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The Role of Social Costs in Response to Labor Market Opportunities: Differences across Race

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Abstract: Using the American Community Survey between 2005 and 2019, this paper investigates the role constraints to migration might play in explaining racial/ethnic disparities in the labor market. We find that Black workers are typically less responsive than White workers to changes in job opportunities, but responsiveness increases when those opportunities present themselves in locations with a higher share own-minority population. We construct an education/race specific Bartik shift-share instrument to control for potential endogeneity of growth in job opportunities.

JEL classification: J61, J15, J18

Key words: racial labor market disparities, migration costs, Delta index, social costs, place-based, people-based, mismatch

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The Role of Social Costs in Response to Labor Market Opportunities: Differences Across Race

1 Introduction and Background

Long-standing disparities in labor market outcomes by race are well documented.[1] At the opening of a conference at the Board of Governors in 2017 highlighting these disparities and their sources, Governor Brainard affirmed that labor market disparities might have negative, "implications for the growth capacity of the economy" (Brainard 2017). Many contributors to these disparities have been identified, including discrimination, educational opportunities, and social networks. An additional contributor could be differences in migration constraints. A greater ability to chase economic opportunity should improve one's labor market outcomes (for example, see El Badaoui, Strobl, and Walsh 2017; Niebuhr et al. 2009; Davis and Haltiwanger 2014). In fact, the "Great Black Migration" has been credited with significantly improving the economic conditions of Black people from the U.S. South during the early 20th century (Boustan 2015).[2] Therefore, racial disparities in the labor market may result, and persist, if a disadvantaged group faces more constraints to migrating. Burns and Hotchkiss (2020) illustrate greater geographic mismatch between jobs and people among racial minorities than among White workers; they interpret this as circumstantial evidence that racial minorities are more constrained in their migration decisions.[3]

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[1] For example, see (Antecol and Bedard 2004; Biddle and Hamermesh 2013; Bradbury 2000; Chetty et al. 2019; Engemann and Wall 2010; Fallick and Krolikowski 2018; Zavodny and Zha 2000; Hotchkiss and Moore 2018).
[2] Not all outcomes from the Great Migration were positive; Black et al. (2015) provide evidence that migration by African Americans from rural southern states to northern urban locations resulted in increased mortality.
[3] Following APA style guidelines, race and ethnic descriptors are capitalized, see https://apastyle.apa.org/style-grammar-guidelines/bias-free-language/racial-ethnic-minorities.

The goal of this paper is two-fold. First, we investigate whether there is any difference in the responsiveness of racial minorities to changing labor market opportunities, compared to the responsiveness of White people. Second, we explore further to uncover what sort of constraints might be hindering migration decisions, with a particular focus on what we are calling "social costs."

Constraints to migration can take many forms -- from social/cultural constraints to financial constraints.[4] Wilson (2021) demonstrates that access to information can be important for informing migration decisions. Cooke (2011) attributes 20 percent of the overall decline in migration rates between 1999 and 2009 to what he calls "secular rootedness," suggesting a social cost to migration.[5] Spilimbergo and Ubeda (2004) also establish family ties as a factor affecting migration in their study for differences in migration rates between White and Black people in the U.S. They find that the reason that Black people move less than White people, despite having many factors commonly associated with high migration, is because the Black population, on average, have stronger family ties. Additionally, investigating migration patterns in the 1990s, Frey et al. (2005) confirm that cultural constraints to migration are more prevalent among racial minorities. This constraint would be in addition to any other differences across race that have been long known to impact migration decisions, such as access to resources, information, and education (for example, see Greenwood 1975).

There may be other indirect contributors to the relationship between migration and labor market outcome gaps. For example, Blair and Chung (2017) provide evidence that occupational

[4] An additional constraint, theorized by Shimer (2007), could include irrational expectations about future local job prospects.
[5] Also see Falcettoni and Nygaard (Forthcoming), who find that they need to specify significant utility costs to moving in order to rationalize observed rates of geographic retention.

licensing reduces racial and gender wage gaps, yet Johnson and Kleiner (2020) find that occupational licensing increases costs of interstate migration. Even though Blacks and Hispanics are less likely to be found in occupations that are licensed (Blair and Chung 2017), such institutional constraints may be contributing to labor market disparities in ways that are not obvious.

An excellent review of the current state of the literature on questions of internal migration is provided by Jia et al. (2023). They cite multiple studies showing that migration is becoming a less important mechanism for demand shock population adjustments. However, our analysis abstracts from these longer trends and asks, in the same dynamic environment, whether migration is an even weaker adjustment mechanism for one racial group than another. And, if so, is there evidence that mechanism is weaker because of some constraint. Our analysis identifies weaker response among racial/ethnic minorities, relative to White, non-Hispanics, to changes in job opportunities across geographic locations. The implication is that worse labor market outcomes among minorities may, at least in part, be the result of greater migration constraints. Additional analysis provides evidence that social costs may play a role in constraining ethnic/minority response to changing labor market opportunities elsewhere.

2 Methodology

2.1 Empirical Specification

The analysis uses annual data and is performed at the commuting zone (CZ) level.[6] CZs are defined for both rural and urban areas, however identification of the CZ of a person living in a sparsely populated county is limited for confidentiality reasons, providing less than exhaustive

[6] CZ definitions are based on county-to-county commuting patterns; details can be found at https://usa.ipums.org/usa-action/variables/COMZONE#description_section.

coverage of movement across the U.S.; future analysis will make use of non-public data made available through a Federal Statistical Research Data Center in order to allow a more comprehensive geographic coverage.

We adopt the empirical model inspired by Amior and Manning (2018b) to relate changes in population to changes in employment opportunities across geographical locations. The innovations of Amior and Manning (2018b)'s analysis is to show that the employment rate (or the percent by which employment is less than population) is a sufficient condition to summarize the area's initial (dis-) equilibrium, which means a measure of real wages to is unnecessary as an identifier for demand driven job opportunities. Lagging the employment rate yields an error correction model (ECM) that recognizes that population doesn't adjust instantaneously (or perfectly) to changes in job opportunities.

The estimating equation is as follows:

$$\left(\%\Delta N_g\right)_{e,r,t} = \zeta + \sum_{r=1}^{3} \sum_{e=1}^{3} \left\{\beta_{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * \left(\%\Delta J_g\right)_{e,r,t}\right\}$$
$$+\omega_1 UR_{g,t-1} + \omega_2 Y_{e,r,g,t-1} + \mu \mathrm{m}_{gt} + \tau_t + \delta_g + d_g + \alpha_g + \varepsilon_{g,e,r,t} \text{, where} \quad (1)$$

$\left(\%\Delta N_g\right)_{e,r,t}$ = the percentage change in the population from *t-1* to *t* of racial group, *r*, in geographic location, *g*, with education, *e*;

$\left(\%\Delta J_g\right)_{e,r,t}$ = the percentage change in employment (jobs) from *t-1* to *t* of people in racial group, *r*, in geographic location, *g*, with education, *e*;

$RACE_{g,t}$ = set of 0,1 regressors indicating White, Black, or Hispanic race/ethnicity;

$EDUC_{g,t}$ = set of 0,1 regressors indicating high school, some college, or college plus;

$UR_{g,t-1}$= one-year lagged unemployment rate for CZ *g* is one measure of disequilibrium (e.g., see Devaraj et al. 2017);

$Y_{e,r,g,t-1} = \left[\left(J_{e,r,g,t-1} - N_{e,r,g,t-1}\right)/N_{e,r,g,t-1}\right]$; a second measure of disequilibrium analogous to Amior and Manning's measure in logs -- the percent difference between the lagged employment and population for each education/race group in location *g*;

τ_t = year fixed effect;

δ_g = CZ-specific distance (population-weighted centroids) from next nearest CZ;

d_g = CZ population density in 1990 (total population in CZ divided by total land area of CZ);

α_g = CZ-specific amenity;

m_{gt} = migrant shift-share; and

$\varepsilon_{g,e,r,t}$ are robust standard errors, clustered by CZ level.

The regressors, δ_g, d_g, α_g , and m_{gt}, are labor supply controls. Amior and Manning (2018b) point out that if population immediately adjusts to job opportunities, then the marginal effects on percentage change in jobs and the initial equilibrium would both be equal to one, as there would be no deviation from equilibrium. Following Amior and Manning (2018b), observations are weighted by lagged CZ population shares, which are computed using the Census counts of population when available, and Census estimates otherwise.[7]

Distance is the (county) population-weighted centroid distance of the CZ to the next nearest CZ; details of its construction are found in Appendix A. It is expected that the closer a CZ is to other CZs, the even greater are job opportunities and access to other amenities. The county level amenity index from the US Department of Agriculture's Natural Amenities Scale (USDA n.d.) is used to quantify amenities in each CZ. The scale "is a measure of the physical characteristics of a county area that enhance the location as a place to live." This scale takes into account a county's average January temperature, average number of sunny January days, average low winter/summer temperature gap, low average July humidity, topical variation, and water

[7] We have taken into consideration the various possible choices for weights and whether it is advisable to even use weights for this analysis (see Solon, Haider, and Wooldridge 2015). Unweighted and weighted (using different weighting choices) results and patterns are similar. Details are provided in Appendix A.

area as a proportion of the total county area. This county-level scale is converted to CZ amenities using county land-area weights of the counties contained within the CZ.

The migrant share is included as the presence of a large share of migrants may either attract (as an enclave) or detract (as competition) population growth. Since the migrant share may be endogenous, migrant shares are replaced with a standard Bartik shift-share instrument (for example, see Card 2001); details of construction of the migrant shift-share regressor are included in Appendix A.

