coverage beginning with the 2005 ACS (and beyond) which allows for the creation of aggregate statistics for a large number of counties in the United States.[42]

The expansion of the ACS in 2005 and beyond is vast; however there are still counties for which aggregate estimates are not available. Due to the fact that we cannot ascertain information for a number of smaller counties we cannot create a perfect geographic match for a number of our metropolitan statistical areas. We can construct 92 MSAs that have the exact same boundaries over the entire time series. The remaining 59 MSAs are not perfectly comparable due to the fact that aggregate information is not available

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[38] The aggregate ACS data is compiled via American Factfinder: http://factfinder.census.gov.

[39] A list of the metropolitan areas constructed from the aggregate ACS data is located in Appendix Table 1. The 151 metropolitan are all observable for at least 8 years over our time series. Of the 151 metropolitan areas, 46 are classified as primary metropolitan statistical areas and 105 are considered metropolitan areas (as defined by the 2000 Census). Two metropolitan areas, Bridgeport, C.T. and Stamford, C.T. are combined for this analysis. This combined metropolitan area is labeled Bridgeport, C.T.

[40] Alexander (2001) summarizes the goals and structure of the American Community Survey and the Census Supplementary Surveys.

[41] Current and historical metropolitan area definitions in the United States used in this analysis are taken from the U.S. Census Bureau: http://www.census.gov/population/www/metroareas/metrodef.html. The ACS updates its geographical definitions of what constitutes a metropolitan area in 2006, 2007, 2008, and 2009 as well. These updates are small additions and subtractions to the 2005 definition changes; however, none of these changes affect major metropolitan area definitions.

[42] This strategy only works as long as county definitions do not change over this time period. The majority of counties in our analysis do not change geographic definitions during 2000 to 2009. Please refer to the link below for the small list of counties who do experience boundary changes in this decade: http://www.census.gov/geo/www/tiger/ctychng.html.

for a county that is necessary for the construction of a consistent geographic definition for the given MSA. The MSAs that are not perfectly comparable across our time series appear in bold lettering in Appendix Table 1.

Individual-Level American Community Survey Data – Gross Flows Construction

We construct yearly inflows, outflows, and gross flows of non-Hispanic white high skill and low skill populations using the 2005-20010 ACS microdata.[43] Prior to 2005, individual-level ACS data only allowed for geographic identification at the state level; beginning in 2005 (and beyond) geographic identifiers at the metropolitan area become available. Yearly population totals between 2005 and 20010 are constructed for both the high skilled and low skilled non-Hispanic white populations. High skilled whites are defined as those individuals 25 years of age and older with educational attainment greater than a high school degree; while low skilled whites are all white individuals 25 years and older with educational attainment equivalent to a high school degree or less.

Yearly inflows into a given metropolitan area are defined using the one year migration question provided in the ACS. An individual is therefore included as part of a yearly inflow into a particular MSA if they were living outside of that MSA one year ago. Yearly outflows are then defined as being the difference between the yearly inflow and the total yearly change in the population in question. The total yearly change is derived by taking the difference in the total population in question between concurrent surveys of the ACS. Gross flows are then defined as the sum of yearly inflows and yearly outflows for each individual MSA.

Calculating yearly outflows in this manner is subject to some criticism. In particular, our measure is subject to error if individuals either age into or out of (in our case, die) our native skill groups, or if individuals transition from low skill to high skill. We assume that rates of age structure and death rates of our MSAs are unaffected by immigration in our short-run windows. Therefore this source of measurement error in the flows should not differ systematically across high and low immigrant inflow cities. However, one may still be concerned that increased immigration affects native transitions across skill groups. There is evidence on this question. Jackson (2010) provides shows that a 1% increase in low skill immigrant inflows leads to 0.33 percent increase in college enrollment among native individuals and that high skill immigrant inflows do not reduce native college enrollment. Therefore, if anything, immigrant inflows should raise the rate of native transition from low skill to high skill groups. Since we find that outflows of low skill populations decline alongside immigrant inflows, this suggests that our results are a lower bound.

