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ORIGINAL PAPER

Are shocks to human capital composition permanent? Evidence from the Mariel boatlift

Seung-hun Chung[1] · Mark D. Partridge[1]

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Abstract

We examine whether shocks to a city's average level of human capital are associated with persistent or permanent changes in human capital. The Mariel boatlift of 1980 represents an exogenous negative shock to Miami's average human capital because it attracted a particularly low-skilled mix of immigrants. To assess whether the boatlift affected Miami's future human capital accumulation, we construct a synthetic control group to analyze the effect of this shock. The results suggest that the Miami metropolitan area experienced slower increases in average human capital than its synthetic control city after the boatlift. This result is robust to alternative estimation strategies, data sets, and alternative hypotheses. The result implies that a decreased level of average skills tends to subsequently attract unskilled skilled workers more strongly than skilled workers, at least in the context of immigration shocks. We discuss plausible mechanisms for this finding and place the findings into the context of the spatial equilibrium model.

JEL Classification J21 · R11 · R12

1 Introduction

Studies have long found that the average human capital level is one of the most important factors for city and regional growth (Bilbao-Osorio and Rodríguez-Pose 2004; Cheshire and Magrini 2000; Glaeser and Saiz 2003; Shapiro 2003; Simon and Nardinelli 2002). Cities with initially high human capital levels have grown substantially faster than others. Such cities also have experienced faster wage and rent growth. Thus, two important questions are: (1) whether cities with high average levels of human capital increase their human capital faster than cities with low average

✉ Mark D. Partridge
partridge.27@osu.edu

Seung-hun Chung
chung.627@osu.edu

1 The Ohio State University, 2120 Fyffe Road Columbus, Columbus, OH 43210, USA

levels (and vice versa), and more directly related to our study, (2) can a city's human capital intensity be permanently or at least persistently altered?

If increases in a city's average human capital tend to accelerate its future growth of human capital, then growth differentials in population, wages, and rents between cities with high and low human capital levels will increase. The growth trajectories across cities and regions will diverge, which has important policy implications because without perfect mobility, people residing in human capital poor regions would suffer.

Despite the importance of the question, few studies have examined whether shocks to a city's average human capital level can permanently change its level over time. Berry and Glaeser (2005) used a deep lag variable as an instrument and found that the average human capital level in cities has diverged. Lee (2016) finds similar results to Berry and Glaeser (2005) when using an education program as a natural experiment. However, using a similar method as Berry and Glaeser, but with more control variables, Betz et al. (2016) find that a city's average level of human capital is not statistically associated with its future growth in human capital, but rather is positively linked to the size of the city. Other studies have examined the migration of skilled workers directly (Kerr et al. 2017; Faggian and McCann 2006; Venhorst 2013), but do not examine aggregate outcomes and feedback effects.

A related literature relates to equilibrium models in which the most prominent is the spatial equilibrium model (SEM) that generally predicts that after an exogenous shock to a region's equilibrium, the region would eventually return to its equilibrium growth path. That is, while there is debate as to how fast the adjustment may take place, the notion is that aggregate outcomes such as total employment or population are not affected in the long run (Partridge et al. 2015). For example, Davis and Weinstein's (2002) seminal paper finds that Japanese cities that were victims of massive Allied bombing during World War II had effectively returned to their long-run growth path within twelve years after the war. Brakman et al. (2004) found similar findings for Germany after the war. Such findings are prevalent in the literature for a host of other shocks such as military base closings (Partridge et al. 2015). However, the SEM has much less to say about whether other regional characteristics remain on the same equilibrium trajectory after an exogenous shock. For example, do demographic shocks such as the Mariel boatlift have permanent effects on a region's skill composition that could have long-term implications for its economic welfare by affecting average wages?

In this paper, we analyze whether shocks to a city's skill composition has permanent, or at least persistent effects to its future skill composition. The most important potential obstacle for such a study is endogeneity in that unobserved factors might influence both the present and future levels of human capital. For instance, long-term local government policy might influence trends in skill composition. To address this issue, we use the synthetic control method (SCM), which allows us to construct a "synthetic" control group for the treatment (Abadie et al. 2010), in conjunction with a natural experiment.

Our treatment group is the Miami metropolitan area, which received a disproportionate share of refugees from the 1980 Mariel boatlift. Most Cuban refugees from the Mariel episode were young and unskilled (Borjas 2015; Card 1990). It is widely accepted that this event was exogenous and that these refugees migrated to Miami due to proximity to Cuba. Another advantage of using the boatlift as a natural experiment is that we can also use results from previous research to perform hypotheses as to the mechanisms behind changes in Miami's skill composition.

We find that the Miami metropolitan area experienced a much slower increase in average human capital than the comparable synthetic control city after the Mariel boatlift. The result implies an influx of unskilled people may lead to slower skill aggregation. These results suggest that shocks to human capital can have permanent effects on future levels of human capital, at least in the context of immigration shocks. We use a variety of data and assumptions to show the robustness of this result.

2 Conceptual framework

Our conceptual framework combines the spatial equilibrium model (SEM) (Roback 1982) with empirical findings from the prior Mariel boatlift literature. In the SEM, two factors—local productivity and local household amenities—determine the spatial distribution of economic activity. To address skill composition issues, we employ Roback's (1988) extension of the SEM to allow for heterogeneous labor by dividing the workforce into skilled and unskilled labor, each having their own representative utility functions.

Formally, the indirect utility function for worker type *j* (skilled or unskilled) in city i for each period t is $V_j\left(W_{ji}^t - C_{ji}^t, A_{ji}^t\right)$, in which W_{ji}^t, A_{ji}^t and C_{ji}^t are wage level, (net) amenity level, and cost of living (monthly rent) for worker type *j,* in city *i*, period t. Indirect utility is positively related to wages and amenities and negatively related to rents. The SEM assumes that labor is perfectly mobile, and in equilibrium, utility for both worker types in city *i* will equal their respective national average utility. The same applies for firms, in which profits are equalized nationally because firms are also assumed to have perfect mobility.

More interesting to our discussion is that even though US household mobility is relatively high, it is imperfect (Partridge et al. 2012, 2015). If there was perfect mobility, we might expect that a given shock to be exactly offset by labor and capital mobility, restoring initial conditions (e.g., skilled/unskilled labor ratio). However, because labor mobility is imperfect, the interim change in conditions after a shock could affect local amenities as governments and the private sector adjust to changes from the shock. For example, a large relatively unskilled Cuban population shock may increase public and private services that cater to their wishes, which could set off further migration that reinforces this process. Such changes could lead to permanent changes in the equilibrium that are not predicted by the standard SEM. Namely, it could permanently alter the workforce skill composition and average productivity, both of which affect *average* Miami's wage.

There is an ongoing debate regarding how the Mariel boatlift affected Miami's labor market. For example, Card (1990) and Borjas (2015) find that Mariel boatlift did not influence wages of Miami's high-skilled workers relative to similar cities (Fig. 4 in Borjas 2015). Yet, its effect on unskilled worker wages is debated (Borjas 2015; Peri and Yasenov 2015), though there is no statistical evidence that their relative wages increased. Saiz (2003) finds that rents for low-quality housing in Miami substantially increased in the immediate aftermath of the boatlift, but not rents for high-income households. From these wage and rent findings, it appears that the *real* wages of low-skilled workers declined as a result of the boatlift, while the *real* wages of skilled workers were unchanged. For spatial equilibrium to be maintained in the long run (after households relocate to restore equilibrium), it must be that Miami's amenities (quality of life) relatively improved for its low-skilled workers to offset the real income loss, though they would remain unchanged for its skilled workers.

The relative productivity of Miami's skilled workers unlikely changed because their nominal wage did not change relative to similar cities (assuming nominal wages reflect productivity).[1] Since Miami's low-skilled nominal wages definitely did not relatively increase, we can rule out that their relative productivity *increased*.

Supporting the possibility that Miami's low-skilled productivity declined, Lewis (2004) provides evidence that the Mariel boatlift delayed computer use in offices, which is a key source of skill-biased technological change. This pattern suggests that Miami firms substituted relatively low-wage less-skilled workers for a combination of high-skilled workers and computing technology. If real wages declined for Miami's low-skilled workforce, then we expect that local consumer amenities for less-skilled workers to increase to maintain spatial equilibrium. To be sure, there can be sorting within skill groups. For example, on balance Hispanics may have been attracted to Miami, while some non-Hispanics may have moved elsewhere.

2.1 Discussion of mechanisms

The evolution of wage and rents after the Mariel boatlift helps isolate potential mechanisms for relative changes in Miami's skill distribution as they help identify changes in productivity and amenities. This leads to the question, how could migration of (say) unskilled workers to Miami affect relative productivity and amenity levels, and in turn, wages and rents in equilibrium? First, a possible mechanism for productivity changes is that positive knowledge spillovers intensify as workers are employed in cities with increasing average levels of human capital (Glaeser and Gottlieb 2009; Glaeser and Saiz 2003; Winters 2013). Yet, above-average levels of human capital can unevenly increase productivity for skilled and unskilled labor. For example, Moretti (2004) argues that an increase in the share of college graduates increases the wages of unskilled workers more than skilled workers, implying that skilled labor and unskilled labor are complementary. In this case, a high average

[1] See Glaeser and Mare (2001) for a discussion of why workers consider real wages in maximizing utility while firms set nominal wages to value of marginal product (i.e., productivity) for profit maximization.

level of human capital may attract low-skilled workers, reducing the city's average skill level.

Another mechanism for changing productivity is that a high (low) level of average human capital can induce skill-biased (unskilled-biased) technology adoption (Acemoglu 1998). Similarly, a high (low) level of human capital in cities can attract high-skilled (low-skilled) intensive industries, increasing the relative productivity of skilled labor compared to unskilled labor.

Turn now to how amenities can change after a population shock. For one, a positive high-skilled/high-income migration shock will attract more non-traded services that cater to their demands (and vice versa), such as high-quality private schooling. In turn, through economies of scale, such services can be less expensive in cities that have higher shares of high-skilled workers. Alternatively, we can consider the cultural difference between unskilled workers and skilled workers. If members of a cultural group tends to be particularly highly skilled (or unskilled) compared to those of other cultural groups on average, then sorting due to cultural differences can lead to long-term changes in a city's skill composition. Such sorting would be reinforced if the sorting attracted non-traded firms that cater to their cultural preferences and income levels (e.g., types of grocery stores and entertainment) that in turn may attract additional similar migrants.

The Mariel boatlift's inflow of the Cuban Hispanic population into Miami, therefore, may have subsequently increased inflows of those attracted to Cuban culture or the Spanish language. Further, by affecting the types of businesses and public services in Miami, this can affect amenity levels for Hispanics in general. The Hispanic population has below-average education levels, meaning that a positive shock of below-average educated Hispanics would attract businesses that tend to cater to lower income groups. (The boatlift population averaged less than a high school degree.) Schelling's (1971) seminal paper describes how this mechanism can be self-sustaining and permanently alter the path of cities that face significant shocks—i.e., permanently (or at least persistently) increase Miami's share of unskilled workers.[2]

3 Empirical strategy

To estimate the effect of a shock in skill composition on the future growth of human capital, we must address endogeneity issues such as unobservable and long-lasting factors that influenced the city's skill level in the past and the future. To do that, we use the 1980 Mariel boatlift as an exogenous shock on Miami's labor market (Bodvarsson, Van den Berg and Lewer 2008; Borjas 2015; Card 1990; Peri and Yasenov 2015).

[2] Besides compositional effects, migration, and human capital externality spillovers, other potential causes for skill intensity to change are intergenerational transmission of low education among new residents, especially the children of Marielitos and Miami's educational system being challenged to improve child outcomes, perhaps influenced by the Mariel inflow (e.g. low tax base).

On April 20, 1980, Fidel Castro, leader of Communist Cuba, announced that Cubans were free to leave the country. Even though the Carter administration worked to improve US–Cuban relations, this was an unexpected event for the Cubans and Miami residents (Card 1990). More than 125,000 Cubans migrated to the USA between April and October of 1980. Lacking basic necessities, most went to Miami, which was the closest to Cuba.