We classify job changes by education and also by race/ethnicity. Hellerstein, Neumark, and McInerney (2008) find that an absence of the availability of jobs, generally, is not enough to explain lower employment rates of Black workers, but it's the absence of jobs *available to Black workers* that matters -- accounting for the distribution of jobs only by education level would ignore this point.[8] This race/education specific job change is our measure of job opportunities in a specific geographic location. One might also argue that a measure of job vacancies would better reflect job opportunities, but because of the importance of identifying race-specific job opportunities, it is not possible to use vacancies for this purpose since it is illegal to specify race when advertising a job opening.[9]

The analysis is restricted to CZ/race/education observations that have non-zero values for current and lagged values of population and jobs. The reason for this restriction is that we do not

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[8] Also see Wozniak (2011) for a unique study documenting the systemic challenges faced by low-skilled Black men, relative to their equally low-skilled White counterparts.

[9] There is a growing body of research using online vacancy data, such as Glassdoor or Vault (for example, see Kureková, Beblavý, and Thum-Thysen 2015). Additionally, the Bureau of Labor Statistics makes available measures of job openings (vacancies) in their Job Openings and Labor Turnover Survey (JOLTS). But these data are available only by industry or broad Census region, not both. In addition, occupation is more reflective of educational requirements than industry, which will employ workers of a much broader range of educational attainment. But more importantly neither online vacancy data nor JOLTS identifies race-specific job opportunities.

know whether a zero race/education combination in a specific location is a true zero, or whether that location was simply not sampled that year or is suppressed due to population disclosure concerns. Counties which have populations under 100,000 are not identified in the public version of the ACS. We further restrict the sample to create a balanced panel; a specific CZ/race/education combination has to have non-zero observations for each year of the analysis to be included. This means that if one race/education combination is missing for a CZ, but another race/education combination does not have missing values, the CZ is retained, but only for those race/education combinations with complete data through the time period. Geography-specific, time-invariant regressors, such as location amenities and distance to the next CZ, are expected to control for geographic fixed effects.[10] The analysis excludes less than high school.

2.2 Endogeneity of Job Change

There is concern that the change in jobs (job opportunities) is endogenous to the change in population, either because there are unobservables affecting both job changes and population changes, or economic growth (reflected through job changes) could be a function of population changes. We address this issue of endogeneity with an education/race Bartik (1991) instrument that uses shifts in national education/race-specific industry employment to identify education/race job opportunities at the local level. Details of the construction of the Bartik instrument can be found in Appendix A.

2.2.a The Standard Bartik

The standard, or aggregated, Bartik takes the following form:

$$B_{g,e,r,t} = \sum_i \phi^i_{g,e,r,t-k} \left(\%\Delta J_{i(-g)}\right)_{e,r,t}, \tag{2}$$

[10] An alternative specification that controls more broadly for location fixed effects will be estimated for robustness in future versions of this paper.

where $\phi^{i}_{g,e,r,t-k}$ is the share of education group *e* and race *r* employed individuals in area *g,* at time *t-k* working in industry *i*, and $\left(\%\Delta J_{i(-g)}\right)_{e,r,t}$ is the percentage change between *t* and *t-k* in national education and race specific employment in industry *i* excluding area *g*. We choose to use a one-year lag of the share variable, rather than its value at a fixed point in time, because of the social cost analysis (below) that depends on a (perhaps evolving) racial/ethnic share of the population over time.

Each interaction of $\left(\%\Delta J_g\right)_{e,r,t}$ with education and race needs to be instrumented. Additionally, since the lagged percent difference between employment and population disequilibrium term includes the lagged population rate, following Amior and Manning (2018b) it will be instrumented with the lagged value of the Bartik in equation (2). Equation (1) is then estimated replacing each endogenous regressor with its predicted value from the first-stage estimation:

$$\left(\%\Delta N_g\right)_{e,r,t} = \zeta + \sum_{r=1}^{3}\sum_{e=1}^{3}\left\{\beta_{re} RACE^{r}_{g,t} * \widehat{EDUC^{e}_{g,t}} * \left(\%\Delta J_g\right)_{e,r,t}\right\}$$

$$+\omega_1 UR_{g,t-1} + \omega_2 \hat{Y}_{e,r,g,t-1} + \mu \mathrm{m}_{gt} + \tau_t + \delta_g + d_{gt} + \alpha_g + \mathrm{a}_{gt} + \varepsilon_{g,e,r,t} \qquad (1')$$

2.2.b The Decomposed Bartik

Robustness analysis, detailed in Appendix A, indicates that results using the standard Bartik are not consistent across different specifications (e.g., different lag structures). However, results are stable and more consistent using what is called a decomposed, or disaggregated, Bartik, where the standard Bartik is decomposed into three broad industry groups: natural resources, mining, and construction (NMC); manufacturing; and service. This decomposition allows each broad industry group, by race and education, to affect each endogenous variable differently. This might be important if different race and education groups are concentrated in different industry clusters (for example, see Cajner et al. 2017). It also allows the impact of the market adjustment dynamic to vary by industry cluster (through the lagged disequilibrium term). Construction of the decomposed Bartik only differs from the standard Bartik in the first stage -- construction of the predicted values in equation (1').

Specifically, the Bartik is constructed separately for the industry aggregates of Service; Natural Resource, Mining, and Construction; and Manufacturing, where *I* indicates the aggregated industry sector:

$$\mathrm{B}^{\mathrm{I}}_{\mathrm{g,e,r,t}} = \sum_{i \in I} \phi^{i}_{g,e,r,t-k} \left(\%\Delta J_{i(-g)}\right)_{e,r,t} . \tag{2'}$$

Each of these industry group Bartiks sum to the aggregated, or standard Bartik:

$$\mathrm{B}_{\mathrm{g,e,r,t}} = \mathrm{B}^{\mathrm{NMC}}_{\mathrm{g,e,r,t}} + \mathrm{B}^{\mathrm{Manufacturing}}_{\mathrm{g,e,r,t}} + \mathrm{B}^{Service}_{\mathrm{g,e,r,t}} . \tag{2''}$$

Results using the one-year lagged standard and decomposed Bartik are consistent with each other, but they diverge using different lag structures. These differences are detailed in Appendix A. Results discussed below correspond to using the decomposed Bartik.

Various tests of plausibility of the identifying assumptions of the Bartik, as suggested by Goldsmith-Pinkham, Sorkin, and Swift (2020), will be presented below. At the very least, we need to reasonably expect that each location's education/race-specific population levels would evolve similarly if all locations received the same national shock of education/race-specific industry (or, industry group) job growth. In other words, the national differences in job growth across industries, partially driven by changing educational requirements through technological advancements, shocks each location differently only because of the different concentration of race/education-specific industry composition in that location. Accounting for race/education differences in the distribution of industry jobs in each location (the share portion of the Bartik) actually strengthens the argument that the identifying national job growth is universal (i.e., the presence of race or education location enclaves is controlled for).

Amior and Manning (2018b) find evidence of significant migratory response to labor market opportunity, but that push-migration (from declining economic opportunity) is much weaker than pull-migration. This means that populations never fully adjust to changing employment opportunities and labor market disequilibrium persists across locations. Our analysis differs in that we evaluate race/education-specific population responses to race/education-specific job growth, and on an annual basis, rather the decadal basis. Varying lags of the Bartik instrument are explored.

2.2 Data

The one-year American Community Survey (ACS) from 2005-2019 is used for the analysis in this paper. Specifically, we utilize extracts of the ACS from the IPUMS.org data extractor.[11] The ACS is a nationally representative cross-sectional survey and has been administered annually since 2005 to about 2 million households and is well suited for subnational analyses.[12] We make use of the ACS-provided individual weights when creating aggregate variables and the analysis in this paper is confined to the 16-64 year old population, excluding the armed forces.

For each year, the median education level (using person weights) is determined for each detailed occupation in order to classify each job by its educational "requirement."[13] Table 1 reports the distribution of occupations across median education. Most occupations have a median education level of a high school degree or some college. Less than half of a percent of all

[11] Steven Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas and Matthew Sobek. IPUMS USA: Version 10.0 ACS. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D010.V10.0. IPUMS provides harmonized variables (such as metro codes and occupation codes) across the entire sample period.
[12] https://www.census.gov/acs/www/methodology/sample-size-and-data-quality/sample-size/
[13] Using the median is preferred since several occupations had multiple "modes."

occupation codes have a median education level of less than a high school degree; the analysis here excludes less than high school. Occupations that have a median education level of less than high school include farm workers, graders and sorters of agricultural produce, mobile home installers, sewing machine operators, pressers of textiles, dishwashers, and stucco masons.

[Table 1 about here]

Table 2 reports the distribution of the 16-64 year-olds in the ACS across race/ethnicity for each educational group. White, non-Hispanics make up the largest share in all education groups, except those with less than a high school degree. The shares of Hispanics decline uniformly in educational attainment whereas the shares of White, non-Hispanics increase uniformly in education; the share of Black, non-Hispanics is lower among college educated than shares in other educational groups.

[Table 2 about here]

The number of job opportunities for a person of a certain race with a certain education level in a certain geographic location is proxied by the number of jobs requiring that education level in that geographic location held by workers (aged 16-64) of that race. The percentage change in job opportunities for a person of race *r*, education *e*, in location *g*, $\left(\%\Delta J_g\right)_{e,r,t}$, is, then, simply the percentage change in these number of jobs from the previous year.

The change in population in each geographic location for each race and education group, $\left(\%\Delta N_g\right)_{e,r,t}$, is calculated simply as the percentage change in the number of people (aged 16-64) of race *r*, with education *e*, in location *g*, from the previous year. Table 3 reports means of the variables used for the analyses for the full sample balanced panel 2007-2019 (we lose two years for lagging). The simple correlation between the education/race specific percentage change in jobs and population is 0.78. The simple correlation between the Bartik instrument and the percentage change in population (jobs) is 0.06 (0.04). On average, across CZs, population increases by 9% from one year to the next, job opportunities increase by 11%, the unemployment rate is 7.5% on average over the time period, and the initial disequilibrium is nearly 8% fewer jobs than population. There is a total of 16,809 observations made up of 168 CZs and 1,293 education/race/location groups.