An alternative measure of yearly outflows can be constructed using the same one year migration questions used to construct yearly inflows, which would in theory eliminate the concerns above. We have experimented with constructing outflows rather than calculating them. However, we have found this approach to be more problematic than our calculation approach. Constructing outflows from summing over individuals living in other areas is subject to error if individuals misreport their prior MSA status. We therefore conduct our analysis by constructing outflows mechanically as the difference between inflows and yearly population changes while recognizing the limitations about such a construction as described above.

Individual-Level American Community Survey Data – Wage and Employment Data

Limitations on wage and employment statistics in the aggregate ACS data force us to construct these statistics using the individual-level microdata from the ACS; however, statistics created from the ACS microdata are limited to years 2005 to 20010.Statistics constructed using microdata reflect yearly MSA averages for the population in question. There are two main populations for which we construct statistics: the low skilled non-Hispanic white and high skilled non-Hispanic white populations. We set age restrictions for both of these population subgroups to include only individuals between the ages of 25 and 60. Skill level

[43] Individual-level ACS data is collected via IPUMS: http://www.ipums.org.

is defined by educational attainment; a high school degree or less corresponds to low skill, while anything greater than a high school degree corresponds to high skill.

We construct a statistic for the percent of the labor force who are currently employed in a given MSA. Individuals are defined as working and in the labor force based on their answers to the question about labor status (empstat). Along with employment, we construct mean hourly wages at the metropolitan area level. In order to construct an hourly wage variable, we determine an individual's total income by combining wage and self-employment income from the previous year. Total income is then deflated into real 1999 dollars using the CPI-U. In order to construct hourly wages we multiply usual hours per week worked by the number of weeks worked last year to construct total number of hours worked last year for each individual person.[44] Hourly wages for the individual are then constructed by dividing total income by the total number of hours worked last year. Wages less than $2 and greater than $90 are eliminated from the analysis. The mean hourly wage and mean employment for each metropolitan area are both weighted by the individual's personal weight.

[44] The only measure of weeks worked last year that is consistently available across all years of the ACS does not provide the actual number of weeks worked but rather provides a range of possible weeks worked (variable name is wkswork2). In order to deal with this problem we take the midpoint of the weeks worked for every possible response and use that as the number of weeks worked last year.

Estimating Equations Appendix

Concerns about generating spurious correlation between immigrant inflows and native population changes via scale effects have led a number of authors to normalize population changes by initial city population size (Card 2001, 2007; Peri and Sparber 2011; Cortes and Tessada 2009). However, a univariate specification that normalizes both the left and right-hand side variables by initial population size is equivalent to a weighted least squares estimator that specifies that heteroscedasticity as a function of the square of population size. This is a testable assumption.

In the table below, we present estimates from the regression of squared residuals on MSA population size in 2000 and its square. The residuals are from a regression of the level change in native population on the level change in immigrant population using univariate and full model specifications, as in the preceding paper. We repeat this exercise omitting the five largest MSAs in our data from the sample. In the full sample of MSAs, residuals from the levels specification are proportional to both initial population (Pop2000) and its square, but the former relationship is stronger and more generally significant. This is contrary to the assumption implicit in specifications that divide levels changes through by an initial period population.

Importantly, the two main adjustments we make in order to reduce concerns about scale effects make a significant difference in these relationships. First, adding MSA time trends and region-year effects (i.e. use of the full model) eliminates the relationship between residual size and initial population size. Omitting the five largest MSAs also makes a big difference. Here the relationships between residuals from even the univariate regression and initial population are statistically much weaker and smaller in magnitude.

We conclude that residuals in the full model, particularly in our full model when the top-five cities are omitted, are well behaved with respect to initial city population size. We believe this minimizes concerns that city size drives the correlations between native and immigrant population changes. However, some possibility for scale effects remains. This would have the effect of obscuring displacement of natives by immigrants in our analysis. However, since we ultimately conclude that significant displacement is occurring in the short-run, we view the bulk of our estimates as on the conservative side.