The majority (50–60 percent) of these people, called *Marielitos*, lived in Miami even in 1990 (Borjas 2015; Card 1990). They were unskilled, as 60 percent of *Marielitos* didn't graduate high school and less than 10 percent were college graduates. This directly corresponded to a 1 percentage point decrease or 5 percent decline in the share of adult college graduates in Miami (Peri and Yasenov 2015). We use the event as a "negative" shock on Miami's average skill level.

To analyze the effect of the boatlift, we need a suitable control group. To address this issue, we use the SCM, which allows us to construct a "synthetic" control group by taking a weighted combination of many "similar" cities. Abadie et al (2010) show that by constructing a synthetic control group whose pre-trends of dependent and control variables match well with the treatment group, we can estimate the treatment effect under quite general conditions. We also estimate a standard difference-in-differences method that confirms that the SCM results are robust.

4 Data

We collect information at the metropolitan statistical area (MSA) level from the U.S. Department of Housing and Urban Development (HUD) *State of the Cities Data System*. It provides aggregate city data from the 1970, 1980, 1990, and 2000 Censuses. The treatment group is the Miami metropolitan area as in Card (1990). From the 1990 Census onwards, this MSA was combined with the Fort Lauderdale metropolitan area to form a larger MSA. However, HUD provides consistent data for the Miami metropolitan area as defined by the 1980 MSA definitions.

For Miami and the possible donor cities, we calculate their college graduate share, which serves as the dependent variable for 1940 to 2000.[3] We use the census data for 1940 to 1970 variables from IPUMS (Ruggles et al. 2015). This has drawbacks since we can only accurately measure a city's college graduate share (and other skill composition measures) every 10 years in the census (for this period). However, a city's demographic changes are usually gradual, so this should not cause serious distortion for the specification and extrapolation.[4]

To construct the synthetic control groups, we construct various predictor variables for each MSA from HUD in 1970 and 1980. We calculate four measures of skill intensity including adult population shares for those with some college or higher, high

[3] The 1940 Census was the first census that provided information on educational attainment. .

[4] We experimented with using CPS data to get more pre-treatment periods. However, there are issues with the selection of synthetic control cities as well as significant measurement error owing to the CPS's small samples. Still, the SCM results from this exercise are broadly consistent with the base results. See Sect. 5.3.

school graduates or higher, college graduates or higher, and those who did not complete high school. We use 1970 and 1980 population, as well as the respective Hispanic and African American population shares as control variables. The total employment share of industries that intensively hire skilled labor in 1970 and 1980 are added to reflect city industry structure.[5] For both 1970 and 1980, the unemployment rate, median home value, and median family income are included to account for economic trends.

We then apply the SCM. The 1980 Census was conducted just before the Mariel boatlift. Thus, we use Census data up to and including 1980 in the construction of the synthetic control to minimize the mean-squared prediction error (MSPE). We exclude all Florida MSAs from being a part of the synthetic control due to the greater possibility of spillovers with Miami.

5 Empirical results

We first examine some descriptive evidence to assess how Miami may have been affected by Mariel boatlift. First, in results available from the author, we construct a SCM for comparing Miami's population to its synthetic control city, finding that Miami's population closely tracked the control unit's over the 1940–2000 period. Because Miami's population trajectory was unchanged after the boatlift, this is consistent with predictions from the SEM in that it quickly returned to its *overall* growth path. This result then implies that any gains among an educational category would need to be offset by corresponding changes in other educational categories.

Regarding Miami's skill composition, the data indicate that growth in its college graduate share greatly slowed after 1980 (not shown). For example, out of the sample's 121 MSAs, Miami's college graduate share, respectively, ranked 55th, 47th, 46th, 70th, and 81st in 1960, 1970, 1980, 1990, and 2000, illustrating Miami's post-1980 decline. Likewise, when comparing the change in growth rates between the 1970s and the 1980s, Miami's *declining* growth of college graduates is the fourth largest among the 121 MSAs, only trailing Pueblo, CO, Jackson, MI, and Houston, TX.,[6,7] Aside from Houston, the other two cities are much smaller than Miami, with 1980 populations below 120,000 (Miami's was 1.27 million).

A key reason for why Houston's college graduate share grew even slower than Miami's is that Houston was a primary resettlement site for South Vietnamese refugees in the 1980s as designated by the Indochinese Assistance and Refugee Assistance Act of 1975 (Chafetz and Ebaugh 2000). Thus, Houston also experienced a similar immigration shock as Miami and thus would not serve as a good control city candidate. Jackson and Pueblo are also poor candidates because small cities tend to

[5] These include FIRE (Finance, Insurance, & Real Estate), Professional Services and Business and Repair Services. Workers in these industries are most likely to be college graduates. See "Appendix 4."

[6] Calculated as $Z = 100 \times (B - A)/A$, where A is the 1970 to 1980 change in the city's share of immigrants and B is the 1980 to 1990 change in the city's share of immigrants (based on HUD census data). Thus, Z is the percent change between the 1980s and 1970s in the growth of the city's immigration share. Exact results are available upon request.

[7] There are only 121 MSAs available for use from 1940, with only a small Sunbelt representation.

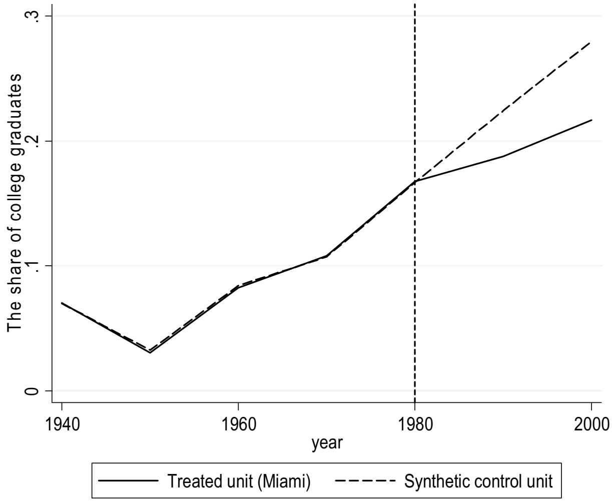

Fig. 1 College graduate share in Miami and the synthetic control unit after 1940

have slower growth in their college graduate shares (Berry and Glaeser 2005; Betz et al. 2016). Thus, they would lag Miami just on that basis.

Miami exhibits a similar trend for other educational categories when comparing the 1970s to the 1980s. For example, the magnitude of Miami's *decline* in the share of adults over 25 years old with some college (but no Bachelors degree) is the third most among the 121 MSAs, its *decline* in its high school graduate share is the second largest, and its *increase* in the share of high school dropouts is the second largest. Overall, the descriptive evidence is consistent with the pattern that Miami's human capital growth declined after 1980.

5.1 Main results

We now turn to the SCM results based on 1940 to 1980 data to identify the donor cities. Figure 1 compares the college graduate shares between the Miami MSA and its synthetic control unit over the 1940 to 2000 period (see Appendix Tables 4, 5 for details). The vertical axis represents the share of college graduates (age 25 or older). After tracking very closely between 1940 and 1980, Miami's college graduate share grew more slowly than for its synthetic control unit in both the 1980s and 1990s.[8] Table 1 provides the point estimates of the estimated difference between Miami and its synthetic control unit. The estimated difference in the college graduate *share* between Miami and the synthetic control unit is −0.037 in 1990 and −0.063 in 2000, illustrating at least a highly persistent departure if not a permanent departure from trend for Miami.

[8] See Appendix D.1 for comparison between Miami and the synthetic control city's variables and weights used in constructing the donor cities.

Table 1 Point estimated differences between Miami and the synthetic control unit

	Year	Difference between Miami and control (control–Miami)
Share of college graduates from 1940 Census	1990	−0.037
	2000	−0.063
Share of some college experience or higher from 1940 Census	1990	−0.068
	2000	−0.106
Share of high school graduates or higher from 1940 Census	1990	−0.102
	2000	−0.126
Share of high school dropouts from 1940 Census	1990	0.102
	2000	0.126

One way to understand the size of this difference is to calculate the "direct effect" from *Marielitos*. The 1980 Census was conducted in early April, just before the boatlift. So we can calculate the direct effect of the mere presence of *Marielitos* on Miami's 1990 proportion of college graduates. Miami's college graduate share among those aged 25 or older in 1980 was 0.168. The number of *Marielitos* aged 16 to 65 who were still in Miami in 1990 was 54,196 (Peri and Yasenov 2015). The 1990 Census indicates that 1,281,295 people in Miami were 25 or older. Among them, 240,460 were college graduates. Even assuming that *none* of the *Marielitos* graduated from college and dropping them from the total count, the share of college graduates among the remaining people age 25 or older in 1990 would have been around 0.196, which is still much smaller than the 0.23 share for the synthetic control unit.[9] Thus, the Mariel boatlift decreased the 1980–1990 change in the college graduate share by about 60% more than would be expected from mechanically adding *Marielitos* to the calculation, suggesting that there was additional sorting due to migration of low- and high-skilled workers.[10]

We now assess the SCM results for the other *broader* measures of skill aggregation using other educational attainment measures other than four-year college graduation or above. Specifically, our two broader measures skill groups are: some college or higher and then high school graduate or higher. In Miami's case, we use some college and above as well as high school and above as measures of "higher skills" because as we noted earlier, there was such a disproportionate share of low-skilled boatlift newcomers that did not have a high school degree. Similar measures are used as to proxy for regional human capital levels in previous studies (Coulombe and Tremblay 2001; Glaeser and Saiz 2003; Goetz and Rupasingha 2009).

Figures 2 and 3, respectively, show that Miami also experienced slower growth in the share who had some college or higher (see Appendix Tables 6, 7 for details),

[9] We include *Marielitos* 16 to 24 in this estimate, which further works to raise the Miami's college graduate share.

[10] We also do the similar analysis for the other educational attainment measures. In the case of some college experience, the direct effect is 15 percent. In the case of high school graduates, the direct effect is only 10 percent.

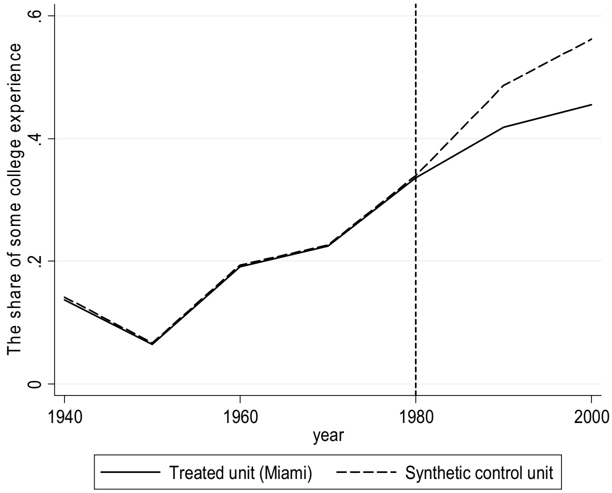

Fig. 2 Some college experience or higher share in Miami and the synthetic control unit after 1940

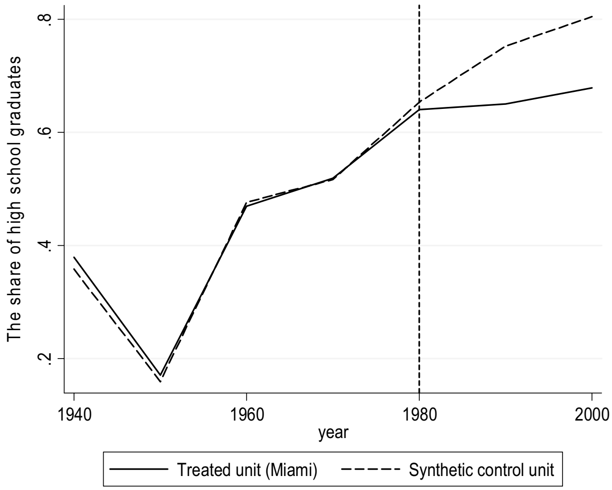

Fig. 3 High school graduate share or higher in Miami and the synthetic control unit after 1940

as well as slower growth in the high school graduate or higher share (see Appendix Tables 8, 9 for details.). These results further support our findings that skill levels fell in Miami after the boatlift. Now turning to the lowest-skilled group, Fig. 4 shows that Miami made significant relative gains in high school dropouts (see Appendix Tables 10, 11 for details.). For these cases, Table 1 reports the estimated point difference between Miami and its synthetic control unit.