[Table 3 about here]

3 Results

3.1 OLS and IV Baseline Marginal Effects

Table 4 contains the marginal effects for the race/education specific percentage change in jobs on the race/education percentage change in population for both the OLS and IV estimations with and without additional controls (both weighted by lagged CZ population share), and for both the standard and decomposed Bartik first-stage specification. Second-stage parameter estimates for both the standard and decomposed Bartik are found in Appendix B. First-stage parameter estimates are available upon request; the Bartik (and/or its interactions) contributes significantly to the determination of the relevant endogenous regressors in the first stage.

[Table 4 about here]

A positive marginal effect indicates that a CZ with a higher percentage increase in education/race jobs over the previous year also sees a higher percentage increase in the population in that education/race group -- suggestive of a positive rage/education specific net migration response to improved job opportunities in the CZ. The IV marginal effect for Whites across CZs, for example, using the decomposed Bartik, suggests that a one percentage point change in job opportunities results in just under one percentage point change in the population of Whites in the CZ. Based on the analysis of Amior and Manning (2018b), we might expect less than a one percentage point response in the presence of persistent disequilibrium in labor markets (although some of their heterogeneous results are greater than one). Results from the standard Bartik, especially for Whites, are often greater than one.

Before looking at differences across ethnic/racial groups, it's of interest to note that the marginal effects mostly conform to conventional wisdom about greater migration among more educated individuals who would have, all else equal, greater access to information and resources to facilitate responding to job opportunities in another location (for example, see Greenwood 1975; Malamud and Wozniak 2012). For example, Black (White), non-Hispanic college graduates are about two times (50 percent) more responsive. Hispanics with only a high school degree appear to be unresponsive (in the IV specification) to changes in job opportunities; perhaps indicating a particular challenge among that group in responding to those opportunities.

We also see in Table 4 that overall, and within education groups (except for Blacks with some college), Blacks and Hispanics are less responsive to changing job opportunities than are Whites. While each of the marginal effects for Blacks and Hispanics is statistically significantly different from the marginal effect estimated for Whites (based on a standard Z test statistic), one could argue there is not much practical difference. However, keep in mind that given the larger population levels of Whites vs. Blacks, a similar percentage point change in population corresponds to an even larger difference in the *level* change in population numbers.

3.2 Social Costs of Migration

The appropriate policy aimed at improving the response rates among racial/ethnic minorities depends on the reason why minorities are less responsive to changes in labor market opportunities. If social costs are keeping racial and ethnic minorities from migrating to better opportunities, then a policy aimed at moving people to jobs is likely to be less successful in improving outcomes than a policy aimed at moving jobs to people.

Strong social ties have been found to be an important determinant of an individual's willingness (or ability) to migrate in response to a negative labor market event (Huttunen, Møen, and Salvanes 2017; Zabek 2019). Kosar, Ransom, and van der Klaauw (2019) find that that strong (and growing) preferences for family and local cultural norms (social ties) partially explain the long-run decline in migration rates in the U.S. A graphical analysis of Facebook connections illustrates how powerful connections from historical events, like the Great Migration in the early 20th century, can dictate geographic connectedness today (Bailey et al. 2018, also see Badger and Bui 2018).[14]

Also, Ananat, Shihe, and Ross (2018) find that as the share of a worker's race in a local area increases, the employment density wage premium for that worker increases, providing yet another reason why we might expect minorities to respond more to employment opportunities in areas with higher own-racial shares (at lease in densely population CZs). This section explores the role of just one of many possible social costs that might be playing a role in weaker responsiveness of minority workers to changes in job opportunities -- the share of own-race population in the location offering job opportunities.

To investigate the importance of own-race population share, equation (1) is modified by adding the interaction of own-race/ethnic population shares with the education and race modifiers on percentage job change. If this type of social consideration is important to the migration decision, we should observe that at least Black and Hispanic people are more willing

[14] A future analysis will make use of the same data to explore responsive to job opportunities in location in which individuals have greater social media connections.

to respond to growing labor market opportunities, all else equal, in locations with larger population shares of their own race/ethnicity. Equation (1) is modified as follows to determine whether responsiveness varies by share of same racial group in location with growing job opportunities:

$$\left(\%\Delta N_g\right)_{e,r,t} = \zeta + \sum_{r=1}^{3}\sum_{e=1}^{3}\left\{\beta_{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * \left(\%\Delta J_g\right)_{e,r,t}\right\}$$
$$+ \sum_{r=1}^{3}\sum_{e=1}^{3}\left\{\vartheta_{r,e} OwnRaceShare_{g,t}^{r} * RACE_{g,t}^{r} * EDUC_{g,t}^{e} * \left(\%\Delta J_g\right)_{e,r,t}\right\}$$
$$+\omega_1 UR_{g,t-1} + \omega_2 Y_{e,r,g,t-1} + \mu \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t}\ , \tag{3}$$

where all regressors are defined above and $OwnRaceShare_{g,t}^{r}$ = the share of the population that is of race *r* (*r* = White, NH; Black, NH; Hispanic).

This allows the race/education specific relationship between $\%\Delta J_{g,e,r,t}$ and $\%\Delta N_{g,e,r,t}$ to vary across different levels of concentration of racial minority population within the CZ. The hypothesis, that own-race share plays a role in migration decisions, would be supported if the relationship between the percentage change in jobs and population is stronger when the CZ has a higher share of own-race population. This would suggest that social/cultural considerations are playing a role in measured responsiveness. It's unclear how Whites' own-race share will affect their responsiveness to jobs since even in the 25th percentile of White race share, a CZ still has a significant (likely majority) representation of Whites. One could make the same argument that whites might be drawn to geographic locations with higher White race share (all else equal). However, there is a robust literature that finds that as the share of a racial minorities grows in a location, outcomes, particularly earnings, of the majority improve, leading to greater inequality (for example, see Frisbie and Neidert 1977; Wilcox and Roof 1978; Tienda and Lii 1987; Tomaskovic-Devey and Roscigno 1996; Cohen 1998). These higher earnings in areas with high shares of racial minorities (relatively lower own-race White shares) may dominate as an incentive to migrate to these areas for Whites.

Each of the terms in equation (3) interacted with percentage change in jobs is instrumented with the race/education-specific decomposed industry Bartik measure described in equation (2) and the Amior and Manning disequilibrium measure ($Y_{e,r,g,t-1}$) is instrumented with the lagged Bartik. Marginal effects from both the OLS and the IV estimation of the social cost specification are reported in Table 5; second-stage parameter estimates found in Appendix B.

[Table 5 about here]

The first thing to notice in Table 5 is that the OLS marginal effects perform as expected for all race groups (except for White, Some College) -- the marginal response to changing job opportunities is larger when those opportunities are found in CZs with an own-race population share in the 75th percentile than when the own-race population share is in the 25th percentile.

Secondly, turning to the IV results, this pattern holds strongly among Black workers -- overall and within each education group (except those with only some college), the marginal effect is stronger as the share of Blacks in the CZ population increases. For example, Blacks are overall nearly 25 percent more responsive to increasing job opportunities in a CZ where the Black population share is in the 75th percentile, relative to the same increase in jobs in a CZ where the Black population share is in the 25th percentile. This pattern is consistent with Stuart and Taylor (2021) who find that, historically, social networks are much more important for determining migration patterns of Blacks than for Whites, especially with the expectation of increased job opportunities.

Among Hispanics, we see the same pattern only among those with at least some college. The strong opposite response among those with a high school degree reverses the OLS pattern, potentially indicating that the industrial distribution of jobs (which comes through the Bartik) employing Hispanics with a high school degree is more powerful than the importance of social costs in motivating Hispanic migration decisions.

And, lastly, the pattern for Whites in the IV estimation is opposite, overall and within each education group, than it is in the OLS results. This may be reflecting the importance of the results from the literature cited above, that the white wage premium is higher in areas with higher shares of minorities. And since even *relatively* low shares of White population (i.e., in the 25th percentile) still means Whites are likely in the majority, this would dominate any concern about loss of social/cultural connectedness.

3.3 Validity of Bartik Instrument

The validity of the Bartik instrument is based on the assumption that each location's population would have evolved similarly if the location hadn't experienced the observe industry job growth shock. The shock varies across location because of different concentrations of industry in each location. As recommended by Goldsmith-Pinkham, Sorkin, and Swift (2020), we undertake a number of diagnostics to assess the plausibility of the assumptions of the Bartik instrument for identifying a causal relationship between job growth and population growth. Details are included in Appendix A. By way of summary, we find that a number of exogenous regressors are correlated with the Bartik, which might make us concerned that the relationship that we estimate between the Bartik instrument and population change is simply reflecting the change in these exogenous regressors *through* the Bartik. However, an additional regression shows that each of those exogenous regressors have only a weak, if at all, relationship with the percentage change in population (the dependent variable), so they are not likely confounding the estimated relationship between the instrument and the dependent variable. Additionally, Tim Bartik (2018) notes that while lack of correlation between all industry shares and national industry growth might be a *sufficient* condition for identifying demand shocks, it is by no means *necessary*.

Further, and most importantly, inclusion or exclusion of these potential confounders in the second-stage regression does not materially affect the results (see Table 4), suggesting we need not to be concerned that correlations between industry shares and Bartik with other regressors are confounding the relationship between (instrumented) change in jobs and change in population (see Altonji, Elder, and Taber 2005). The bottom line is that these diagnostic efforts offer some degree of confidence that the only channel through which the industry shares (or the Bartik IV) predict the change in population is through the change in the number of jobs, giving us confidence in our causal interpretation of the instrument.

3.4 Robustness of IV Results

While validity is difficult to establish with certainty, it's useful to assess whether the IV results are sensitive to construction of the instrument. The Bartik we employ here lags CZ industry shares by one year. One might argue that this is not a long enough time to free the Bartik from concerns of endogeneity. Hence, we repeat the analysis with a Bartik lagged two and three years, as well as with a Bartik that is fixed at an historical point in time. Marginal effects for theses alternative specifications are found in Table A4 of Appendix A. The marginal effects (for the decomposed Bartik) with three lags and fixed shares (and mostly two lags) are slightly smaller than with one lag, but the conclusions are the same.[15] The standard Bartik pretty much fails these same robustness tests.