Table EE: Regression of residuals from levels specification on initial population size variables

	Panel A: All MSAs available in 2000 ACS					
Residual-generating model	**Univariate**			**Full model**		
Dependent variable in model	*All citizens*	*HSW*	*LSW*	*All citizens*	*HSW*	*LSW*
Pop2000	0.011 p=0.00	0.0036 p=0.00	-0.0022 p=0.001	4.18e-11 p=1.0	-2.68e-11 p=1.0	-1.73e-11 p=1.0
Pop2000^2	-9.73e-10 p=0.00	-2.46e-10 p=0.011	-3.70e-11 p=0.65	-1.35e-17 p=1.0	4.39e-18 p=1.0	3.30e-18 p=1.0
	Panel B: Omitting 5 MSAs with largest Pop2000					
	Univariate			**Full model**		
	All citizens	*HSW*	*LSW*	*All citizens*	*HSW*	*LSW*
Pop2000	-0.01 p=0.025	.0016 p=0.34	-.0038 p=0.01	1.21e-10 p=1.0	-7.78e-11 p=1.0	-7.58e-12 p=1.0
Pop2000^2	5.53e-09 p=0.0	1.65e-10 p=0.72	4.42e-10 p=0.26	-1.91e-17 p=1.0	3.68e-17 p=1.0	-4.45e-19 p=1.0

Notes: Columns report coefficients and associated p-values from a regression of residuals on MSA population in 2000 and its square plus a constant. The residual generating models regress the change in native population on the change in immigrant population (both in levels, immigrants measured as in Table 4 in paper, natives measured as noted). N in top panel regressions is 1341; in bottom panel is 1296.

Robustness Check Appendix

Table RA1 reports results from two sets of additional checks. The first of these, shown in Panel (i), consist of changes to the way the SPIV is constructed. The second set, in Panel (ii), makes other changes to the specification, variables, or sample. The table reports coefficients (with significance indicated) from the full model plus lag specifications of Tables 2 and 4. We report robustness results from this specification because the lag often has larger causal impacts for the high skilled than concurrent period inflows. The table also reports the Angrist-Pischke F-statistics from the relevant first stage. In almost all cases, the Fs are smaller than in Table 4 but still attain levels that indicate an acceptably strong first stage.

The first two sets of results in Panel (i) change the "weight" on the US immigrant inflow change in the SPIV to an MSA's share of total US immigrants in an earlier period than 2000, the year used in the SPIV in Tables 3 and 4. Constructing these weights from earlier periods can further alleviate the concerns about serially correlated demand shocks already discussed. The first set of results uses an MSA's share of the US immigrant population constructed from 1990 Census data, and the second uses the share from 1980 Census data.[45] Others have shown that immigrant population growth, and its origin country composition, differ across these three decades; we verify this in unreported results. Weights from earlier decades therefore rely on relatively older stocks of immigrants for identification. These older stocks are less likely to pull in new immigrants with knowledge of local demand shocks, since the composition of older stocks differs from that of the current immigrant inflow, and identification comes more from a city's fixed characteristic as an immigrant destination rather than from possible chain migration. As might be expected from using older data, the F-statistics are much smaller than in other settings. However, the point estimates are largely unchanged from the main IV estimates in Table 4 regardless of whether the 1980 or 1990 weights are used.

The final set of results in Panel (i) uses an origin-country weighted version of the SPIV. This is defined as in Smith (2010) and Cortes and Tessada (2009) by constructing the SPIV in Equation (5) separately for country-of-origin immigrant groups and then summing over all groups within the MSA and year. In this case, one F-statistic is below 10. This is likely related to the loss of roughly one third of our observations due to missing (censored) data on immigrant populations by country of origin. Yet the point estimates are little changed from Table 4. Therefore although there are some small differences, we conclude that our main IV results are robust to these changes in the construction of the SPIV.

In Panel (ii), we use the SPIV as specified in (5), but we make a number of other changes to the Table 4 specifications. First, we change our measure of the immigrant population from non-citizens by birth to current non-citizens. This potentially restricts our immigrant population to relatively more recent arrivals. Again, the point estimates are generally similar to those in Table 4 although the effects for all citizens and for high skilled whites are not significant. The second set of estimates uses state-year instead of region-year fixed effects in the Table 4 specification.[46] This is an important innovation since we now have a fully flexible set of controls for any time-varying changes that are common across MSAs in a state, not necessarily across all MSAs in a region. Concerns about unobserved time-varying local labor demand shocks are greatly reduced in this specification. The results are essentially unchanged from our main IV estimates in Table 4. Finally, we run our Table 4 specification omitting any MSAs whose boundary definitions changed in the course of the ACS data period. As described in the Data Appendix, it is not possible to construct a perfectly consistent set of MSA definitions over the entire time period, although we come close. Nevertheless, there may be concerns that in bridging the MSA definitions over time, we generate artificial jumps in the population data. Although omitting MSAs with definition changes greatly reduces our sample size, the final set of estimates in Table RA1 show that our main IV estimates are largely unaffected by this change.