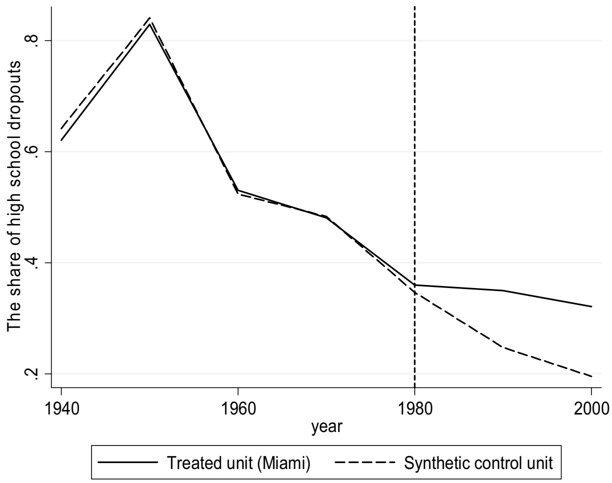

Fig. 4 High school dropout share in Miami and the synthetic control unit after 1940

5.1.1 Inference and placebo tests

We now use a standard method to help infer classical statistical significance of the SCM treatment effect (Abadie et al. 2010; Cavallo et al. 2013). First, we construct a new synthetic control for each of the "donor" MSAs that are used to construct Miami's synthetic control. Then we obtain a distribution of differences in the dependent variable between each donor and its synthetic control unit after "treatment"—i.e., "in-place placebo effects" (Abadie et al. 2010; Cavallo et al. 2013). Then we compare Miami's estimated treatment effect to this distribution. From the distribution of donors, a pseudo-p-value is calculated for where Miami's treatment effects sit in the distribution. If Miami's treatment effect is in the tails of this distribution, it implies that Miami's effect is more likely to arise from the boatlift, not by chance.

Table 2 Pseudo-*P*-values for synthetic control treatment effects

	Year	*P*-value
Share of college graduates from 1940 Census	1990	0.042
	2000	0.008
Share of some college experience or higher from 1940 Census	1990	<0.001
	2000	<0.001
Share of high school graduates or higher from 1940 Census	1990	<0.001
	2000	<0.001
Share of high school dropouts from 1940 Census	1990	<0.001
	2000	<0.001

The two-sided *p*-value representing the percentage of donors who experience a change in the college graduate share (from their synthetic control) that is at least as large as Miami's is 4.2 percent in 1990 and 0.8 percent in 2000. Although this *p*-value may not have classical statistical significance, these values generally imply that Miami's estimated treatment effect is larger than for other cities. With the same method, we also calculate the *p*-values for the alternative educational attainment measures. Table 2 summarizes the results, in which their estimated *p*-values are even smaller.

5.2 Robustness checks

5.2.1 In-time placebo test

For another robustness check, we perform the "in-time placebo test." This test assesses the possibility that Miami's slower increase in human capital might have actually began before 1980. By setting the treatment year before 1980 to construct the synthetic control, we appraise whether Miami's human capital level diverged before 1980. For this, we use 1970 (10 years before the boatlift) as the imagined treatment time for this placebo test (we use the control variables up till 1970). The corresponding results for the college graduate share, the share with some college or higher, high school graduate or higher share, and high school dropout share are shown in Figs. 5, 6, 7 and 8 (for the comparison between Miami and the synthetic control unit and donor MSA weights, see Appendix Tables 12, 13, 14, 15, 16, 17, 18, 19). The results clearly show that the results are robust with human capital in Miami and its synthetic control beginning to diverge after 1980.

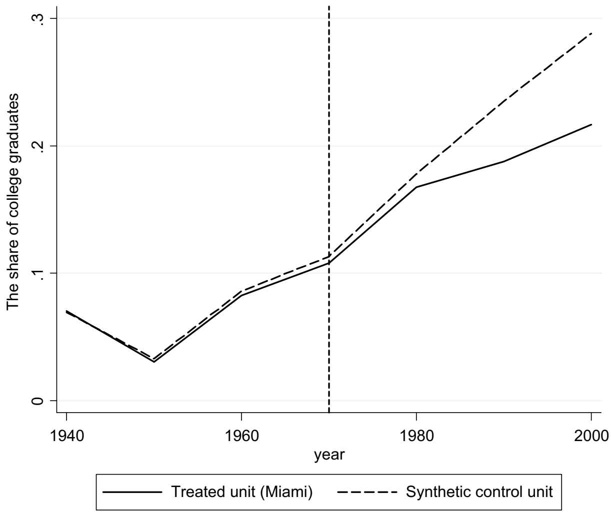

Fig. 5 In-time placebo test: college graduate share in Miami and the synthetic control after 1940

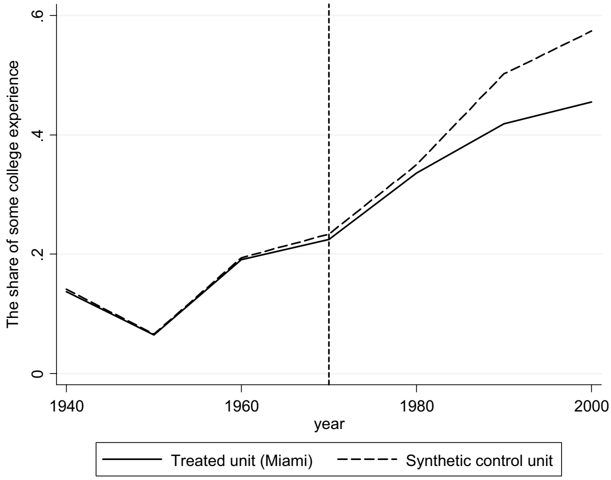

Fig. 6 In-time placebo test: some college experience or higher share in Miami and synthetic control unit after 1940

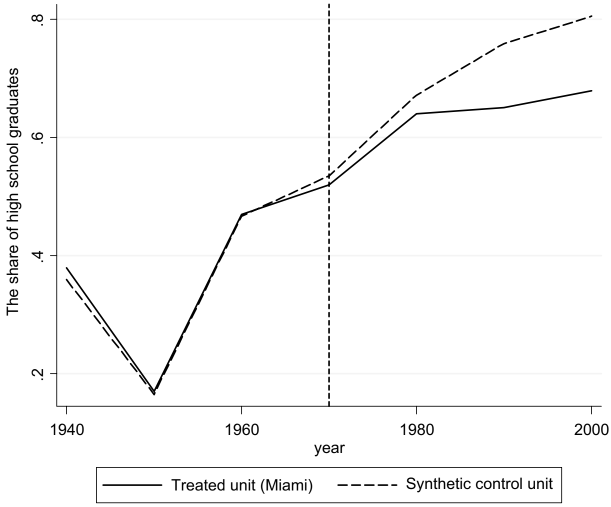

Fig. 7 In-time placebo test: high school graduates share or higher in Miami and synthetic control after 1940

5.2.2 Matching on early pre-periods

Recently, Kaul et al. (2018) noted that controlling for all of the pre-treatment periods can lead to misleading results. Thus, following their suggestion, we drop 1980 as a pre-treatment period (recall 1980 census period is just before treatment). Figures 9, 10, 11 and 12 present the results (for comparisons between

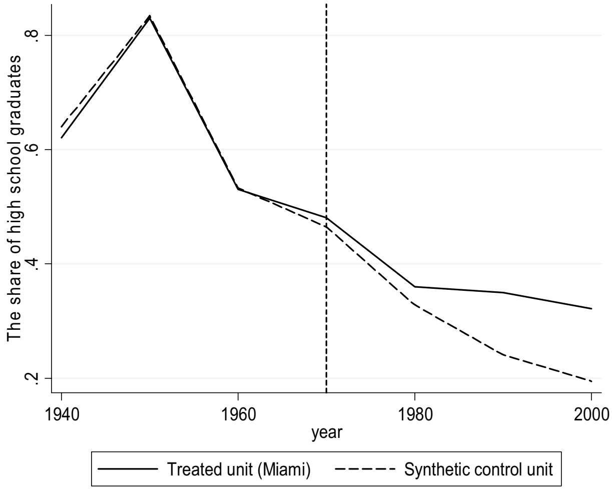

Fig. 8 In-time placebo test: high school dropouts share in Miami and synthetic control after 1940

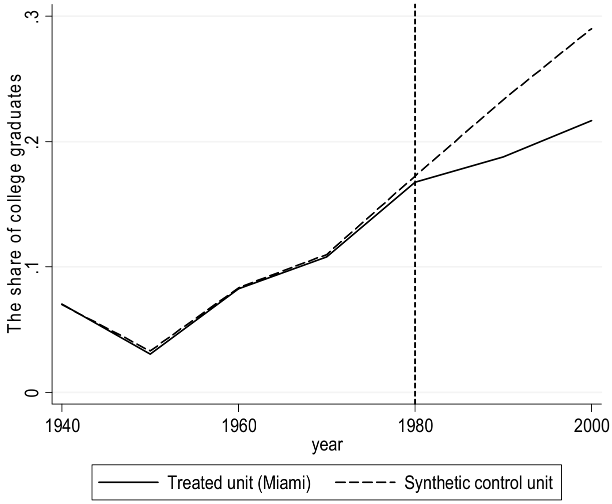

Fig. 9 Matching on early pre-periods: college graduate share in Miami and synthetic control from 1940

Miami and the synthetic control and the MSA donor weights, see Appendix Tables 20, 21, 22, 23, 24, 25, 26, 27). Even further, by dropping 1970, we construct another synthetic control unit for each human capital measure by only using the pre-treatment outcomes for 1940, 1950, and 1960. Even though there is a full 20 year period between the latest pre-treatment period and the treatment year, the model is remarkably robust (see Appendix Figs. 19, 20, 21, 22. Tables for comparisons between Miami and the synthetic control and the MSA donor weights are available upon request).

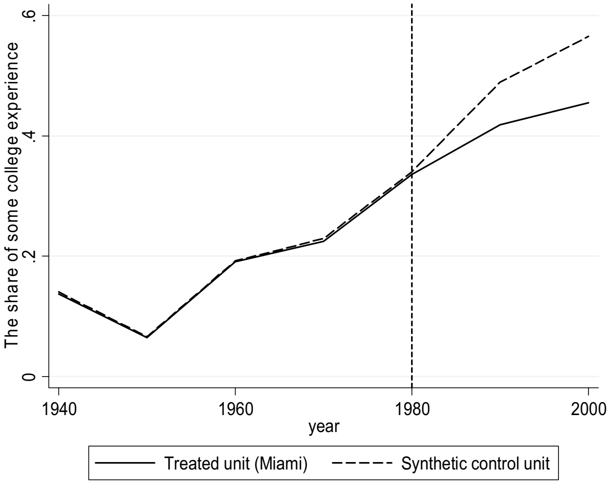

Fig. 10 Matching on early pre-periods: some college experience or higher share in Miami and synthetic control unit after 1940

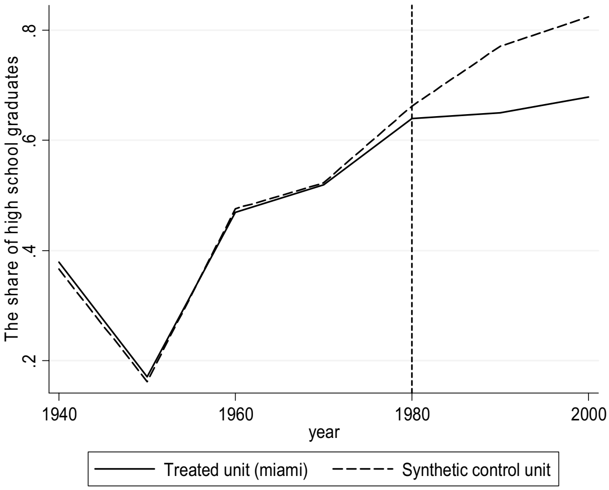

Fig. 11 Matching on early pre-periods: high school graduate share or higher in Miami and synthetic control unit after 1940

5.2.3 Other robustness checks

Two concerns with using pre-treatment outcomes up to 40 years before the treatment (pre-dating World War II) are: (1) that is a long time to expect parallel pre-treatment trends and (2) the number of Sunbelt cities available in the data is considerably less for constructing the synthetic control. However, even when we use pre-treatment outcomes from 1970 to 1980 to allow for more Sunbelt cities and a

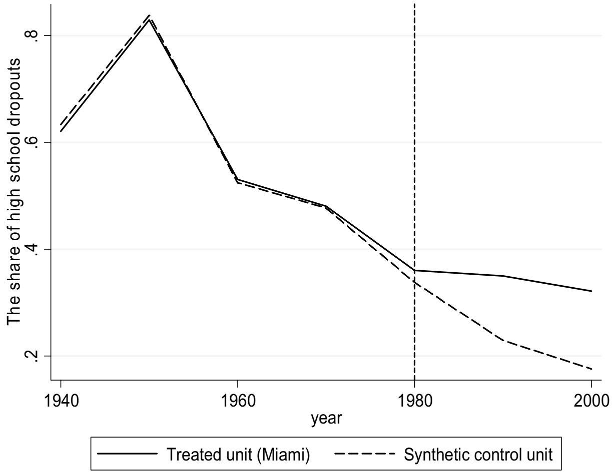

Fig. 12 Matching on early pre-periods: high school dropouts share in Miami and synthetic control unit after 1940

shorter pre-treatment trend, our conclusions remain unchanged (results available on request).