[15] Also note that a previous version of this paper (Burns and Hotchkiss 2019), estimating a different specification of the model, also come to the same conclusions found here.

4 Conclusions and Policy Considerations

The analysis in this paper finds differences in migration responses by education and race to changing job opportunities. The relationship between the change in education/race specific job opportunities in a location and the change in education/race specific population is larger among White, non-Hispanics than it is for Black, non-Hispanics and for Hispanics. Additional analysis provides evidence that social costs may play a role in constraining ethnic/minority response to changing labor market opportunities elsewhere, and that the weaker response among Blacks is likely driven by weaker response to job opportunities in areas with low Black population shares.

The stronger response when job opportunities arise in locations with greater minority representation is not entirely unexpected. Some have found that racial and ethnic minorities experience significant gains from social and cultural networks that are accessible when living in close proximity with one another (e.g., Montgomery 1991; Edin, Fredriksson, and Åslund 2003; Elliott 2005). This would suggest that efforts directed toward decreasing disparate labor market outcomes should focus on adjusting the human capital of minorities (e.g., by improving educational opportunities) to better match the occupational demands of the area, or by improving economic opportunities that better match the educational attainment of the population, rather than necessarily promoting migration.

On the other hand, Xie and Gough (2011) don't find any evidence of benefits to immigrants working in "ethnic enclaves" relative to immigrants working outside of the enclave. In addition, Dickerson (2007) finds that employment outcomes are worse for Blacks in segregated cities, suggesting that geographic concentration may indeed be harmful for economic outcomes of minorities, and that easing other migration constraints might prove useful for improving labor market disparities.

Picard and Zenou (2018) provide a theoretical model showing how minority workers, faced with a mismatch of location and jobs, could benefit from a variety of policy approaches. Place-based policies, such as neighborhood regeneration (which provides incentives for majority workers to move there providing improved networking contacts) and establishment of enterprise zones (attracting firms providing additional employment opportunities) are ways in which specific geographic locales can attract both residents and firms. Contrastingly, people-based policies, such as the Moving to Opportunity programs, provide housing subsidies in order to improve outcomes by moving people closer to jobs.[16] Incentivizing people to move, however, is a tall order (for example see Harrison and Raice 2018) and may results in unintended reactions from receiving populations (Derenoncourt 2022). However, Cáceres-Delpiano et al. (2021) and Cáceres-Delpiano et al. (2023) offer evidence of a broader benefit to policies that potentially move people out of their comfort zones; they find that exposure to different regional peculiarities allows individual to identify cultural and social commonalities that span geography, increasing the willingness to migrate.

The potential conflict in policies focused on *either* people *or* place is long-standing in the urban literature, described in a phrase coined by Winnick (1966)-- 'Place Prosperity vs. People Prosperity' (also see Bolton 1992; Partridge and Rickman 2007). This leads to a potential role for indirect policies, such as improving public transportation or access to information (see Waldrip et al. 2015; Wilson 2021) for improving employment outcomes among minorities.

[16] Also see Mueller 1981, who describes the apparent success of a relocation assistance program in the 1970s in getting people to move to better job opportunities, even those who expressly indicated they didn't want to move.

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Table 1 Distribution of occupations across median education of those employed in the occupation 2005-2019.

Median Education in Occupation	Percent of Occupation codes across years
Less than high school	0.44 %
High school degree only	32.62 %
Some college	39.85 %
College degree and above	27.10 %

Notes: Authors calculations using the ACS.

Table 2 Distribution of 16-64 year old population across race/ethnicity by educational attainment, 2005-2019.

	Percent of Education Category		
	White, NH	Black, NH	Hispanic
Less than HS	34	13	52
HS degree	60	17	23
Some College	66	16	18
College degree or more	81	10	9

Notes: Authors calculations using the ACS person weight. Row totals may not sum to 100 due to rounding.

Table 3 Means and standard deviations for variables used in the analyses.

	Mean (st. dev.)
$\left(\%\Delta N_g\right)_{e,r,t}$	0.0866
	[1.0906]
$\left(\%\Delta J_g\right)_{e,r,t}$	0.1126
	[1.3627]
$B_{g,e,r,t}$	0.0219
	[0.0437]
Supply Controls	
Distance	50.9877
	[18.972]
Amenities	0.9892
	[2.864]
Migrant shift-share	0.0213
	[0.024]
Population Density	0.2832
	[0.4877]
Measures of Diseq.	
$\left[\left(J_{e,r,g,t-1} - N_{e,r,g,t-1}\right)/N_{e,r,g,t-1}\right]$	-0.0781
	[0.4126]
Lagged Urate (percent)	7.5712
	[2.8382]
Observations	16,809
Number of CZs	168
Number of race/education/CZ groups	1,293

Note: American Community Survey 2007-2019, balanced panel.

Table 4 Marginal effects of the percentage change in jobs on the percentage change in population by race and education, OLS (equation 1) and IV (equation 1').

	No additional regressors			All regressors		
		IV			IV	
N= 16,809	OLS (1)	Standard Bartik (2)	Decomposed Bartik (3)	OLS (4)	Standard Bartik (5)	Decomposed Bartik (6)
White, NH	0.9411***	2.0228***	0.9731***	0.9498***	2.0075***	0.9884***
	[0.0444]	[0.3051]	[0.1482]	[0.0398]	[0.3072]	[0.1477]
High School	0.7647***	-0.0507	0.5012***	0.7794***	-0.0814	0.4963***
	[0.0670]	[0.2112]	[0.0968]	[0.0630]	[0.2122]	[0.0979]
Some College	0.9829***	3.6873***	0.9855***	0.9880***	3.6563***	1.0106***
	[0.0775]	[0.6206]	[0.3117]	[0.0715]	[0.6151]	[0.3023]
College and Above	1.0780***	2.4207***	1.4413***	1.0841***	2.4372***	1.4672***
	[0.0172]	[0.3882]	[0.1976]	[0.0183]	[0.4002]	[0.2062]
Black, NH	0.7583***	1.0942***	0.9619***	0.7697***	1.0933***	0.9631***
	[0.0356]	[0.0766]	[0.0534]	[0.0372]	[0.0758]	[0.0533]
High School	0.4736***	0.4195***	0.4459***	0.4746***	0.4201***	0.4458***
	[0.0026]	[0.0588]	[0.0281]	[0.0026]	[0.0584]	[0.0282]
Some College	1.4700***	1.5917***	1.5332***	1.4709***	1.5905***	1.5345***
	[0.0673]	[0.0770]	[0.0576]	[0.0650]	[0.0766]	[0.0577]
College and Above	0.3149***	1.2690***	0.8988***	0.3476***	1.2671***	0.9015***
	[0.0880]	[0.1944]	[0.1453]	[0.0942]	[0.1932]	[0.1453]
Hispanic	0.7593***	0.9016***	0.6554***	0.7647***	0.8974***	0.6677***
	[0.1265]	[0.1601]	[0.1900]	[0.1232]	[0.1581]	[0.1858]
High School	0.7500***	0.3122	0.0569	0.7396***	0.2959	0.0824
	[0.0239]	[0.5085]	[0.5384]	[0.0214]	[0.5058]	[0.5299]
Some College	0.7592***	1.2255***	0.9654***	0.7666***	1.2287***	0.9739***
	[0.1873]	[0.0743]	[0.0678]	[0.1824]	[0.0742]	[0.0669]
College and Above	0.7690***	1.1686***	0.9460***	0.7884***	1.1690***	0.9486***
	[0.2147]	[0.0828]	[0.1012]	[0.2063]	[0.0826]	[0.1005]

Notes: All regressions include the regressor of interest (percentage change in jobs) and year fixed effects. Robust standard errors are clustered at the CZ level. Observations are weighted by lagged CZ population shares. Marginal effects in columns (4) - (6) are from regressions that also include CZ initial employment disequilibrium measure (the percent difference between race/education-specific employment and population in the previous year, one year lagged CZ unemployment rate), the distance from the next nearest CZ, CZ amenity index, CZ population density, and CZ migrant shift-share regressors. The decomposed Bartik splits the standard Bartik into three industry groups: natural resources, mining, and construction; manufacturing; and service.
*, **, *** => statistical significance at the 90, 95, and 99 percent level. All marginal effects for Black and Hispanics are statistically significantly different from those for whites at the 99 percent confidence level (overall and for each education level). Sample includes 16-64 year-olds with at least a high school degree and 2007-2019 years of data. Full estimation results are included in Appendix B.

Table 5 Marginal effects of the percentage change in jobs on the percentage change in population by race and education from decomposed Bartik IV estimation (eq. 3), at different points in the distribution of own-race population share.