[45] Using the 5% public use microdata extract from the 1980 and 1990 US Censuses, we construct the share of the total foreign-born population in each of our MSAs for each census year (1980 and 1990).

[46] This drops eight MSAs from our data, since we do not always observe more than one MSA in the state.

Table RA1: Robustness checks for main IV results

		All Citizens	HSW	LSW	1st Stage
i. Changes to Instrument					
Using city's share of Immigrants from 1990 in SPIV	ΔM_t	0.42 (0.43)	-0.39 (0.14)***	0.36 (0.17)**	13.3
…from 1980	ΔM_t	0.44 (0.63)	-0.53 (0.27)*	0.40 (0.23)*	6.05
Ethnicity weighted SPIV	ΔM_t	0.12 (0.36)	-0.47 (0.20)**	0.25 (0.17)	14.7
ii. Changes to Specification					
Immigrants defined as current non-citizens	ΔM_t	0.77 (0.75)	-0.57 (0.23)**	0.65 (0.27)**	18.2
State-year instead of region-year fixed effects	ΔM_t	0.47 (0.48)	-0.48 (0.16)***	0.45 (0.17)***	13.1
Restrict to MSAs with consistent definitions	ΔM_t	0.35 (0.56)	-0.40 (0.19)**	0.28 (0.19)	13.4

Notes: Data collected by the authors from the MSA-level population estimates of the American Community Surveys, 2000-2010. Estimates in "All Citizens", "HSW" and "LSW" columns are second stage coefficients from the full model in Table 4. "1st Stage" column reports F-statistic on SPIV. N varies across specifications. Robust standard errors clustered on MSA in parentheses. * indicates significance at the 10% level; ** 5%; *** 1%.