In constructing the synthetic control unit, including all MSAs as potential donors may be problematic because many MSAs are quite different from Miami (Abadie et al. 2010; Cavallo et al. 2013). Thus, as another robustness check, we restrict our potential donor pool to only MSAs in the south and southwestern USA with populations between 500,000 and 4 million between 1970 and 2000 (24 MSAs).[11] The results, available from the authors, indicate that the results remain robust to using this regionally more consistent donor pool.

5.3 Using CPS data

When using the SCM, it is often desirable to have many pre-treatment periods. Thus, we experimented with using monthly Current Population Survey (CPS) data to allow for more pre-treatment periods, although small CPS sample sizes increase measurement errors. To minimize measurement error, we use the three-year average share of college graduates (though we caution that the sample sizes are still miniscule compared to the census). For example, the "1980 college graduate share" is the average share over 1978 to 1980. In results available from the authors, Miami had a lower college graduate than its synthetic control over the 1980 to 2000 period, which echoes

[11] These include: Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, Texas, California, New Mexico, and Arizona. All Florida MSAs are excluded from the donor pool to reduce spillover effects. The population of Miami (Dade County) was 1267,792 in 1970 and 2,253,362 in 2000. Thus, as a lower bound, we use 500,000 (one-half of Miami's 1970 population) and 4,000,000 as the upper bound (double Miami's 2000 population) for the potential donor cities for the synthetic control. In this case, we use pre-treatment outcomes from 1970 (322 US. MSAs are available) to include more potential donors in constructing the synthetic control unit.

the base findings. Miami also had much lower shares of adults with some college and high school graduates, which by default means greater shares of high school dropouts (see Appendix Figs. 23, 24, 25, 26 and Appendix Tables 28, 29, 30, 31, 32, 33, 34, 35 for comparisons between Miami and the synthetic control and MSA donor weights).

5.4 Alternative identification strategy

In this subsection, we use a linear difference-in-differences (DiD) as an alternative to the SCM. The resulting estimation equation is:

$$\begin{aligned} D_{\mathrm{it}} = \alpha + \beta_{1970} * \text{treatment} \\ + \sum_{t=1980,1990,2000} \beta_t * \text{Year dummy}_t * \text{treatment} \\ + \sum_{t=1980,1990,2000} \text{Year Fixed effect}_t \\ + \sum \text{MSA Fixed effect}_t + \varepsilon_{\mathrm{it}} \end{aligned}$$

This is a response function form of the DiD approach. D_{it} is a measure of the skill level defined as either the share of college graduates, some college or higher, or high school graduates or higher, whereas treatment is Miami. Since the Mariel boatlift occurred just after the 1980 Census, the coefficients of interest are β_{1990} and β_{2000}. For the control group, we pick MSAs that have a less than 0.01 percentage point difference in the growth of the college graduate share with Miami over the 1970 to 1980 period. Control groups were chosen analogously for high school graduates or higher and of some college or higher. Appendix Table 36 shows that the 1980 treatment effect is statistically insignificant, consistent with the parallel trends assumption. Further, there is a significantly negative influence of the Mariel boatlift on the shares of college graduates, some college and above, and high school graduates and above. The sizes of their effects are stable even after including MSA fixed effects and are comparable to the estimated impacts from the SCM, and all specifications show the effect grows over time.

6 Proposed mechanisms for the post-Mariel boatlift findings

In this section, we analyze some mechanisms for changes in relative productivity and amenities along with the SEM to help interpret our results. First, we assess relative changes in Miami's wage and rents using the SCM.[12] Figures 13, 14, 15, 16 and 17 show the comparison of *overall* average wages and average wages by education group (college graduates, some college, high school graduates,

[12] For wage and rent data, we use census data from IPUMS. However, rent data is only available from 1960.

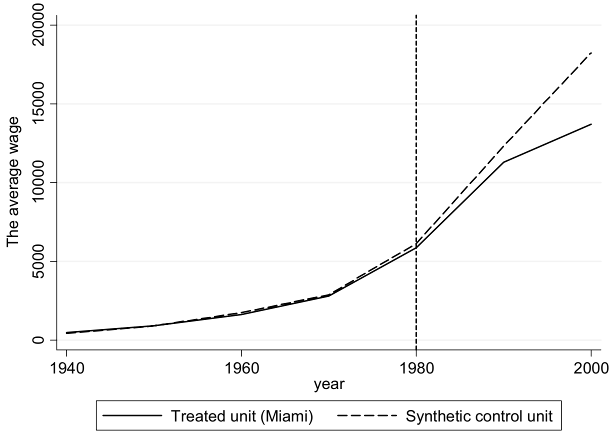

Fig. 13 Average wage in Miami and synthetic control from 1940

and high school dropouts[13]) to Miami's synthetic control unit (for comparisons between Miami and the synthetic control and the MSA donor weights, see Appendix Tables 37, 38, 39, 40, 41, 42, 43, 44, 45, 46). To be sure, unlike the prior case, these groups are only for the listed group (e.g., high school graduates) and not for additional categories with more education (e.g., not some college and college graduates in the case of high school graduates). Figure 18 reports the corresponding comparison for *overall* average rent levels (for comparisons between Miami and the synthetic control and the MSA donor weights, see Appendix Tables 47, 48). The results show that there is some evidence that Miami wages for high school dropouts and high school graduates is slightly below the synthetic control, but the evidence suggest little or no wage difference for those with some college, as well as college graduates. Likewise, Miami's *overall* average (nominal) wage declined over the period, but any response could be mainly from a composition effect of having relatively more lower-paid less-skilled workers—i.e., indicating no clear productivity change among individuals in Miami's workforce.

Figure 18 likewise shows no clear trend in relative rents, though Miami may have slightly lagged its synthetic control after 1990. Yet, because there are possible compositional effects entangled in overall rents, we do not make strong claims based on the SCM rent results. However, given that Saiz (2003) more carefully examined housing composition effects, finding evidence that Miami's relative rents for low-income residents increased, we believe that it is likely that *real* wages of the less-skilled declined in Miami in the aftermath of the boatlift. Thus, under this assumption, the SEM model suggests that the amenities for Miami's low-skilled workers increased, leading to in-migration of more low-skilled households and an ensuing decline in their *real* wage to reestablish spatial equilibrium.

To further assess whether there was a compositional shift, we appraise whether there was a change in Miami's industry structure after the boatlift. As a first pass at

[13] In this case, we use the non-overlapping education attainment group. In other words, each group doesn't contain people with higher level of education.

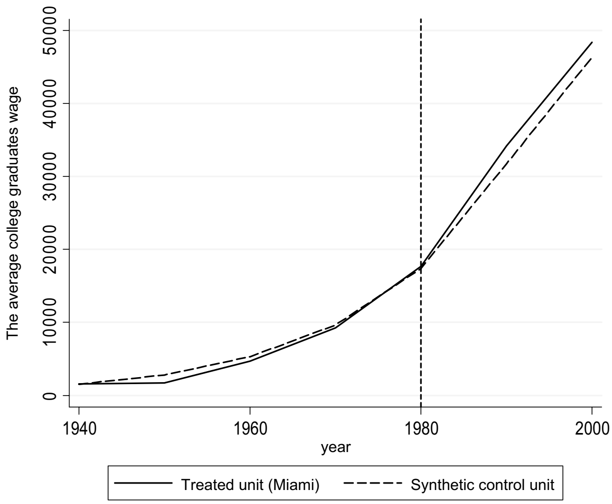

Fig. 14 Average college graduates wage in Miami and synthetic control from 1940

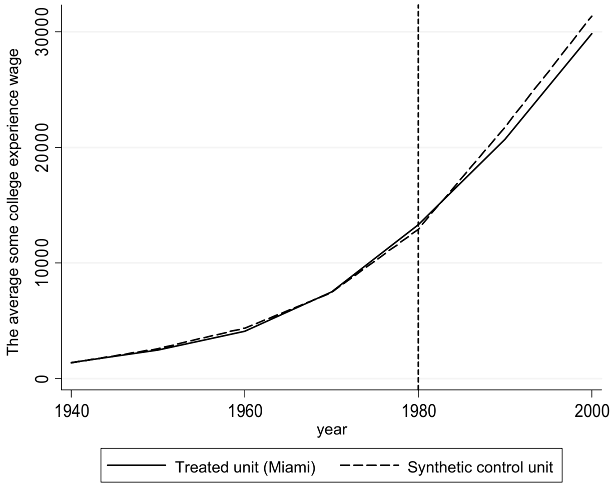

Fig. 15 Average some college experience wage in Miami and synthetic control from 1940

this, we use the SCM to investigate this question for broadly defined industry divisions (see Appendix Tables 49, 50, 51, 52 for details). Appendix Fig. 28 shows that Miami's share of low-skilled-intensive industries significantly increased relative to the synthetic control unit following the boatlift.[14] Likewise, Appendix Fig. 27 shows that Miami experienced a slower growth of skilled-intensive industries compared to the synthetic control from 1980 to 1990, though overall the difference is not striking

[14] Agriculture, Mining and other extractive industries, Transportation, Communication, and Wholesale and Retail Trade. See Appendix Table 3.

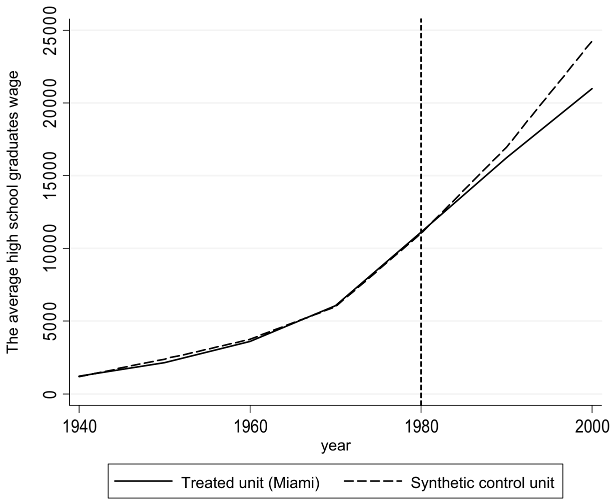

Fig. 16 Average high school graduates wage in Miami and synthetic control from 1940

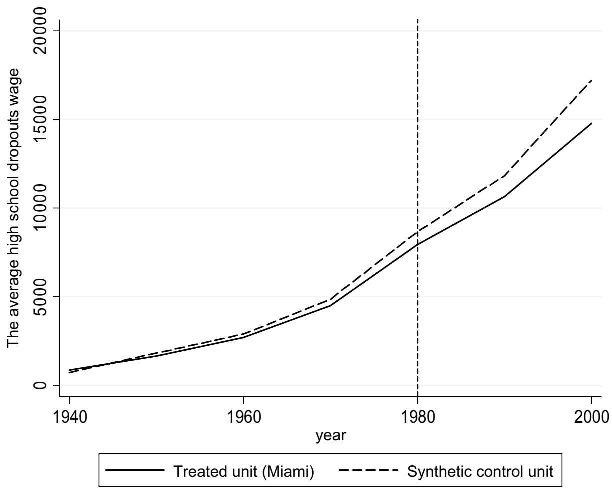

Fig. 17 Average high school dropouts wage in Miami and synthetic control from 1940

compared to the change for low-skilled-intensive industries. Thus, the evidence suggests that Miami's industry composition adjusted to the relative increase in supply of less-skilled workers.