	OLS				IV			
		Own race pop share in CZ, percentile				Own race pop share in CZ, percentile		
N = 16,809	Overall m.e. of %ΔN wrt change in %ΔJ	25th Percentile	50th Percentile	75th Percentile	Overall m.e. of %ΔN wrt change in %ΔJ	25th Percentile	50th Percentile	75th Percentile
M.E. for Whites, NH	0.9214***	0.9509***	0.9687***	0.9808***	1.1749***	0.9589***	0.8311***	0.7436***
	[0.0816]	[0.0401]	[0.0392]	[0.0523]	[0.2279]	[0.1386]	[0.1245]	[0.1401]
High School	0.6333***	0.7793***	0.8657***	0.9249***	0.5234***	0.4587***	0.4205***	0.3942***
	[0.0927]	[0.0648]	[0.0582]	[0.0600]	[0.1214]	[0.0861]	[0.0995]	[0.1205]
Some College	1.0608***	0.9915***	0.9505***	0.9224***	1.3492***	1.0306***	0.8419***	0.7128**
	[0.1494]	[0.0673]	[0.0659]	[0.0929]	[0.4706]	[0.2823]	[0.2543]	[0.2898]
College or Above	1.0701***	1.0841***	1.0923***	1.0980***	1.6587***	1.3947***	1.2385***	1.1315***
	[0.0869]	[0.0184]	[0.0523]	[0.0851]	[0.2945]	[0.1777]	[0.1360]	[0.1338]
M.E. for Blacks, NH	1.3136***	0.6287***	0.7928***	1.0010***	1.2205***	0.8332***	0.9255***	1.0425***
	[0.0954]	[0.0445]	[0.0232]	[0.0409]	[0.1249]	[0.0759]	[0.0456]	[0.0541]
High School	1.0967***	0.2473***	0.4511***	0.7094***	0.9614***	0.2659**	0.4328***	0.6443***
	[0.1460]	[0.0522]	[0.0049]	[0.0557]	[0.3115]	[0.1159]	[0.0246]	[0.1191]
Some College	1.8679***	1.3353***	1.4631***	1.6251***	1.4745***	1.5163***	1.5063***	1.4936***
	[0.4316]	[0.1468]	[0.0592]	[0.1813]	[0.2535]	[0.1220]	[0.0542]	[0.0968]
College or Above	0.9616***	0.2890***	0.4504***	0.6549***	1.2146***	0.7073***	0.8290***	0.9833***
	[0.0988]	[0.0307]	[0.0400]	[0.0613]	[0.1362]	[0.1266]	[0.1109]	[0.1072]
M.E. for Hispanics	1.1150***	0.4342***	0.5589***	0.8907***	0.6504***	0.7510***	0.7323***	0.6826***
	[0.0282]	[0.0605]	[0.0472]	[0.0200]	[0.1892]	[0.1017]	[0.1058]	[0.1477]
High School	0.7672***	0.6932***	0.7067***	0.7429***	-0.1853	0.5915**	0.449	0.0698
	[0.0292]	[0.1143]	[0.0887]	[0.0226]	[0.4512]	[0.2775]	[0.2845]	[0.3655]
Some College	1.2075***	0.2874***	0.4562***	0.9053***	1.0360***	0.8581***	0.8907***	0.9776***
	[0.0463]	[0.0960]	[0.0744]	[0.0307]	[0.0986]	[0.0802]	[0.0687]	[0.0724]
College or Above	1.3706***	0.3216***	0.5141***	1.0262***	1.1010***	0.8031***	0.8578***	1.0032***
	[0.0567]	[0.0416]	[0.0327]	[0.0368]	[0.1129]	[0.0856]	[0.0762]	[0.0852]

Notes: See notes to Table 4. All marginal effects at the 25th and 75th percentile are statistically different from one another at the 99 percent confidence level (overall and for each education level). IV results are estimated using the decomposed Bartik specification.

Appendix A: Sample and Variable Construction Details

A1 Construction Distance to Next Nearest Commuting Zone

The GEOcorr1990 data from the Missouri Census Data Center (https://mcdc.missouri.edu/applications/geocorr1990.html) provides the latitude and longitude for the centroid of each county in the U.S. We multiply each of these by the county population and divide by the county's CZ population, then sum over counties within the CZ. This renders population-weighted centroid for each commuting zone. These can then be used to calculate the distance between each commuting zones.

A2 Construction of Migrant Shift-share Regressor

The regressions estimated include a regressor measuring the share of the population that are foreign-born (non-native). Because of the well-known existence of immigrant enclaves, this regressor could be endogenous to population growth and is, hence, instrumented using a Bartik-type instrument. The regressor included in the regression is constructed as follows (see Amior and Manning 2018a, Section D.3):

$$\mathrm{m}_{gt} = \frac{\sum_o \sigma^o_{g,t-1} N^F_{o(-g)t}}{N_{g,t-1}} \ , \tag{A1}$$

where $\sigma^o_{g,t-1}$ is the share of the population in area *g* at time *t-1* that is native to origin country *o*; $N^F_{o(-g)t}$ is the stock of new origin-specific foreign migrants (excluding those living in area *g*) who arrived in the U.S. between *t-1* and *t*; this product is scaled by the initial total population of area *g*.

Shares of foreign-born population by county are obtained from IPUMS, NHGIS.[17] Five-year averages from 2005-2015 from the American Community Survey of the following tables are used:

Nativity in the United States: provides total number of native and foreign born in each county

Place of birth for the foreign-born in the United States: number of people by place of birth

The year of data in the analysis corresponds to the first year in the five years over which the population numbers are averaged. Data trends are extended backward one year (to allow for lagging) and forward through 2019 to match years of analysis. Due to small sample sizes, foreign-born are aggregated to the following geographic regions: Africa, Latin America, North America, Asia, Europe, and Oceania.

A3 Weighting Considerations and Sensitivity

The use of weights is typically helpful for comparing estimates of different regressions from different samples and when the effect of interest varies with the size of the geographic units in the sample or there are heterogeneous effects. Weights may be called for here if the average population response varies with CZ size or with racial population size. In other words, is the same percentage change in jobs more attractive in larger CZ than in smaller CZ, or in CZ with a different racial mix?

When we apply differential weights by CZ or racial group size, the weighted regression puts greater weight on the largest CZ or the largest racial group. However, if the effect does not vary with CZ or racial group size, weighting becomes a less efficient regression strategy than using unweighted regression. When this happens, unweighted regression estimates may be more

[17] Steven Manson, Jonathan Schroeder, David Van Riper, Tracy Kugler, and Steven Ruggles. IPUMS National Historical Geographic Information System: Version 16.0 [dataset]. Minneapolis, MN: IPUMS. 2021. http://doi.org/10.18128/D050.V16.0

precise due to effective unweighted variation than weighted variation in the CZ sample (see T. J. Bartik and Sotherland 2019).

Additionally, the use of weights affects what the estimates of a regression represent. Weighted estimates show the average impact of a change in jobs on change in population for the United States, or, the average person in the U.S. When the change in jobs is modified by race/education, the estimates reflect the average impact for the average person of that race/education group in the U.S. Unweighted estimates show the average response for the average geographic unit in the sample.

Solon, Haider, and Wooldridge (2015) argue that one should have a good understanding of why weights are being applied to the regression(s) in an analysis. They identify three reasons for weighting regressions: (1) to achieve more precise estimates in the presence of heteroskedasticity, (2) to achieve consistent estimates by correcting for endogenous sampling, and/or (3) to identify average partial effects in the presence of heterogeneous effects. Each of these points is discussed and comparison of marginal effects with and without weights in Table A1.

In order to determine whether heteroskedasticity should motivate the decision to apply weights, we performed a number of diagnostics and found that in the second-stage IV unweighted regression, the null hypothesis of homoskedastic standard errors is rejected (results available upon request). Using the fitted values of the dependent variable, the Pagan-Hall most general test statistics (not requiring normality) does not reject homoskedasticity of the standard errors in the second-stage weighted IV regression. This may be reason enough to apply weights, but, in addition, since we are interested in heterogenous affects across CZs of widely varying sizes, Solon, Haider, and Wooldridge (2015) suggest that using weights may considerably improve the precision of the estimates (which is what we see in Table A1).

Regarding endogenous sampling, the suppression of location information for observations from small counties in the public ASEC might be a source of concern if the relationship between job creation and population growth is related to county size. If this is the case, the error term would likely be related to the sample creation. However, Solon, Haider, and Wooldridge (2015) suggest if the unweighted and weighted results were "similar," this would ease concern over endogenous sampling and, hence, weighting is unnecessary and may lead to less efficient estimates. The similarity in pattern of results in Table A1 between the unweighted and weighted marginal effects (except for some negative marginal effects in the unweighted results), suggests weighting is unnecessary. However, the presence of heteroskedasticity and interest in heterogenous effects leads us to report results from the weighted regression. We use weights constructed from CZ population shares for consistency with Amior and Manning (2018b).

Table A1: Marginal effects of the percentage change in jobs on the percentage change in population by race and education, IV (eq. 1') using one-year decomposed Bartik lag, both measures of disequilibrium **-- comparing weights**

	No Weights (1)	CZ Pop Share (baseline results from Table 4) (2)
# Observations =	N = 16809	N = 16809
White, NH	0.8188^{***}	0.9884^{***}
	[0.2704]	[0.1477]
High School	0.7133^{***}	0.4963^{***}
	[0.2157]	[0.0979]
Some College	-0.1714	1.0106^{***}
	[0.6957]	[0.3023]
College and Above	2.0105^{***}	1.4672^{***}
	[0.4160]	[0.2062]
Black, NH	0.8648^{***}	0.9631^{***}
	[0.0935]	[0.0533]

High School	0.4034***	0.4458***
	[0.0761]	[0.0282]
Some College	1.3219***	1.5345***
	[0.1650]	[0.0577]
College and Above	0.8572***	0.9015***
	[0.1416]	[0.1453]
Hispanic	0.4189	0.6677***
	[0.2941]	[0.1858]
High School	-0.5206	0.0824
	[0.9017]	[0.5299]
Some College	0.9099***	0.9739***
	[0.1274]	[0.0669]
College and Above	0.8825***	0.9486***
	[0.1107]	[0.0826]

Notes: All regressions include year fixed effects. Robust standard errors are clustered at the CZ level. All regressions include CZ initial employment disequilibrium measure (the percent difference between race/education-specific employment and population in the previous year, one year lagged CZ unemployment rate), the distance from the next nearest CZ, CZ amenity index, population density in 1990, and CZ migrant shift-share regressors. *, **, *** => statistical significance at the 90, 95, and 99 percent level. Sample includes 16–64-year-olds with at least a high school degree and 2007-2019 years of data. Full estimation results are included in Appendix B.

A4 Construction of Bartik Instrument and Validity

Equation (1') is identified by instrumenting the change in the number of jobs with the Bartik shift-share $B_{g,e,r,t}$ (Bartik, 1991). We make use of the same ACS data to construct the following race/education/industry-specific Bartik instrument:

$$B_{g,e,r,t} = \sum_i \phi^i_{g,e,r,t-k} \ \left(\%\Delta J_{i(-g)}\right)_{e,r,t}, \tag{A2}$$

where $\phi^i_{g,e,r,t-k}$ is the share of education group *e* and race *r* individuals in area *g* employed in industry *i* at time *t-k*, and $\left(\%\Delta J_{i(-g)}\right)_{e,r,t}$ is the percentage change in national education/race-specific employment in an industry *i* (excluding area *g*). We perform most of the aggregation described below using the collapse command in Stata, and we apply person weights, when available.