Appendix Table 1: Metropolitan Statistical Areas

Akron, OH*
Albany-Schenectady-Troy, NY
Allentown-Bethlehem-Easton, PA
Anchorage, AK
Ann Arbor, MI*
Appleton-Oshkosh-Neenah, WI
Atlanta, GA
Atlantic-Cape May, NJ*
Augusta-Aiken, GA-SC
Austin-San Marcos, TX
Bakersfield, CA
Baton Rouge, LA
Beaumont-Port Arthur, TX
Bergen-Passaic, NJ*
Biloxi-Gulfport-Pascagoula, MS
Birmingham, AL
Boise City, ID
Boston, MA*
Boulder-Longmont, CO*
Bridgeport, CT**
Brockton, MA*
Brownsville-Harlingen-San Benito, TX
Buffalo-Niagara Falls, NY
Canton-Massillon, OH
Charleston-North Charleston, SC
Chicago, IL*
Cleveland-Lorain-Elyria, OH*
Colorado Springs, CO
Columbia, SC
Corpus Christi, TX
Dallas, TX*
Davenport-Moline-Rock Island, IA-IL
Daytona Beach, FL
Dayton-Springfield, OH
Denver, CO*
Des Moines, IA
Detroit, MI*
Dutchess County, NY*
El Paso, TX
Erie, PA
Eugene-Springfield, OR
Fayetteville, NC
Fayetteville-Springdale-Rogers, AR
Flint, MI*
Fort Lauderdale, FL*
Fort Myers, FL
Fort Pierce-Port St. Lucie, FL
Fort Wayne
Fort Worth-Arlington, TX*
Fresno, CA
Galveston-Texas City, TX*
Grand Rapids-Muskegon-Holland, MI
Greensboro-Winston Salem-High Point, NC
Greenville-Spartanburg-Anderson, SC
Hamilton-Middletown, OH*
Harrisburg-Lebanon-Carlisle, PA
Hartford, CT
Hickory-Morgantown-Lenoir, NC
Honolulu, HI
Houston, TX*
Huntsville, AL
Indianapolis, IN
Jackson, MS
Jacksonville, FL
Jersey City, NJ*
Johnson City-Kingsport-Bristol, TN-VA
Kalamazoo-Battle Creek, MI
Kansas City, MO-KS
Killeen-Temple, TX
Knoxville, TN
Lafayette, LA
Lakeland-Winter Haven, FL
Lancaster, PA
Lansing-East Lansing, MI
Lexington, KY
Little Rock-North Little Rock, AR
Los Angeles-Long Beach, CA*
Lowell, MA-NH*
Macon, GA
Madison, WI
McAllen-Edinburg-Mission, TX
Melbourne-Titusville-Palm Bay, FL
Miami, FL*
Middlesex-Somerset-Hunterdon, NJ*
Milwaukee-Waukesha, WI*
Mobile, AL
Modesto, CA
Monmouth-Ocean, NJ*
Montgomery, AL
Nashville, TN
Nassau-Suffolk, NY*
New Haven-Meriden, CT*
New Orleans, LA
New York, NY*
Newark, NJ*
Oakland, CA*
Oklahoma City, OK
Orange County, CA*
Orlando, FL
Pensacola, FL
Peoria-Pekin, IL
Philadelphia, PA*
Pittsburgh, PA
Providence-Fall River-Warwick, RI-MA
Provo-Orem, UT
Raleigh-Durham-Chapel Hill, NC
Reading, PA
Reno, NV
Richmond-Petersburg, VA
Riverside-San Bernardino, CA*
Rochester, NY
Rockford, IL
Sacramento, CA*
Saginaw-Bay City-Midland, MI
Salem, OR*
Salinas, CA
Salt Lake City-Ogden, UT
San Antonio, TX
San Diego, CA
San Francisco, CA*
San Jose, CA*
Santa Barbara-Santa Maria-Lompoc, CA
Santa Rosa, CA*
Sarasota-Bradenton, FL
Savannah, GA
Scranton-Wilkes-Barre-Hazleton, PA
Seattle-Bellevue-Everett, WA*
Shreveport-Bossier City, LA
South Bend, IN
Spokane, WA
Springfield, MA
Springfield, MO
St. Louis, MO-IL
Stockton-Lodi, CA
Syracuse, NY
Tacoma, WA*
Tallahassee, FL
Tampa-St. Petersburg-Clearwater, FL
Toledo, OH
Trenton, NJ*
Tucson, AZ
Tulsa, OK
Utica-Rome, NY
Vallejo-Fairfield-Napa, CA*
Ventura, CA*
Visalia-Tulare-Porterville, CA
West Palm Beach-Boca Raton, FL
Wichita, KS
Worcester, MA-CT*
York, PA
Youngstown-Warren, OH

Notes:
1) * - The metropolitan statistical area is designated as a primary metropolitan statistical area under the U.S. Office of Management and Budget as of June 30, 1999. ** - The metropolitan statistical area labeled Bridgeport, CT is actually a combination of two metropolitan statistical areas: Bridgeport, CT and Stamford, CT. The combined entity is labeled Bridgeport, CT
2) If the metropolitan statistical area is in bold then there is not an exact comparison between the metropolitan area as it is defined by the U.S. Office of Management and Budget as of June 30, 1999 and later definitions which are used in more recent years of the American Community Survey. See the data appendix describing the construction of the aggregate American Community Survey dataset for a more detailed discussion.