According to the HUD census data, Miami also experienced a large increase in its Hispanic population share after 1980, moving from 35% in 1980 to 56% by 2000 (and 70% in 2010). Miami's share of non-Hispanic whites declined from 46% in 1980 to 20% in 2000 (10% in 2010). So the Mariel boatlift appears to have been a "tipping point" in shifting Miami to a strong hub of Hispanic culture, which is consistent with the previous literature (Card et al. 2008; Schelling 1971). To more

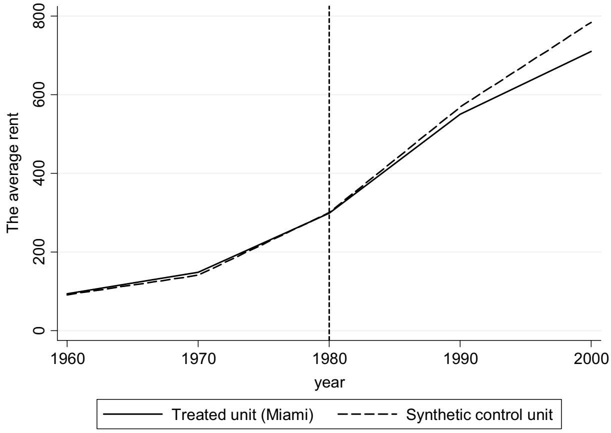

Fig. 18 Average rent in Miami and synthetic control from 1960

formally test this proposition, we use the SCM to appraise how Miami's Hispanic population share evolved (see Appendix Tables 53, 54 for details). The results indicate that Miami's Hispanic share was 10 percentage points higher than its synthetic control in 1990, with the gap growing to 17 percentage points in 2000.

We can then perform the following back-of-the-envelope calculation. It is known from Census data that the percentage of Hispanics who have a bachelor's degree is approximately 15 percentage points lower compared to non-Hispanic whites (Stella et al. 2012). Then the change in the Hispanic share after 1980 can explain approximately 40 percent of the difference between the share of college graduates in Miami and the synthetic control unit in 1990 and 2000. On the other hand, for 1990 and 2000, the change in the Hispanic share can explain approximately 30 percent of the difference between those with some college in Miami and its synthetic control unit, and 20 percent of the difference between the share of high school graduates in Miami and it synthetic control unit, respectively.

Miami role as a "gateway city" that takes in a large number of immigrants (generally lower-skilled compared to natives) also cannot explain the relative decline in Miami's skill aggregation after 1980. That is, Miami's relative immigration flows did not increase after 1980, owing to the fact that migration to Miami was already very high before 1980. Calculate $Z = 100 \times \frac{B-A}{A}$, where A is the 1970 to 1980 change in the city's share of immigrants and B is the 1980 to 1990 change in the city's share of immigrants (based on HUD census data). Thus, Z is the percent change between the 1980s and 1970s in the growth of the city's immigration share. The higher this value, the greater the growth in that city's immigrant share after 1980. The value of Z for Miami is negative (-0.139) and ranks 116th out of 323 MSAs.[15] So, changes in Miami's immigrant inflow after 1980 are unlikely to explain its relative skill-level decline.

[15] There are 322 MSAs available from 1970.

Lastly, one might argue that rather than the effects of the boatlift, violent crime drove out the skilled population. Indeed, Miami was the inspiration of the 1980s popular television program *Miami Vice* that depicted it as the home of drug-running gangs. It is true that Miami's crime rate has been historically high. However, Appendix Fig. 30 shows that the Miami's homicide rate (whether measured for Dade County or just for the city of Miami) declined substantially in the 1980s and 1990s (with an especially sharp decline in the early 1980s).[16] This pattern is in contrast to homicide rate trends in other major US cities, which experienced a sharp increase in homicide rate in the 1980s (Murder Rates in 50 American Cities 2017) before declining in the mid-1990s. Therefore, the changes in Miami's relative skill composition cannot be attributed to violent crime.

7 Conclusion

We find that the Mariel boatlift considerably slowed Miami's relative human capital growth rate, representing at least a highly persistent change if not a permanent one. We find our results are robust to using decennial census data or CPS data, the use of different pre-treatment periods, using different MSAs to form the control group, and to using the standard DiD approach. We find that Miami's average rents did not diverge from its control group and there was some (weak) evidence that real wages for low-skilled workers declined, consistent with enhanced household amenities for low-income households to reestablish spatial equilibrium. Further, it seems that the results might be partially due to a type of cultural or racial sorting due to agglomeration of household amenities. Therefore, this result is likely to be generalizable to other cities as long as cultural characteristics are correlated with education and income levels.

For future study, it would be worthwhile to consider in other settings how shocks may have permanent effects. However, we suspect that given the strength of spatial equilibrium in the USA, it is generally not the case that localized shocks lead to a permanent shift in the aggregate growth of a region's employment and population, though changes in demographic composition such as what we observed seems more likely. If so, it is worthwhile to understand the conditions that regions can (say) upskill to enhance future growth. In addition, future research should also conduct a

[16] The homicide rate is derived using National Archive of Criminal Justice Data (NACJD).

fuller analysis on how Miami's industry composition changed following the boatlift to better understand how shifts in a region's skill composition may affect industry structure.

Appendix 1

The HUD system provides the number of employed workers in each industry category by city. However, it does not provide the share of skilled workers in each industry. Thus, we calculate the correlation between the share of college graduates in each city and the number of employed workers in each industry category.

This table indicates that three industries—Professional Services, Finance, Insurance, and Real Estate (FIRE), and Business and Repair Services—are distinctively positively correlated with the share of college graduates in cities. Thus, we use the share of these industries as the share of skill intensive industries in my main regression. On the other hand, Agriculture, Mining and other extractive industries, Transportation, Communication and Public Utilities and Wholesale and Retail Trade are very negatively correlated with the share of college graduates. Thus we use the share of these industries as the share of non-skill-intensive industries in Sect. 6 (Table 3).

Table 3 Correlation between share of college graduates in each city and number of employed workers in each industry category

Variables	(1) Share of college graduates
Agriculture, mining and other extractive industries	−0.0345
	(0.0525)
Construction	0.159*
	(0.0926)
Professional services	0.863***
	(0.0457)
Manufacturing	0.0855**
	(0.0383)
Transportation, communication, and public utilities	−0.304***
	(0.0803)
Wholesale and retail trade	−0.236***
	(0.0594)
Finance, insurance, and real estate	1.068***
	(0.0777)
Business and repair services	1.831***
	(0.0784)
Personal services	0.208***
	(0.0657)
Constant	−0.118***
	(0.0389)
Observations	1292
R^2	0.759
N	1292
df_m	9
F	448.2
rss	1.807
ll	2412

Standard errors in parentheses

***$p<0.01$, **$p<0.05$, *$p<0.1$

Appendix 2

We construct the synthetic control city by using 1940, 1950, 1960, 1970, and 1980 Census to estimate the treatment effect on the share of college graduates. Appendix Table 4 shows the comparison between Miami and the synthetic control city. Appendix Table 5 shows weights of each MSA contained in the synthetic control for Miami. Root-mean-squared prediction error (RMSPE) is 0.001009.

See Tables 4 and 5.

Table 4 Comparison between Miami and synthetic control city

		Miami	Synthetic
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0700
	1950	0.0303	0.0325
	1960	0.0826	0.0843
	1970	0.1079	0.1072
	1980	0.1677	0.1667
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6368
	1950	0.8295	0.8405
	1960	0.5303	0.5242
	1970	0.4807	0.4829
	1980	0.3600	0.3478
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2419
	1980	0.3203	0.2938
Median family income	1970	9245	9386.691
	1980	18642	19,317.13
Median home value	1970	19,088	15,988.55
	1980	57,235	46,978.09
Unemployed rate	1970	0.0368	0.0333
	1980	0.0491	0.0486
Total population	1970	1,267,792	1,381,883
	1980	1,625,781	1,521,105
African American share (1980)		0.1659	0.1225
Hispanic share (1980)		0.3574	0.0716

Table 5 MSA weights in synthetic control

	Weight
Amarillo, TX	0.012
Charlotte/Gastonia/Rock Hill, NC/SC	0.44
Columbia, SC	0.039
Corpus Christi, TX	0.058
Dallas, TX	0.031
Los Angeles/Long Beach, CA	0.125
Portland, ME	0.294

Appendix 3

We construct the synthetic control city by using 1940, 1950, 1960, 1970, and 1980 Census to estimate the treatment effect on the share of some college or higher. Appendix Table 6 shows the comparison between Miami and the synthetic control city. Appendix Table 7 shows weights of each MSA contained in the synthetic control for Miami. RMSPE is 0.0030255.

See Tables 6 and 7.

Table 6 Comparison between Miami and synthetic control city

		Miami	Synthetic
Share of people with some college experience or higher in the population aged 25 or older	1940	0.1370	0.1414
	1950	0.0647	0.0664
	1960	0.1911	0.1938
	1970	0.2245	0.2262
	1980	0.3356	0.3394
Share people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6455
	1950	0.8295	0.8388
	1960	0.5303	0.5300
	1970	0.4807	0.4817
	1980	0.3600	0.3440
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2396
	1980	0.3203	0.2932
Median family income	1970	9245	9606.162
	1980	18,642	19,492.59
Median home value	1970	19,088	16,994.02
	1980	57,235	50,899.35
Unemployed rate	1970	0.0368	0.0350
	1980	0.0491	0.0519
Total population	1970	1,267,792	1,395,478
	1980	1,625,781	1,520,664
African American share (1980)		0.1659	0.1190
Hispanic share (1980)		0.3574	0.0470

Table 7 MSA weights in synthetic control

	Weight
Atlantic/Cape May, NJ	0.048
Bridgeport, CT	0.039
Charlotte/Gastonia/Rock Hill, NC/SC	0.456
Los Angeles/Long Beach, CA	0.127
Phoenix/Mesa, AZ	0.305
San Francisco, CA	0.025

Appendix 4

We construct the synthetic control city by using 1940, 1950, 1960, 1970, and 1980 Census to estimate the treatment effect on the share of high school or higher. Appendix Table 8 shows the comparison between Miami and the synthetic control city. Appendix 9 shows weights of each MSA contained in the synthetic control for Miami. RMSPE is 0.0129239

See Tables 8 and 9.

Table 8 Comparison between Miami and synthetic control city

		Miami	Synthetic
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0691
	1950	0.0303	0.0329
	1960	0.0826	0.0853
	1970	0.1079	0.1079
	1980	0.1677	0.1679
Share of people graduated high school or higher in the population aged 25 or older	1940	0.3791	0.3580
	1950	0.1705	0.1592
	1960	0.4697	0.4762
	1970	0.5193	0.5165
	1980	0.6400	0.6532
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2444
	1980	0.3203	0.2946
Median family income	1970	9245	9486.198
	1980	18,642	19,429.96
Median home value	1970	19,088	16,803.16
	1980	57,235	53,262.05
Unemployed rate	1970	0.0368	0.0388
	1980	0.0491	0.0535
Total population	1970	1,267,792	1,379,909
	1980	1,625,781	1,529,948
African American share (1980)		0.1659	0.1211
Hispanic share (1980)		0.3574	0.0751

Table 9 MSA weights in synthetic control

	Weight
Bridgeport, CT	0.002
Charlotte/Gastonia/Rock Hill, NC/SC	0.463
Columbia, SC	0.017
Fresno, CA	0.101
Los Angeles/Long Beach, CA	0.113
Portland, ME	0.231
San Diego, CA	0.039
San Francisco, CA	0.034

Appendix 5

We construct the synthetic control city by using 1940, 1950, 1960, 1970, and 1980 Census to estimate the treatment effect on the share of high school dropouts. Appendix Table 10 shows the comparison between Miami and the synthetic control city. Appendix 11 shows weights of each MSA contained in the synthetic control for Miami. RMSPE is 0.0129239.