To obtain the education and race-specific industry number of annual jobs at the national level, $\left(\%\Delta J_{i(-g)}\right)_{e,r,t}$, we collapse the county data by year, industry, race, and education before we merge in the county CZ crosswalk. We obtain the CZ total number of education and race-specific jobs for each year and industry by summing county data to the CZ level. To overcome the potential endogeneity of the change in the national education and race-specific industry employment to shocks within the local labor market, we subtract each CZ's education and race-specific industry number of jobs from the national education and race-specific industry jobs (hence, the *-g* subscript).

Education and race specific industry shares for each CZ and year ($\phi^{i}_{g,e,r,t}$) are derived by dividing each CZ's education and race-specific industry jobs by the CZ's total number of jobs for that education and racial group. This share term is then lagged by one year (hence, the *t-k* subscript, where *k*=1 here).

The following steps outline how the Bartik shift-share instrument is constructed. The sample is restricted to workers aged 16-64 and consider only private sector employment (excluding Public Administration), which are the same sample restrictions for the baseline (OLS) estimation (construction of *J*).

(i) obtain the total number of jobs by race, education, and industry:
collapse (sum) $EMP_{e,r,i,t}$ = obs [fweight=perwt], by (year educ_cat race_cat naics), and afterwards merge in the county czone crosswalk but keep only observations that merge across the two datasets.

(ii) Afterwards, get the total number of education and race-specific industry jobs for each czone: collapse (sum) $EMP_{e,r,i,g,t}$ = obs [fweight=perwt], by (year czone educ_cat race_cat naics),

(iii) then sum over industries to get the education and race-specific jobs for each czone: collapse (sum) $EMP_{e,r,g,t}$ = obs [fweight=perwt], by (year czone educ_cat race_cat naics).

(iv) Now, we take the dataset in step (iii) and merge it into that from (ii):
merge m:1 year educ_cat race_cat czone using dataset (iii).

(v) Next, merge the dataset from (i) into the dataset generated in (iv):
merge m:1 year educ_cat race_cat naics using dataset from (iv).

(vi) To address the concern of the endogeneity of national jobs to local employment count, subtract local education and race-specific industry jobs from the national education and race specific industry jobs:[18]

$$EMP_{e,r,i,t} - EMP_{e,r,i,g,t} = \left(J_{i(-g)}\right)_{e,r,t}.$$

Then, the percentage change in education, race, and industry jobs, is calculated:

$$\left(\%\Delta J_{i(-g)}\right)_{e,r,t} = \frac{\left(J_{i(-g)}\right)_{e,r,t} - \left(J_{i(-g)}\right)_{e,r,t-1}}{\left(J_{i(-g)}\right)_{e,r,t-1}}.$$

(vii) We obtain the industry shares in each CZ by dividing the number of the CZ's education, race, and industry jobs by the count of education and race specific jobs in that CZ:

$\phi^{i}_{g,e,r,t} = \frac{EMP_{e,r,i,g,t}}{EMP_{e,r,g,t}}$. And we lag by one year to get $\phi^{i}_{g,e,r,t-1}$.

(viii) In the final step, we multiply the industry shares by the national change in employment, and sum across CZs, education, race, and year to get the race/education/geography specific instrument for each CZ and year, $B_{g,e,r,t} = \sum_i \phi^{i}_{g,e,r,t-k} \left(\%\Delta J_{i(-g)}\right)_{e,r,t}$:
collapse (sum) $B_{g,e,r,t}$=$B_{g,e,r,i,t}$, by (year czone educ_cat race_cat).

The validity of the Bartik instrument is based on the assumption that each location's population would have evolved similarly (the shift portion) if the location hadn't experienced the observe industry job growth shock. The shock varies across location because of different concentrations of industry in each location (the share portion). While the assumptions for identification are not directly testable, there are a number of ways to assess the *plausibility* of the assumption of exogeneity of the Bartik instrument.

[18] See Goldsmith-Pinkham, Sorkin, and Swift (2017); and Autor and Duggan (2003).

We posit that the only channel through which the Bartik instrument affects the change in population is the endogenous regressor, change in jobs. The validity of the instrument would be in question if it predicts the change in population through other channels. To assess whether the Bartik instrument predicts change in population other than through change in job, we run separate regressions for each industry share, and the Bartik instrument, on some potential observed predictors of the change in population. The results in Table A2 suggest that the Bartik and some of our industry shares are correlated with some of our exogenous regressors.

We may also be concerned if those factors found to be correlated to industry share or the Bartik instrument significantly and independently predict changes in population, suggesting that the estimated relationship between the instrument and the dependent variable is simply reflecting the influence of these confounders (see Goldsmith-Pinkham, Sorkin, and Swift 2020). Table A3 shows that each of those exogenous regressors have only a week, if at all, relationship with the percentage change in population (the dependent variable), so they are not likely confounding the estimated relationship between the instrument and the dependent variable. These diagnostics offer a degree of confidence that the only channel through which the Bartik instrument predicts the change in population is through the change in the number of jobs.

Additionally, since inclusion or exclusion of these potential confounders in the second-stage regression does not materially affect the results (see Table 4 in the text), we need not to be concerned that correlations between industry shares and Bartik with other regressors are confounding the relationship between (instrumented) change in jobs and change in population (see Altonji, Elder, and Taber 2005).[19]

[19] Future versions of this paper will consider alternatives to the 2SLS estimator, such as limited information maximum likelihood.

Lastly, Goldsmith-Pinkham, Sorkin, and Swift (2020) recommend constructing what they call "Rotemberg weights" in order to see which industries might be accounting for a higher degree of identifying variation. However, as pointed out by Tim Bartik (2018), this exercise is unnecessary as a lack of correlation between all industry shares and national industry growth might be a *sufficient* condition for identifying demand shocks, it is by no means *necessary*, rendering information about which industry shares might not be exogenous, in our case, as superfluous. He points out that, "the Bartik IV might be uncorrelated with local labor supply shocks even if the local industry shares have some correlation with variables related to local supply shocks."

Table A2 Relationship between the Lag of Race and Education Specific Industry Shares and Czone Characteristics; regressions of the lag of race and education specific local industry share and Bartik on each exogenous regressor to see whether the contribution of industry shares (or Bartik) are affecting population growth through the channel of other regressors (rather than exclusively through the regressor being instrumented — job growth).

	Manufac-turing	Trade, Transporta-tion and Utilities	Information	Financial Activities	Education and Health	Leisure and Hospitality	Natural Resources, Mining and Construction	Professional, Business Service and Other Service	Bartik Instrument
Distance (00)	-0.0113	-0.0049	-0.0080***	0.0128	0.0439*	0.0049	-0.0116	-0.0259**	-0.0016
	[0.0295]	[0.0156]	[0.0030]	[0.0187]	[0.0256]	[0.0161]	[0.0114]	[0.0109]	[0.0013]
Amenities	-0.0062***	0.0016*	0.0007***	0.0003	-0.0032**	0.0006	0.0021***	0.0042***	0.0001**
	[0.0019]	[0.0009]	[0.0001]	[0.0006]	[0.0015]	[0.0010]	[0.0006]	[0.0008]	[0.0001]
Migshare	-0.1396	0.0608	-0.0592***	-0.3811***	0.6072***	0.0954	0.3481***	-0.5315***	0.0335***
	[0.1779]	[0.1260]	[0.0187]	[0.1035]	[0.2088]	[0.1428]	[0.1062]	[0.1300]	[0.0090]
1990 Pop Density	-0.0157***	-0.0018*	0.0002	0.0049***	0.0102***	0.0017	-0.0044***	0.0049*	0.0003***
	[0.0021]	[0.0011]	[0.0003]	[0.0012]	[0.0022]	[0.0013]	[0.0014]	[0.0026]	[0.0001]
1990 Land Area (00000)	-0.0009	-0.0009	0.0007*	-0.0015	-0.0072	0.009	-0.0033	0.0041**	0.0005***
	[0.0052]	[0.0021]	[0.0004]	[0.0023]	[0.0055]	[0.0066]	[0.0021]	[0.0017]	[0.0002]
Lagged Urate	0.0025	0.0013	-0.0004**	-0.0026***	0.0027	0.0005	-0.0005	-0.0037***	0.0001
	[0.0017]	[0.0009]	[0.0002]	[0.0008]	[0.0018]	[0.0006]	[0.0007]	[0.0013]	[0.0001]
Adj. R^2	0.126	0.007	0.02	0.049	0.015	0.128	0.022	0.059	0.191

Notes: The results in each column represents estimates from a single regression of each lag education and race specific local industry share on local characteristics. All but one, land area 1990, of these local characteristics are the controls in our main analysis equation. We exclude the disequilibrium measure as a local characteristic because we treat it as an endogenous regressor in all of our two stage regressions. Each result is weighted by one year lag of racial population share. Robust standard errors are in parenthesis and are clustered at the CZ level. *, **, *** => statistical significance at the 90, 95, and 99 percent level. Sample includes 2007-2019 years of data.

Table A3 Correlation between the Change in Population and Commuting Zone Characteristics.

N =16809	$\left(\%\Delta N_g\right)_{e,r,t}$
Distance (00)	-0.205
	[0.2969]
Amenities	0.0004
	[0.0054]
Migrant Share	0.7028*
	[0.4238]
Population Density (1990)	-0.0362
	[0.0260]
Land Area (1990) (00000)	0.0109
	[0.0315]
Czone Urate Lag	0.0019
	[0.0083]
Adj. R^2	0.009

Notes: Results represents the estimates from regressing the change in population on commuting zone characteristics. Results are weighted by one year lag of population share. Robust standard errors are in parenthesis and are clustered at the CZ level. *, **, *** => statistical significance at the 90, 95, and 99 percent level. Sample includes 2007-2019 years of data.