Appendix Table 2: List of American Community Survey Variables

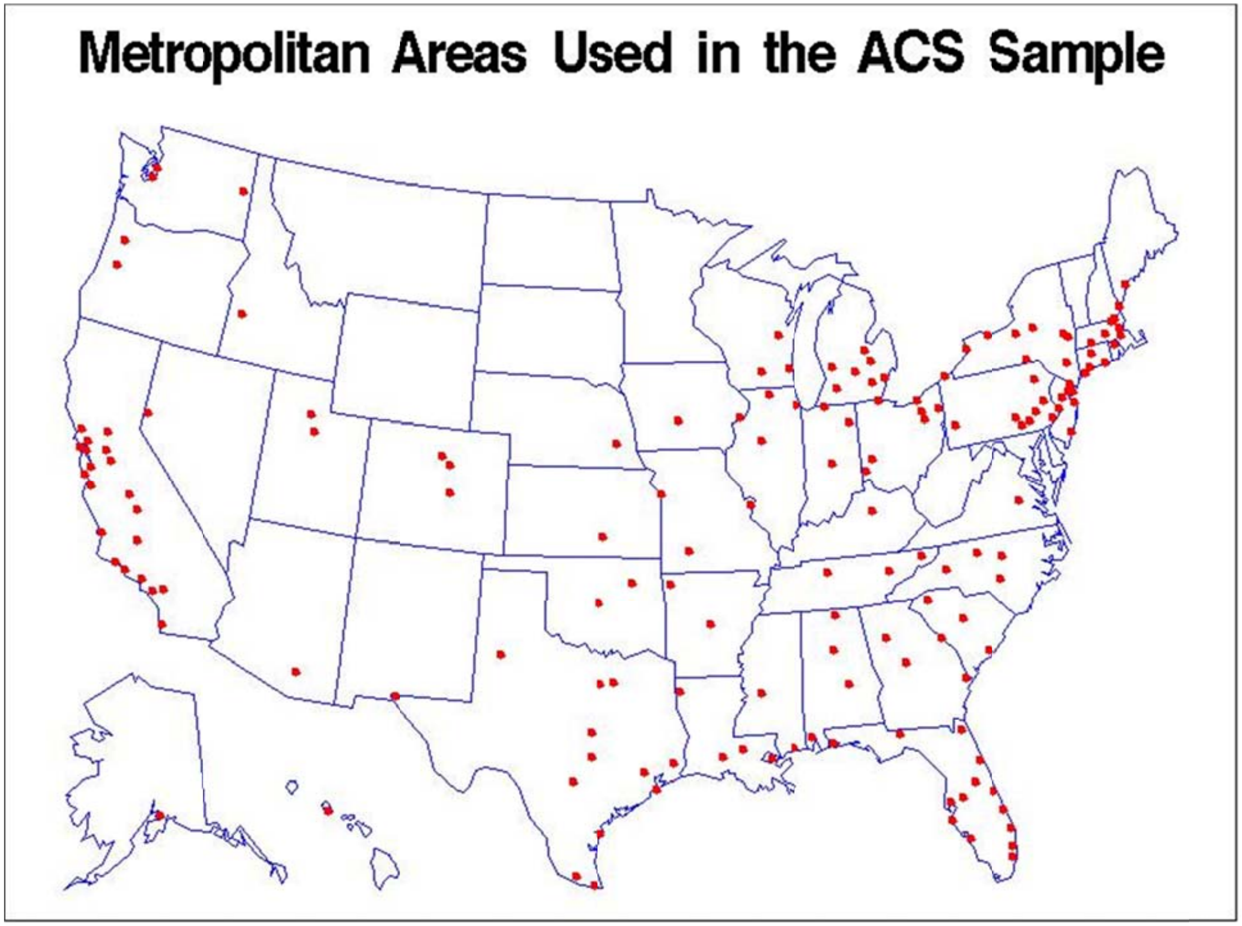
Population Count Categories	Universe for Category Population Counts	Variable Name 2000-2003	Variable Name 2004-2009
Aggregate Variables from American Community Survey used in Analysis downloaded via American Factfinder			
Total Population	Total Population	P001	B01003
Sex by Educational Attainment	Population 25 Years and Older *	PCT035A-PCT035K	B15002A-B15002I
Nativity by Language Spoken at Home by Ability to Speak English	Population 5 Years and Older	PCT020	B16005
Place of Birth by Citizenship Status	Total Population	P038	B05002
Place of Birth By Year of Entry by Citizenship Status	Foreign Born Population	PCT028	B05007
Residence 1 Year Ago (State, County, and Place Level)	Population 1 Year and Older	P041	B07204 (B07202 in 2004)
Aggregate Variables from American Community Survey not used in Analysis downloaded via American Factfinder			
Race	Total Population	P002	B02001
Hispanic or Latino by Race	Total Population	P003	B03002
Sex by Age	Total Population*	P005A-P005K	B01001A-B01001I
Language Spoken at Home	Population 5 Years and Older	P034	B16001
Age by Language Spoken at Home by Ability to Speak English	Population 5 Years and Older	P035	B16004
Citizenship Status	Total Population	P037	B05001
Place of Work (State and County Level)	Employed Civilian Population 16 Years and Older	P043	B08007
Place of Work (Place Level)	Employed Civilian Population 16 Years and Older	P044	B08008
Sex by Industry	Employed Civilian Population 16 Years and Older	P066	B24030
Sex by Occupation	Employed Civilian Population 16 Years and Older	P067	B24010
Household Income in Past 12 Months	All Households	P069	B19001
Family Income in the Past 12 Months	All Families	P100	B19101
Place of Birth	Foreign Born Population	PCT027	B05006
Sex by School Enrollment	Population 3 Years and Older	PCT031	B14003
Sex by College or Graduate School Enrollment by Age	Population 15 Years and Older	PCT033	B14004
Sex by Age by Educational Attainment	Population 18 Years and Older	PCT033	B15001
MSA Level Means constructed from Individual-Level Data from American Community Survey (2005-2009)			
Variable Constructed	**Universe (the non-Hispanic white population)**		
Employment for the non-Hispanic white population	adults ages 25-60 who are currently defined as being in the labor force		
Hourly Wages for the non-Hispanic white population	adults ages 25-60 who report working in the previous year and report positive wages/earnings		
Inflows of the non-Hispanic white population	adults ages 25-60 who moved into a metropolitan area during the past year		
Outflows of the non-Hispanic white population	total yearly change in the population in a given MSA minus the inflow of individuals into that given MSA		