See Tables 10 and 11.

Table 10 Comparison between Miami and synthetic control city

		Miami	Synthetic
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0691
	1950	0.0303	0.0329
	1960	0.0826	0.0853
	1970	0.1079	0.1079
	1980	0.1677	0.1679
Share people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.642
	1950	0.8295	0.8408
	1960	0.5303	0.5238
	1970	0.4807	0.4835
	1980	0.36	0.3468
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2444
	1980	0.3203	0.2946
Median family income	1970	9245	9486.198
	1980	18,642	19,429.96
Median home value	1970	19,088	16,803.16
	1980	57,235	53,262.05
Unemployed rate	1970	0.0368	0.0388
	1980	0.0491	0.0535
Total population	1970	1,267,792	1,379,909
	1980	1,625,781	1,529,948
African American share (1980)		0.1659	0.1211
Hispanic share (1980)		0.3574	0.0751

Table 11 MSA weights in synthetic control

	Weight
Bridgeport, CT	0.002
Charlotte/Gastonia/Rock Hill, NC/SC	0.463
Columbia, SC	0.017
Fresno, CA	0.101
Los Angeles/Long Beach, CA	0.113
Portland, ME	0.231
San Diego, CA	0.039
San Francisco, CA	0.034

Appendix 6: In-time placebo test for college graduates

See Tables 12 and 13.

Table 12 Comparison between Miami and synthetic control city for Fig. 5 (In-time placebo test) (RMSPE: 0.0035276)

		Miami	Synthetic
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0692
	1950	0.0303	0.0327
	1960	0.0826	0.0858
	1970	0.1079	0.1130
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6431
	1950	0.8295	0.8397
	1960	0.5303	0.5322
	1970	0.4807	0.4641
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2665
Median family income	1970	9245	9479.8
Median home value	1970	19,088	16,372.24
Unemployed rate	1970	0.0368	0.0298
Total population	1970	1,267,792	1,290,496
African American share (1970)		0.1499	0.1315
Hispanic share (1970)		0.2258	0.0140

Table 13 MSA weights in synthetic control for Fig. 5 (In-time placebo test)

	Weight
Charlotte/Gastonia/Rock Hill, NC/SC	0.21
Des Moines, IA	0.018
Los Angeles/Long Beach, CA	0.033
New York, NY	0.062
Oklahoma City, OK	0.164
Portland/Vancouver, OR/WA	0.275
Richmond/Petersburg, VA	0.212
Topeka, KS	0.026

Appendix 7: In-time placebo test for some college experience or higher

See Tables 14 and 15.

Table 14 Comparison between Miami and synthetic control city for Fig. 6 (In-time placebo test) (RMSPE: 0.0057033)

		Miami	Synthetic
Share of people with some college experience or higher in the population aged 25 or older	1940	0.1370	0.1408
	1950	0.0647	0.0660
	1960	0.1911	0.1938
	1970	0.2245	0.2333
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6487
	1950	0.8295	0.8419
	1960	0.5303	0.5346
	1970	0.4807	0.4672
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2692
Median family income	1970	9245	9711.413
Median home value	1970	19,088	16,853.83
Unemployed rate	1970	0.0368	0.0283
Total population	1970	1,267,792	1,269,125
African American share (1970)		0.1499	0.1425
Hispanic share (1970)		0.2258	0.0174

Table 15 MSA weights in synthetic control for Fig. 6 (In-time placebo test)

	Weight
Charlotte/Gastonia/Rock Hill, NC/SC	0.187
Dallas, TX	0.136
Des Moines, IA	0.112
New York, NY	0.071
Portland, ME	0.251
Richmond/Petersburg, VA	0.238
Tulsa, OK	0.006

Appendix 8: In-time placebo test for high school or higher

See Tables 16 and 17.

Table 16 Comparison between Miami and synthetic control city for Fig. 7 (In-time placebo test) (RMSPE: 0.0144967)

		Miami	Synthetic
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0693
	1950	0.0303	0.0294
	1960	0.0826	0.0858
	1970	0.1079	0.1116
Share of people graduated high school or higher in the population aged 25 or older	1940	0.3791	0.3592
	1950	0.1705	0.1651
	1960	0.4697	0.4665
	1970	0.5193	0.5344
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2672
Median family income	1970	9245	8967.043
Median home value	1970	19,088	14,463
Unemployed rate	1970	0.0368	0.0351
Total population	1970	1,267,792	1,271,626
African American share (1970)		0.1499	0.0816
Hispanic share (1970)		0.2258	0.1296

Table 17 MSA weights in synthetic control for Fig. 7 (In-time placebo test)

	Weight
Amarillo, TX	0.108
Charlotte/Gastonia/Rock Hill, NC/SC	0.157
Los Angeles/Long Beach, CA	0.102
Oklahoma City, OK	0.131
Portland, ME	0.136
San Antonio, TX	0.311
Topeka, KS	0.054

Appendix 9: In-time placebo test for high school dropouts

See Tables 18 and 19.

Table 18 Comparison between Miami and synthetic control city for Fig. 8 (In-time placebo test) (RMSPE: 0.0144967)

		Miami	Synthetic
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0693
	1950	0.0303	0.0294
	1960	0.0826	0.0858
	1970	0.1079	0.1116
Share of high school dropouts in the population aged 25 or older	1940	0.6209	0.6408
	1950	0.8295	0.8349
	1960	0.5303	0.5335
	1970	0.4807	0.4656
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2672
Median family income	1970	9245	8967
Median home value	1970	19,088	14,463
Unemployed rate	1970	0.0368	0.0351
Total population	1970	1,267,792	1,271,626
African American share (1970)		0.1499	0.0816
Hispanic share (1970)		0.2258	0.1296

Table 19 MSA weights in synthetic control for Fig. 8 (In-time placebo test)

	Weight
Amarillo, TX	0.108
Charlotte/Gastonia/Rock Hill, NC/SC	0.157
Los Angeles/Long Beach, CA	0.102
Oklahoma City, OK	0.131
Portland, ME	0.136
San Antonio, TX	0.311
Topeka, KS	0.054

Appendix 10: Matching on early pre-periods for college graduates

See Tables 20 and 21 and Figs. 19, 20, 21 and 22.

Table 20 Comparison between Miami and synthetic control city for Fig. 9 (matching on early pre-periods) (RMSPE: 0.0026085)

		Miami	Synthetic
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0698
	1950	0.0303	0.0328
	1960	0.0826	0.0833
	1970	0.1079	0.1098
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6336
	1950	0.8295	0.8376
	1960	0.5303	0.5242
	1970	0.4807	0.4769
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2438
	1980	0.3203	0.2963
Median family income	1970	9245	9539
	1980	18,642	19,517
Median home value	1970	19,088	16,348
	1980	57,235	47,666
Unemployed rate	1970	0.0368	0.0324
	1980	0.0491	0.0476
Total population	1970	1,267,792	1,366,777
	1980	1,625,781	1,526,679
African American share (1980)		0.1659	0.1270
Hispanic share (1980)		0.3574	0.0451

Table 21 MSA weights in synthetic control for Fig. 9 (matching on early pre-periods)

	Weight
Bridgeport, CT	0.007
Charlotte/Gastonia/Rock Hill, NC/SC	0.425
Columbia, SC	0.039
Dallas, TX	0.104
Los Angeles/Long Beach, CA	0.109
Portland, ME	0.314
San Diego, CA	0.002

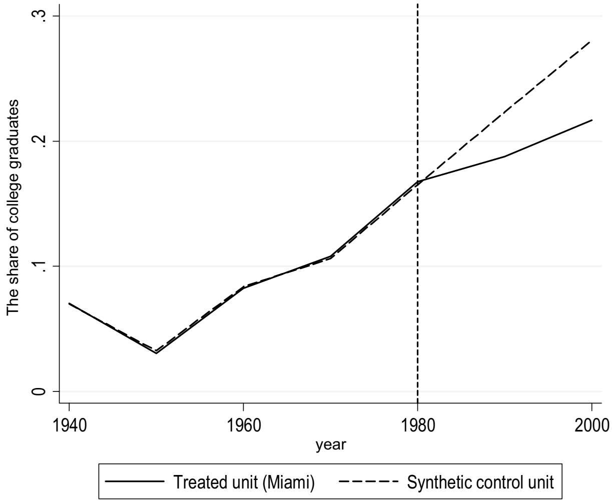

Fig. 19 College graduate share in Miami and the synthetic control unit after 1940

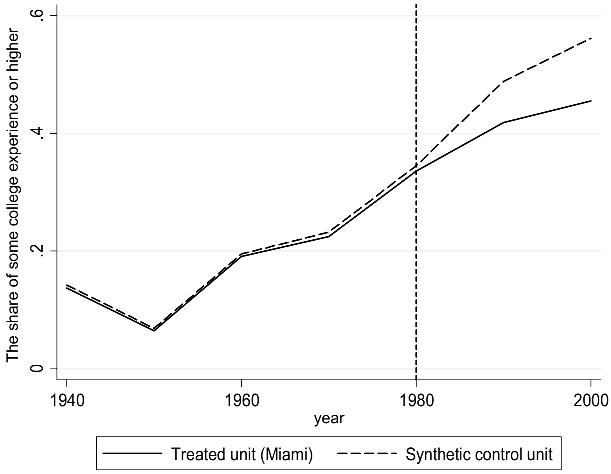

Fig. 20 Some college experience or higher share in Miami and the synthetic control unit after 1940

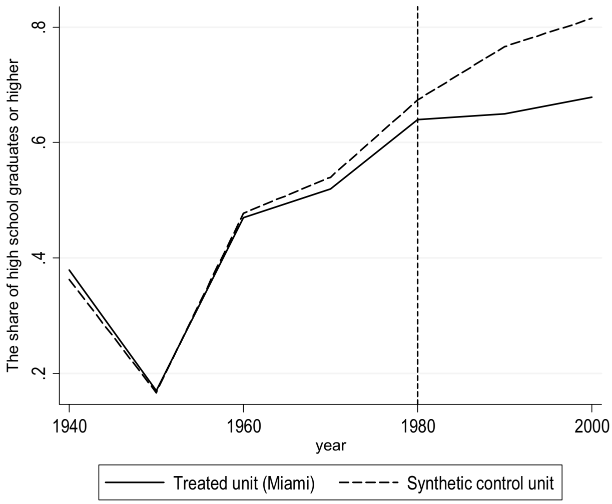

Fig. 21 High school graduate share or higher in Miami and the synthetic control unit after 1940

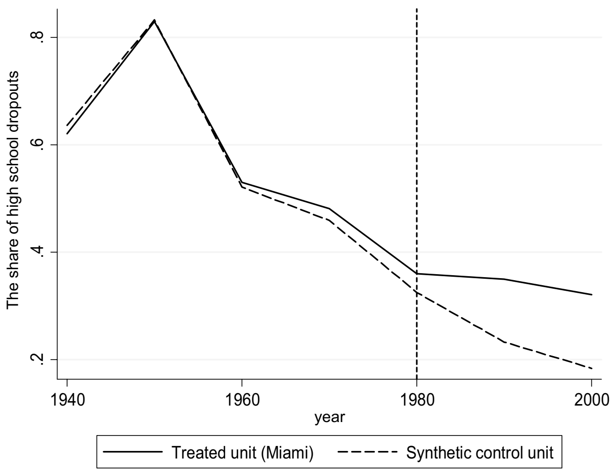

Fig. 22 High school dropout share in Miami and the synthetic control unit after 1940

Appendix 11: Matching on early pre-periods for some college or higher

See Tables 22 and 23.