A5 Alternative Bartik Instruments

In addition to investigating the implication of lagging the Bartik by two years (rather than one), we present an alternative that has been suggested by others (for example, see (Goldsmith-Pinkham, Sorkin, and Swift 2020; Amior and Manning 2018a) -- the decomposed, or disaggregated, Bartik.[20] Construction of the decomposed Bartik involves splitting the single Bartik instrument into three, each corresponding to one of three broad industry groups -- in our

[20] Another alternative we considered, but rejected, was to fix CZ industry share at an historical point of time under the theory that a fixed share component further in the past will have the best chance of removing bias from endogeneity. The fixed-share Bartik takes on the following form, where y is the historical reference year and national industry employment growth continues to very by year: $\sum_i \phi^i_{g,e,r,y} \ \left(\%\Delta J_{i(-g)}\right)_{e,r,t}$. We tried the year 2000 to fix industry shares since it is five years prior to the start of our sample period and since it is the first year the ACS was administered. With this form of the Bartik, it is only the cross-sectional variation in the industry distributions across CZ that is identifying the effect. This degree of variation was apparently not sufficient as the marginal effects were all nonsensical and statistically zero. This is not entirely unsurprising since the premise of this analysis is that variation over time in industry composition by race/education is important.

case, natural resources, mining, and construction; manufacturing; and service. This decomposition allows each broad industry group, by race and education, to affect each endogenous variable differently. This might be important if different race and education groups are concentrated in different industry clusters (for example, see Cajner et al. 2017). It also allows the impact of the market adjustment dynamic to vary by industry cluster (through the lagged disequilibrium term).

The first-stage equations are transformed to the following. where *P* corresponds to the three broad industries, Natural Resource, Construction and Mining; Manufacturing; and Services. Results are reported in Table 7 in the text.

$$\begin{aligned}\left[White * HighSchool * \left(\%\Delta J_g\right)_{e,r,t}\right] &= \lambda_0 + \sum_{p \in P}\left[\sum_{r=1}^{3}\sum_{e=1}^{3}\lambda_{1,p}^{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * B_{p,g,e,r,t} + \lambda_{2,p} B_{p,g,t-1}^{e,r}\right] \\ &\quad + \lambda_3 UR_{g,t-1} + \lambda_4 \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t}\end{aligned} \tag{3}$$

$$\begin{aligned}\left[White * SomeCollege * \left(\%\Delta J_g\right)_{e,r,t}\right] &= \upsilon_0 + \sum_{p \in P}\left[\sum_{r=1}^{3}\sum_{e=1}^{3}\upsilon_{1,p}^{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * B_{p,g,e,r,t} + \upsilon_{2,p} B_{p,g,t-1}^{e,r}\right] \\ &\quad + \upsilon_3 UR_{g,t-1} + \upsilon_4 \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t}\end{aligned} \tag{4}$$

$$\begin{aligned}\left[White * CollegePlus * \left(\%\Delta J_g\right)_{e,r,t}\right] &= \pi_0 + \sum_{p \in P}\left[\sum_{r=1}^{3}\sum_{e=1}^{3}\pi_{1,p}^{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * B_{p,g,e,r,t} + \pi_{2,p} B_{p,g,t-1}^{e,r}\right] \\ &\quad + \pi_3 UR_{g,t-1} + \pi_4 \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t}\end{aligned} \tag{5}$$

$$\begin{aligned}\left[Black * HighSchool * \left(\%\Delta J_g\right)_{e,r,t}\right] &= \varphi_0 + \sum_{p \in P}\left[\sum_{r=1}^{3}\sum_{e=1}^{3}\varphi_{1,p}^{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * B_{p,g,e,r,t} + \varphi_{2,p} B_{p,g,t-1}^{e,r}\right] \\ &\quad + \varphi_3 UR_{g,t-1} + \varphi_4 \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t}\end{aligned} \tag{6}$$

$$
\begin{aligned}
&\left[Black * SomeCollege * \left(\%\Delta J_g\right)_{e,r,t}\right] \\
&\quad = \theta_0 + \sum_{p \in P} \left[\sum_{r=1}^{3} \sum_{e=1}^{3} \theta_{1,p}^{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * B_{p,g,e,r,t} + \theta_{2,p} B_{p,g,t-1}^{e,r}\right] \\
&\qquad + \theta_3 UR_{g,t-1} + \theta_4 \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t} \qquad (7)
\end{aligned}
$$

$$
\begin{aligned}
&\left[Black * CollegePlus * \left(\%\Delta J_g\right)_{e,r,t}\right] \\
&\quad = \kappa_0 + \sum_{p \in P} \left[\sum_{r=1}^{3} \sum_{e=1}^{3} \kappa_{1,p}^{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * B_{p,g,e,r,t} + \kappa_{2,p} B_{p,g,t-1}^{e,r}\right] \\
&\qquad + \kappa_3 UR_{g,t-1} + \kappa_4 \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t} \qquad (8)
\end{aligned}
$$

$$
\begin{aligned}
&\left[Hispanic * HighSchool * \left(\%\Delta J_g\right)_{e,r,t}\right] \\
&\quad = \eta_0 + \sum_{p \in P} \left[\sum_{r=1}^{3} \sum_{e=1}^{3} \eta_{1,p}^{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * B_{p,g,e,r,t} + \eta_{2,p} B_{p,g,t-1}^{e,r}\right] \\
&\qquad + \eta_3 UR_{g,t-1} + \eta_4 \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t} \qquad (9)
\end{aligned}
$$

$$
\begin{aligned}
&\left[Hispanic * SomeCollege * \left(\%\Delta J_g\right)_{e,r,t}\right] \\
&\quad = \varsigma_0 + \sum_{p \in P} \left[\sum_{r=1}^{3} \sum_{e=1}^{3} \varsigma_{1,p}^{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * B_{p,g,e,r,t} + \varsigma_{2,p} B_{p,g,t-1}^{e,r}\right] \\
&\qquad + \varsigma_3 UR_{g,t-1} + \varsigma_4 \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t} \qquad (10)
\end{aligned}
$$

$$
\begin{aligned}
&\left[Hispanic * CollegePlus * \left(\%\Delta J_g\right)_{e,r,t}\right] \\
&\quad = \varkappa_0 + \sum_{p \in P} \left[\sum_{r=1}^{3} \sum_{e=1}^{3} \varkappa_{1,p}^{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * B_{p,g,e,r,t} + \varkappa_{2,p} B_{p,g,t-1}^{e,r}\right] \\
&\qquad + \varkappa_3 UR_{g,t-1} + \varkappa_4 \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t} \qquad (11)
\end{aligned}
$$

$$
\begin{aligned}
&\left[\frac{\left(J_{e,r,g,t-1} - N_{e,r,g,t-1}\right)}{N_{e,r,g,t-1}}\right] = \psi_0 + \sum_{p \in P} \left[\sum_{r=1}^{3} \sum_{e=1}^{3} \psi_{1,p}^{re} RACE_{g,t}^{r} * EDUC_{g,t}^{e} * B_{p,g,e,r,t} + \psi_{2,p} B_{p,g,t-1}^{e,r}\right] \\
&\qquad + \psi_3 UR_{g,t-1} + \psi_4 \mathrm{m}_{gt} + \tau_t + \delta_g + \alpha_g + \varepsilon_{g,e,r,t} \qquad (12)
\end{aligned}
$$

Marginal effects from the decomposed Bartik are in the main body of the paper. Table A4 contains the results from the standard Bartik with a two-year lag. None of the conclusions changes with this specification, but, again, the scale of the marginal effects is theoretically too large.

Table A4: Marginal effects of the percentage change in jobs on the percentage change in population by race and education, IV (eq. 1'); standard and decomposed Bartik with varying lags and fixed industry shares.

	Standard Bartik IV				Decomposed Bartik IV			
	k=1	k=2	k=3	Fixed Shares	k=1	k=2	k=3	Fixed Shares
# Observations =	N = 16,809	N=15,300	K=13948	K=16666	N = 16809	K=15300	K=13948	K=16666
White, NH	2.0075***	1.9506***	-3.0232	0.9258	0.9884***	0.8934***	0.6029***	0.9487***
	[0.3072]	[0.5310]	[14.2690]	[4.1977]	[0.1477]	[0.1102]	[0.1039]	[0.1220]
High School	-0.0814	-0.4931***	6.6518	2.1649	0.4963***	0.2887***	0.2627***	0.3968***
	[0.2122]	[0.1807]	[22.3920]	[8.1873]	[0.0979]	[0.0501]	[0.0645]	[0.0741]
Some College	3.6563***	2.4629***	0.4908	2.1102	1.0106***	1.0289***	0.6731***	1.1910***
	[0.6151]	[0.3570]	[1.3088]	[5.3777]	[0.3023]	[0.1883]	[0.2058]	[0.2141]
College and Above	2.4372***	3.9040***	-16.423	-1.5624	1.4672***	1.3679***	0.8758***	1.2626***
	[0.4002]	[1.4378]	[65.8536]	[15.6333]	[0.2062]	[0.1652]	[0.1612]	[0.1442]
Black, NH	1.0933***	1.8639***	-2.6549	-0.7149	0.9631***	0.9838***	0.8629***	0.9384***
	[0.0758]	[0.3350]	[12.9814]	[8.0281]	[0.0533]	[0.0735]	[0.0768]	[0.0546]
High School	0.4201***	1.0921***	-1.5494	-2.7531	0.4458***	0.5830***	0.2380*	0.4537***
	[0.0584]	[0.1737]	[6.3598]	[13.9868]	[0.0282]	[0.0789]	[0.1397]	[0.0269]
Some College	1.5905***	2.0866***	-0.665	0.4303	1.5345***	1.2677***	1.3708***	1.4716***
	[0.0766]	[0.4945]	[8.7949]	[4.9834]	[0.0577]	[0.1532]	[0.1225]	[0.0942]
College and Above	1.2671***	2.4185***	-5.8124	0.1859	0.9015***	1.0993***	0.9759***	0.8833***
	[0.1932]	[0.4321]	[24.0432]	[5.0848]	[0.1453]	[0.1088]	[0.1082]	[0.1163]
Hispanic	0.8974***	0.5484**	2.6554	-1.1016	0.6677***	0.8819***	0.7224***	0.8902***
	[0.1581]	[0.2173]	[7.4190]	[7.4713]	[0.1858]	[0.0750]	[0.0694]	[0.0617]
High School	0.2959	-1.1258	11.237	-3.3058	0.0824	0.6203***	0.5267***	0.6171***
	[0.5058]	[0.9695]	[40.1438]	[13.0039]	[0.5299]	[0.1846]	[0.1369]	[0.1602]
Some College	1.2287***	1.2892***	-0.4559	-0.2777	0.9739***	0.9476***	0.7825***	1.0525***
	[0.0742]	[0.1444]	[4.6118]	[5.7441]	[0.0669]	[0.0606]	[0.0721]	[0.0641]
College and Above	1.1690***	1.4871***	-2.8532	0.3003	0.9486***	1.0797***	0.8590***	1.0017***
	[0.0826]	[0.2337]	[13.4496]	[3.6087]	[0.1005]	[0.0796]	[0.0666]	[0.0790]