Notes: * - This variable is available for the following universes: total population; White alone; Black or African American alone; American Indian or Alaska Native alone; Asian Alone; Hawaiian and other Pacific Islander alone; Some other race alone; Two or more race alone; Hispanic or Latino alone; White alone, Not Hispanic or Latino. All MSA level variables created from the individual-level American Community Survey data are constructed for high-skilled and low-skilled populations. High-skill individuals refer to those with an educational attainment greater than a high school degree. Low-skill individuals have educational attainment less than or equal to a high school degree.

Appendix Table 3: 25 Largest Metropolitan Areas in the ACS Sample

Rank by 2000 Pop	MSA or PMSA Name	2000 Population	Share of US Immigrant Pop in 1990
1	Los Angeles--Long Beach, CA PMSA; Los A	9,344,086	0.13
2	New York, NY PMSA; New York--Northern N	9,092,551	0.12
3	Chicago, IL PMSA; Chicago--Gary--Kenosh	8,123,328	0.043
4	Philadelphia, PA--NJ PMSA; Philadelphia	4,947,731	0.015
5	Detroit, MI PMSA; Detroit--Ann Arbor--F	4,381,235	0.012
6	Houston, TX PMSA; Houston--Galveston--B	4,105,445	0.020
7	Atlanta, GA MSA	4,036,627	0.006
8	Dallas, TX PMSA; Dallas--Fort Worth, TX	3,466,200	0.011
9	Boston, MA--NH PMSA; Boston--Worcester-	3,309,622	0.017
10	Riverside--San Bernardino, CA PMSA; Los	3,175,436	0.017
11	Orange County, CA PMSA; Los Angeles--Ri	2,803,924	0.026
12	San Diego, CA MSA	2,716,820	0.021
13	Nassau--Suffolk, NY PMSA; New York--Nor	2,703,677	0.014
14	St. Louis, MO--IL MSA	2,551,156	0.003
15	Seattle--Bellevue--Everett, WA PMSA; Se	2,379,184	0.008
16	Oakland, CA PMSA; San Francisco--Oaklan	2,353,485	0.016
17	Tampa--St. Petersburg--Clearwater, FL M	2,348,178	0.008
18	Pittsburgh, PA MSA	2,290,408	0.002
19	Miami, FL PMSA; Miami--Fort Lauderdale,	2,207,391	0.041
20	Cleveland--Lorain--Elyria, OH PMSA; Cle	2,204,978	0.005
21	Denver, CO PMSA; Denver--Boulder--Greel	2,080,106	0.004
22	Newark, NJ PMSA; New York--Northern New	1,990,053	0.013
23	Kansas City, MO--KS MSA	1,728,084	0.002
24	San Francisco, CA PMSA; San Francisco--	1,689,490	0.020
25	Fort Worth--Arlington, TX PMSA; Dallas-	1,673,643	0.004

FIGURE 1.



Notes: States/regions not represented in our dataset are Delaware, Maryland, Minnesota, Montana, New Mexico, North Dakota, South Dakota, Vermont, and the District of Columbia.