Table 22 Comparison between Miami and synthetic control city for Fig. 10 (matching on early pre-periods) (RMSPE: 0.0036858)

		Miami	Synthetic
Share of people with some college experience or higher in the population aged 25 or older	1940	0.1370	0.1402
	1950	0.0647	0.0659
	1960	0.1911	0.1920
	1970	0.2245	0.2292
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6376
	1950	0.8295	0.8387
	1960	0.5303	0.5272
	1970	0.4807	0.4737
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2395
	1980	0.3203	0.2947
Median family income	1970	9245	9467
	1980	18,642	19,123
Median home value	1970	19,088	16,253
	1980	57,235	47,476
Unemployed rate	1970	0.0368	0.0333
	1980	0.0491	0.0507
Total population	1970	1,267,792	1,374,170
	1980	1,625,781	1,501,432
African American share (1980)		0.1659	0.1123
Hispanic share (1980)		0.3574	0.0411

Table 23 MSA weights in synthetic control for Fig. 10 (matching on early pre-periods)

	Weight
Charlotte/Gastonia/Rock Hill, NC/SC	0.399
Greensboro/Winston-Salem/High Point, NC	0.071
Los Angeles/Long Beach, CA	0.129
Mobile, AL	0.009
Portland, ME	0.392

Appendix 12: Matching on early pre-periods for high school or higher

See Tables 24 and 25.

Table 24 Comparison between Miami and synthetic control city for Fig. 11 (matching on early pre-periods) (RMSPE: 0.0132511)

		Miami	Synthetic
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0698
	1950	0.0303	0.0328
	1960	0.0826	0.0833
	1970	0.1079	0.1098
Share of people graduated high school or higher in the population aged 25 or older	1940	0.3791	0.3664
	1950	0.1705	0.1624
	1960	0.4697	0.4758
	1970	0.5193	0.5231
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2438
	1980	0.3203	0.2963
Median family income	1970	9245	9539
	1980	18,642	19,517
Median home value	1970	19,088	16,348
	1980	57,235	47,666
Unemployed rate	1970	0.0368	0.0324
	1980	0.0491	0.0476
Total population	1970	1,267,792	1,366,777
	1980	1,625,781	1,526,679
African American share (1980)		0.1659	0.1270
Hispanic share (1980)		0.3574	0.0451

Table 25 MSA weights in synthetic control for Fig. 11 (matching on early pre-periods)

	Weight
Bridgeport, CT	0.007
Charlotte/Gastonia/Rock Hill, NC/SC	0.425
Columbia, SC	0.039
Dallas, TX	0.104
Los Angeles/Long Beach, CA	0.109
Portland, ME	0.314
San Diego, CA	0.002

Appendix 13: Matching on early pre-periods for high school dropouts

See Tables 26 and 27.

Table 26 Comparison between Miami and synthetic control city for Fig. 12 (matching on early pre-periods) (RMSPE: 0.0132511)

		Miami	Synthetic
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0698
	1950	0.0303	0.0328
	1960	0.0826	0.0833
	1970	0.1079	0.1098
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6336
	1950	0.8295	0.8376
	1960	0.5303	0.5242
	1970	0.4807	0.4769
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2438
	1980	0.3203	0.2963
Median family income	1970	9245	9539
	1980	18,642	19,517
Median home value	1970	19,088	16,348
	1980	57,235	47,666
Unemployed rate	1970	0.0368	0.0324
	1980	0.0491	0.0476
Total population	1970	1,267,792	1,366,777
	1980	1,625,781	1,526,679
African American share (1980)		0.1659	0.1270
Hispanic share (1980)		0.3574	0.0451

Table 27 MSA weights in synthetic control for Fig. 12 (matching on early pre-periods)

	Weight
Bridgeport, CT	0.007
Charlotte/Gastonia/Rock Hill, NC/SC	0.425
Columbia, SC	0.039
Dallas, TX	0.104
Los Angeles/Long Beach, CA	0.109
Portland, ME	0.314
San Diego, CA	0.002

Appendix 14: Fig. 2

There are several issues with using the CPS. First, we can only identify 30 MSAs from the IPUMS distribution of the data, as we start from 1973 (the earliest year when Miami itself is identified). And it contains a large number of Midwestern MSAs but few in the South, which means that it is unlikely to contain good control candidates for the synthetic control of Miami.

Second, there are potentially very serious measurement errors compared to city aggregation information from HUD. For instance, according to the CPS data, the share of college graduates did not increase from 1973 to 1980 (in fact, it declined slightly, from 14.7 percent in 1973 to 13.5 percent in 1980). This result is starkly inconsistent

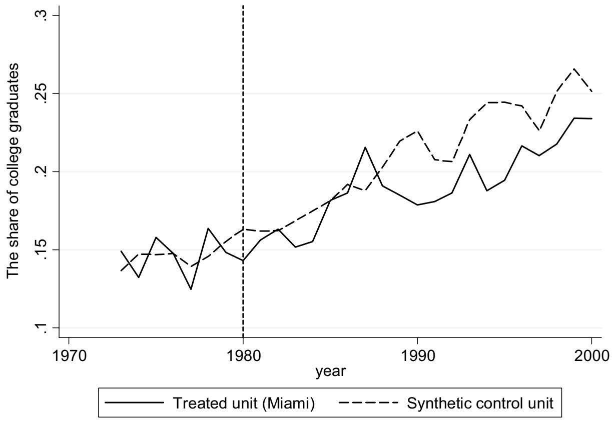

Fig. 23 College graduate share in Miami and synthetic control

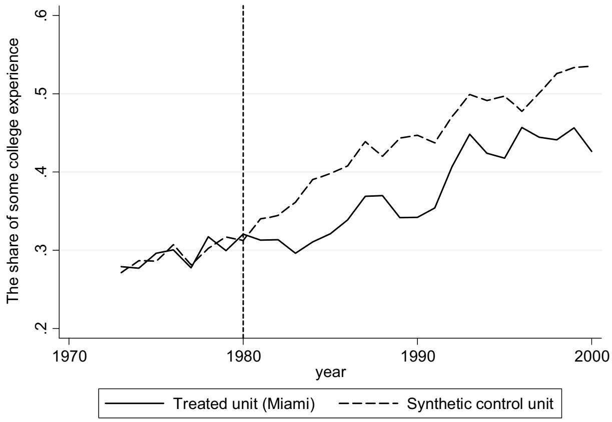

Fig. 24 Some college or higher share in Miami and synthetic control

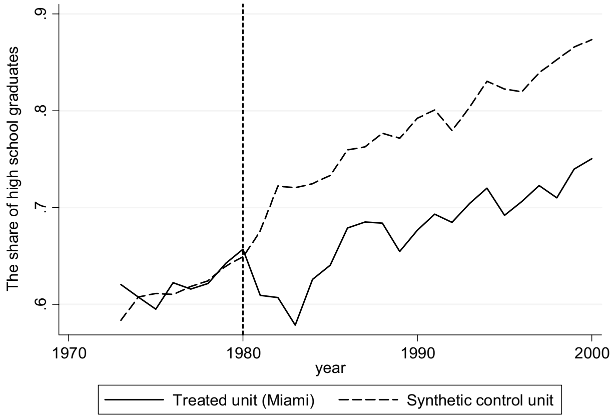

Fig. 25 High school graduate or higher share in Miami and synthetic control

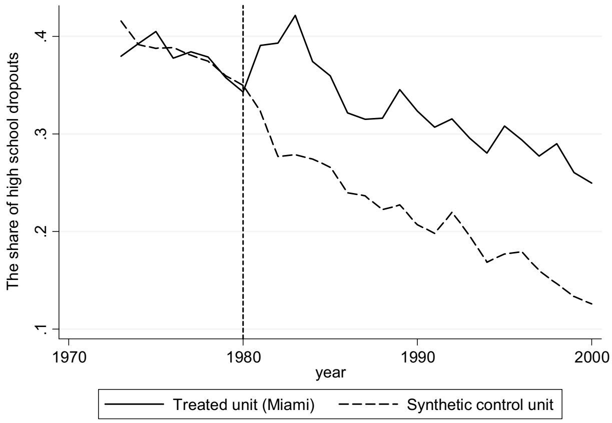

Fig. 26 High school dropouts share in Miami and synthetic control

Table 28 MSA weights in synthetic control (RMSPE: 0.012427)

	Weight
Buffalo–Niagara Falls, NY	0.11
Detroit, MI	0.171
Newark, NJ	0.333
Riverside/San Bernardino, CA	0.387

Table 29 Comparison between Miami and synthetic control city

		Miami	Synthetic
Average share of people with Bachelor's degree or higher in the population aged 25 or older	1973–1975	0.1463	0.1436
	1974–1976	0.1459	0.1472
	1975–1977	0.1432	0.1445
	1976–1978	0.1452	0.1441
	1977–1979	0.1455	0.1467
	1978–1980	0.1517	0.1546

Table 30 MSA weights in synthetic control: share of some college or higher (RMSPE: 0.0110246)

	Weight
Buffalo–Niagara Falls, NY	0.032
Houston, TX	0.359
New Orleans, LA	0.006
Newark, NJ	0.414
Philadelphia, PA/NJ	0.189

Table 31 Comparison between Miami and synthetic control city: share of some college or higher

		Miami	Synthetic
Average share of people with some college experience or higher in the population aged 25 or older	1973–1975	0.2840	0.2812
	1974–1976	0.2912	0.2931
	1975–1977	0.2913	0.2913
	1976–1978	0.2983	0.2968
	1977–1979	0.2979	0.3000
	1978–1980	0.3124	0.3104

Table 32 MSA weights in synthetic control: high school or higher (RMSPE: 0.0159895)

	Weight
Buffalo–Niagara Falls, NY	0.157
Cincinnati, OH/KY/IN	0.139
Philadelphia, PA/NJ	0.686
Riverside/San Bernardino, CA	0.017

Table 33 Comparison between Miami and synthetic control city: high school or higher (RMSPE: 0.0110246)

		Miami	Synthetic
Average share of people graduate high school or higher in the population aged 25 or older	1973–1975	0.6077	0.6007
	1974–1976	0.6082	0.6097
	1975–1977	0.6110	0.6134
	1976–1978	0.6198	0.6178
	1977–1979	0.6265	0.6274
	1978–1980	0.6403	0.6377

Table 34 MSA weights in synthetic control: high school graduates

	Weight
Buffalo–Niagara Falls, NY	0.157
Cincinnati, OH/KY/IN	0.139
Philadelphia, PA/NJ	0.686
Riverside/San Bernardino, CA	0.017

Table 35 Comparison between Miami and synthetic control city: high school dropouts

		Miami	Synthetic
Average share of people who didn't graduate high school in the population aged 25 or older	1973–1975	0.3923	0.3983
	1974–1976	0.3918	0.3893
	1975–1977	0.3890	0.3856
	1976–1978	0.3802	0.3822
	1977–1979	0.3735	0.3716
	1978–1980	0.3597	0.3613

with the results from HUD (specifically, that the share of college graduates increased from 10 to 17 percent in Miami from 1970 to 1980).

See Figs. 23, 24, 25, 26 and Tables 28, 29, 30, 31, 32, 33, 34 and 35.

Appendix 15

See Table 36.

Table 36 Difference-in-differences outcome

Variables	The share of college graduates		The share of some college experience		The share of high school graduates	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	−0.01***	0.0004	−0.0036	−0.0032	−0.0519***	0.0402***
	(0.00302)	(0.00802)	(0.00559)	(0.00445)	(0.0108)	(0.0114)
1980*Treatment	0.000378	0.000378	0.00107	0.00107	−0.000829	−0.000829
	(0.00445)	(0.00155)	(0.00795)	(0.00210)	(0.0152)	(0.00436)
1990*Treatment	−0.0180***	−0.0180***	−0.0550***	−0.0550***	−0.0671***	−0.0671***
	(0.00468)	(0.00144)	(0.00792)	(0.00189)	(0.0136)	(0.00359)
2000*Treatment	−0.0308***	−0.0308***	−0.0853***	−0.0853***	−0.0839***	−0.0839***
	(0.00498)	(0.00198)	(0.00774)	(0.00300)	(0.0132)	(0.00571)
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes
MSA Fixed	No	Yes	No	Yes	No	Yes
Observations	496	496	368	368	284	284
R^2	0.645	0.970	0.846	0.989	0.586	0.962
F	–	–	–	–	–	–
rss	0.719	0.0612	1.000	0.0718	1.711	0.158

Robust standard errors in parentheses

***$p<0.01$, **$p<0.05$, *$p<0.1$

Appendix 16

See Tables 37, 38, 39, 40, 41, 42, 43, 44, 45 and 46.