Notes: All regressions include year fixed effects and are observations are weighted by lagged CZ population shares.. Robust standard errors are clustered at the CZ level. All regressions also include CZ initial employment disequilibrium measure (the percent difference between race/education-specific employment and population in the previous year, one year lagged CZ unemployment rate), the distance from the next nearest CZ, CZ amenity index, and CZ migrant shift-share regressors. *, **, *** => statistical significance at the 90, 95, and 99 percent level. Sample includes 16-64 year-olds with at least a high school degree and 2007-2019 years of data. Full estimation results are available upon request.

Appendix B: Parameter Coefficient Estimates

Table B1 Parameter estimates (and standard errors) for the second-stage OLS (equation 1) and IV (equation 1') estimations that produce the marginal effects in Table 4.

N= 16,809	OLS	IV	
		Standard Bartik	Decomposed Bartik
$White * HighSchool * (\%\Delta J_g)_{e,r,t}$	0.7794***	-0.0814	0.4963***
	(0.0630)	(0.2122)	(0.0979)
$White * SomeCollege * (\%\Delta J_g)_{e,r,t}$	0.9880***	3.6563***	1.0106***
	(0.0715)	(0.6151)	(0.3023)
$White * CollegePlus * (\%\Delta J_g)_{e,r,t}$	1.0841***	2.4372***	1.4672***
	(0.0183)	(0.4002)	(0.2062)
$Black * HighSchool * (\%\Delta J_g)_{e,r,t}$	0.4746***	0.4201***	0.4458***
	(0.0026)	(0.0584)	(0.0282)
$Black * SomeCollege * (\%\Delta J_g)_{e,r,t}$	1.4709***	1.5905***	1.5345***
	(0.0650)	(0.0766)	(0.0577)
$Black * CollegePlus * (\%\Delta J_g)_{e,r,t}$	0.3476***	1.2671***	0.9015***
	(0.0942)	(0.1932)	(0.1453)
$Hispanic * HighSchool * (\%\Delta J_g)_{e,r,t}$	0.7396***	0.2959	0.0824
	(0.0214)	(0.5058)	(0.5299)
$Hispanic * SomeCollege * (\%\Delta J_g)_{e,r,t}$	0.7666***	1.2287***	0.9739***
	(0.1824)	(0.0742)	(0.0669)
$Hispanic * CollegePlus * (\%\Delta J_g)_{e,r,t}$	0.7884***	1.1690***	0.9486***
	(0.2063)	(0.0826)	(0.1005)
Supply Controls			
Distance	-0.0113	0.0197	-0.0146
	(0.0108)	(0.0347)	(0.0134)
Amenities	0.0018**	0.0034**	0.0021***
	(0.0009)	(0.0014)	(0.0007)
Migrant shift-share	-0.4963**	-1.1155***	-0.7900***
	(0.2217)	(0.2681)	(0.2116)
Population Density	-0.0042***	0.0062	-0.0026
	(0.0015)	(0.0059)	(0.0024)
Measures of Disequilibrium			
$\left[\left(J_{e,r,g,t-1} - N_{e,r,g,t-1}\right)/N_{e,r,g,t-1}\right]$	0.2712***	0.1973***	0.1134***
	(0.0392)	(0.0445)	(0.0383)
Lagged Urate	0.0009	-0.0005	-0.0009
	(0.0015)	(0.0019)	(0.0015)
Adjusted R2	0.928	0.782	0.897

Notes: The dependent variable is the education/race-specific change in CZ population. Coefficients not reported here are the year fixed effects and the education/race-specific percentage change in jobs and its separate interaction with race and education. Robust standard errors are clustered at the CZ level. *, **, *** => statistical significance at the 90, 95, and 99 percent level. Sample includes 16-64 year-olds with at least a high school degree and 2007-2019 years of data.

Table B2 Parameter estimates (and standard errors) for the second-stage OLS (equation 3) and Bartik IV (equation 3') estimations that produce the marginal effects in Table 5.

N = 16,809	OLS	IV	
		Standard Bartik	Decomposed Bartik
$White * HighSchool * (\%\Delta J_g)_{e,r,t}$	0.4415***	0.3311	0.6085***
	(0.1419)	(0.5585)	(0.2153)
$White * SomeCollege * (\%\Delta J_g)_{e,r,t}$	1.1519***	4.3723**	1.7680**
	(0.2811)	(1.8259)	(0.7939)
$White * CollegePlus * (\%\Delta J_g)_{e,r,t}$	1.0517***	3.1865**	2.0056***
	(0.1964)	(1.3869)	(0.4714)
$Black * HighSchool * (\%\Delta J_g)_{e,r,t}$	0.0181	0.2033	0.0782
	(0.1057)	(0.1963)	(0.2295)
$Black * SomeCollege * (\%\Delta J_g)_{e,r,t}$	1.1915***	1.2596***	1.5276***
	(0.2920)	(0.2341)	(0.2151)
$Black * CollegePlus * (\%\Delta J_g)_{e,r,t}$	0.1075***	0.7633***	0.5704***
	(0.0360)	(0.2106)	(0.1533)
$Hispanic * HighSchool * (\%\Delta J_g)_{e,r,t}$	0.6746***	1.1191**	0.7862***
	(0.1494)	(0.4365)	(0.2928)
$Hispanic * SomeCollege * (\%\Delta J_g)_{e,r,t}$	0.0567	1.2017***	0.8135***
	(0.1266)	(0.1448)	(0.1023)
$Hispanic * CollegePlus * (\%\Delta J_g)_{e,r,t}$	0.0586	0.9326***	0.7284***
	(0.0576)	(0.1408)	(0.1060)
$SHAREWhite * White * HighSchool * (\%\Delta J_g)_{e,r,t}$	0.6052***	-0.6353	-0.2682
	(0.1806)	(0.8919)	(0.3525)
$SHAREWhite * White * SomeCollege * (\%\Delta J_g)_{e,r,t}$	-0.2874	-1.2349	-1.3212
	(0.4342)	(2.7527)	(1.1214)
$SHAREWhite * White * CollegePlus * (\%\Delta J_g)_{e,r,t}$	0.0580	-1.4849	-1.0944*
	(0.3488)	(1.7981)	(0.5972)
$SHAREBlack * Black * HighSchool * (\%\Delta J_g)_{e,r,t}$	3.4031***	1.6500	2.7865
	(0.7941)	(1.4873)	(1.7014)
$SHAREBlack * Black * SomeCollege * (\%\Delta J_g)_{e,r,t}$	2.1343	2.4969	-0.1675
	(2.2510)	(1.8693)	(1.4470)
$SHAREBlack * Black * CollegePlus * (\%\Delta J_g)_{e,r,t}$	2.6947***	3.5583***	2.0328***
	(0.3578)	(1.2341)	(0.6179)
$SHAREhisp * Hispanic * HighSchool * (\%\Delta J_g)_{e,r,t}$	0.2922	-4.9209**	-3.0653**
	(0.5546)	(2.2264)	(1.4172)
$SHAREhisp * Hispanic * SomeCollege * (\%\Delta J_g)_{e,r,t}$	3.6308***	0.0515	0.7021

N = 16,809	OLS	IV	
		Standard Bartik	Decomposed Bartik
	(0.4993)	(0.6746)	(0.4910)
$SHAREhisp * Hispanic * CollegePlus * \left(\%\Delta J_g\right)_{e,r,t}$	4.1396***	1.1527**	1.1753**
	(0.3119)	(0.5099)	(0.5115)
Supply Controls			
Distance	-0.0122	0.0157	-0.0199*
	(0.0131)	(0.0317)	(0.0119)
Amenities	-0.0001	0.0039***	0.0021***
	(0.0007)	(0.0012)	(0.0006)
Migrant shift-share	-0.3384*	-0.9243***	-0.7025***
	(0.1852)	(0.2505)	(0.1948)
Population Density	-0.0061***	0.0052	-0.0034**
	(0.0014)	(0.0055)	(0.0017)
Measures of Disequilibrium			
$\left[\left(J_{e,r,g,t-1} - N_{e,r,g,t-1}\right)/N_{e,r,g,t-1}\right]$	0.2404***	0.1806***	0.0874***
	(0.0318)	(0.0393)	(0.0249)
Lagged Urate	-0.0000	-0.0013	-0.0015
	(0.0011)	(0.0020)	(0.0014)
Adjusted R2	0.946	0.789	0.908

Notes: The dependent variable is the education/race-specific change in CZ population. Coefficients not reported here are the year fixed effects and the education/race-specific percentage change in jobs and its separate interaction with race and education. Robust standard errors are clustered at the CZ level. *, **, *** => statistical significance at the 90, 95, and 99 percent level. Sample includes 16–64-year-olds with at least a high school degree and 2007-2019 years of data.