Table 37 Comparison between Miami and synthetic control city: average wage (RMSPE: 26.42229)

		Miami	Synthetic
Average wage	1940	477.250	424.528
	1950	903.135	890.984
	1960	1607.235	1738.647
	1970	2787.584	2875.104
	1980	5862.711	6118.477
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0688
	1950	0.0303	0.0363
	1960	0.0826	0.0915
	1970	0.1079	0.1145
	1980	0.1677	0.1700
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6664
	1950	0.8295	0.8547
	1960	0.5303	0.5412
	1970	0.4807	0.4860
	1980	0.3600	0.3362
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2419
	1980	0.3203	0.2886
Median family income	1970	9245	9487.712
	1980	18,642	19,645.65
Median home value	1970	19,088	17,066.14
	1980	57235	51006.64
Unemployed rate	1970	0.0368	0.0407
	1980	0.0491	0.0551
Total population	1970	1267792	1325494
	1980	1625781	1463126
African American share (1980)		0.1659	0.1378
Hispanic share (1980)		0.3574	0.0505

Table 38 MSA weights in synthetic control: average wage

	Weight
Columbia, SC	0.111
Greensboro/Winston-Salem/High Point, NC	0.437
Los Angeles/Long Beach, CA	0.078
New York, NY	0.019
Salt Lake City/Ogden, UT	0.222
Stockton/Lodi, CA	0.041
Tacoma, WA	0.093

Table 39 Comparison between Miami and synthetic control city: college graduates wage (RMSPE: 384.6324)

		Miami	Synthetic
Average wage of people with Bachelor's degree or higher in the population aged 25 or older	1940	1613.686	1540.519
	1950	1680.126	2809.575
	1960	4723.263	5307.415
	1970	9246.232	9654.034
	1980	17679.95	17400.63
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0680
	1950	0.0303	0.0280
	1960	0.0826	0.0889
	1970	0.1079	0.1109
	1980	0.1677	0.1680
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6708
	1950	0.8295	0.8502
	1960	0.5303	0.5469
	1970	0.4807	0.4704
	1980	0.3600	0.3320
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2712
	1980	0.3203	0.3156
Median family income	1970	9245	8732.482
	1980	18,642	18,711.79
Median home value	1970	19,088	14,288.57
	1980	57,235	44,345.28
Unemployed rate	1970	0.0368	0.0408
	1980	0.0491	0.0531
Total population	1970	1,267,792	1,175,575
	1980	1,625,781	1,329,512
African American share (1980)		0.1659	0.0968
Hispanic share (1980)		0.3574	0.1324

Table 40 MSA weights in synthetic control: college graduates wage

	Weight
Fresno, CA	0.025
Greensboro/Winston-Salem/High Point, NC	0.114
Knoxville, TN	0.147
Little Rock/North Little Rock, AR	0.125
Los Angeles/Long Beach, CA	0.084
Oklahoma City, OK	0.176
Salt Lake City/Ogden, UT	0.037
San Antonio, TX	0.206
Spokane, WA	0.086

Table 41 Comparison between Miami and synthetic control city: some college experience wage (RMSPE: 247.6642)

		Miami	Synthetic
Average wage of people with some college experience in the population aged 25 or older	1940	1371.432	1340.738
	1950	2463.017	2569.887
	1960	4082.555	4355.196
	1970	7477.838	7437.911
	1980	13310.18	12,899.43
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0692
	1950	0.0303	0.0304
	1960	0.0826	0.0903
	1970	0.1079	0.1089
	1980	0.1677	0.1619
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6523
	1950	0.8295	0.8438
	1960	0.5303	0.5364
	1970	0.4807	0.4725
	1980	0.3600	0.3386
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2595
	1980	0.3203	0.2992
Median family income	1970	9245	9291.545
	1980	18,642	19,583.92
Median home value	1970	19,088	15,505.26
	1980	57,235	52,720.67
Unemployed rate	1970	0.0368	0.0514
	1980	0.0491	0.0597
Total population	1970	1,267,792	1,321,153
	1980	1,625,781	1,490,586
African American share (1980)		0.1659	0.1027
Hispanic share (1980)		0.3574	0.1296

Table 42 MSA weights in synthetic control: some college experience wage

	Weight
Charlotte/Gastonia/Rock Hill, NC/SC	0.185
Dallas, TX	0.052
Fresno, CA	0.208
Los Angeles/Long Beach, CA	0.103
Oklahoma City, OK	0.305
Stockton/Lodi, CA	0.147

Table 43 Comparison between Miami and synthetic control city: high school graduates wage (RMSPE: 97.23357)

		Miami	Synthetic
Average wage of high school graduates in the population aged 25 or older	1940	1203.041	1186.677
	1950	2130.379	2402.813
	1960	3605.83	3765.045
	1970	6062.182	6010.164
	1980	11,129.53	11,032.41
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0696
	1950	0.0303	0.0316
	1960	0.0826	0.0923
	1970	0.1079	0.1112
	1980	0.1677	0.1687
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6613
	1950	0.8295	0.8558
	1960	0.5303	0.5353
	1970	0.4807	0.4874
	1980	0.3600	0.3484
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2625
	1980	0.3203	0.3038
Median family income	1970	9245	8993.84
	1980	18,642	19,253.16
Median home value	1970	19,088	16,127.18
	1980	57,235	50,609.74
Unemployed rate	1970	0.0368	0.0421
	1980	0.0491	0.0553
Total population	1970	1,267,792	1,349,471
	1980	1,625,781	1,515,736
African American share (1980)		0.1659	0.1596
Hispanic share (1980)		0.3574	0.0932

Table 44 MSA weights in synthetic control: high school graduates wage

	Weight
Charlotte/Gastonia/Rock Hill, NC/SC	0.224
Columbia, SC	0.124
Dallas, TX	0.037
Fresno, CA	0.172
Greensboro/Winston-Salem/High Point, NC	0.042
Little Rock/North Little Rock, AR	0.214
Los Angeles/Long Beach, CA	0.116
Oklahoma City, OK	0.033
Salt Lake City/Ogden, UT	0.038

Table 45 Comparison between Miami and synthetic control city: high school dropouts wage (RMSPE: 411.9051)

		Miami	Synthetic
Average wage of people didn't graduate high school in the population aged 25 or older	1940	845.0716	715.9728
	1950	1633.762	1808.16
	1960	2696.866	2886.247
	1970	4486.973	4847.565
	1980	7944.184	8648.898
Share of people with Bachelor's degree or higher in the population aged 25 or older	1940	0.0703	0.0694
	1950	0.0303	0.0316
	1960	0.0826	0.0892
	1970	0.1079	0.1105
	1980	0.1677	0.1673
Share of people didn't graduate high school in the population aged 25 or older	1940	0.6209	0.6621
	1950	0.8295	0.8428
	1960	0.5303	0.5410
	1970	0.4807	0.4906
	1980	0.3600	0.3418
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2616
	1980	0.3203	0.3075
Median family income	1970	9245	8851.847
	1980	18,642	18,810.01
Median home value	1970	19,088	15,040.8
	1980	57,235	45,394.36
Unemployed rate	1970	0.0368	0.0377
	1980	0.0491	0.0480
Total population	1970	1,267,792	1,374,346
	1980	1,625,781	1,570,054
African American share (1980)		0.1659	0.1064
Hispanic share (1980)		0.3574	0.2224

Table 46 MSA weights in synthetic control: high school dropouts wage

	Weight
Charlotte/Gastonia/Rock Hill, NC/SC	0.21
Columbia, SC	0.035
Little Rock/North Little Rock, AR	0.076
Los Angeles/Long Beach, CA	0.095
Salt Lake City/Ogden, UT	0.171
San Antonio, TX	0.413

Appendix 17: Evolution of Rent in Miami

See Figs. 27, 28, 29 and Tables 47 and 48.

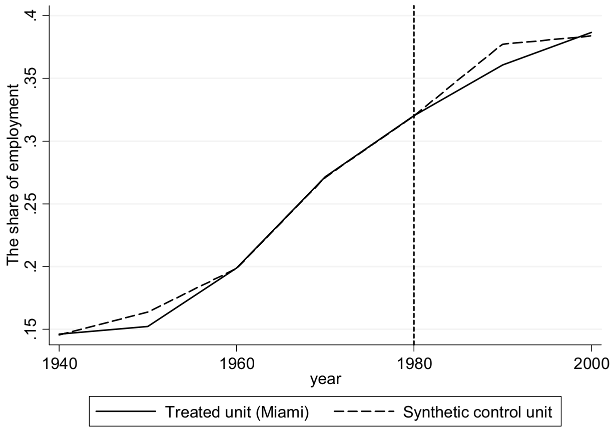

Fig. 27 High-skilled-intensive industries employment share in Miami and synthetic control unit after 1940

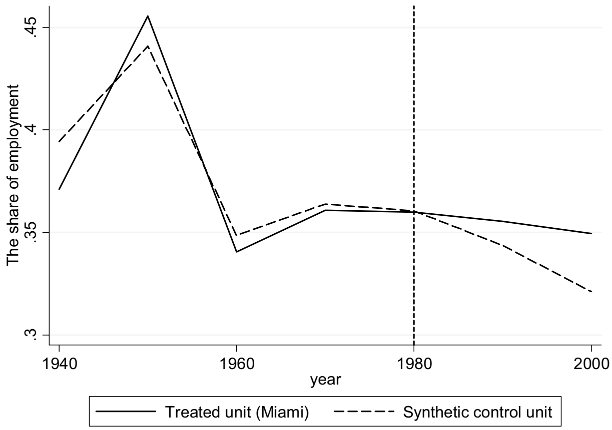

Fig. 28 Low-skilled-intensive industries employment share in Miami and the synthetic control unit after 1940

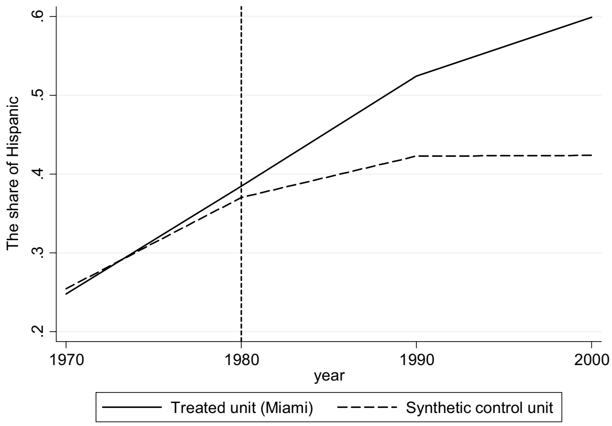

Fig. 29 Hispanic share in Miami and synthetic control unit

Table 47 Comparison between Miami and synthetic control city: average rent (RMSPE: 4.839338)

		Miami	Synthetic
Average rent	1960	93.720	90.959
	1970	148.333	140.499
	1980	298.895	299.913
Share of people with Bachelor's degree or higher in the population aged 25 or older	1960	0.0826	0.0845
	1970	0.1079	0.1087
	1980	0.1677	0.1578
Share of people didn't graduate high school in the population aged 25 or older	1960	0.5303	0.5425
	1970	0.4807	0.4632
	1980	0.3600	0.3284
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2458
	1980	0.3203	0.2772
Median family income	1970	9245	10,469.19
	1980	18,642	21,191.67
Median home value	1970	19,088	19,483.69
	1980	57,235	61,095.23
Unemployed rate	1970	0.0368	0.0408
	1980	0.0491	0.0586
Total population	1970	1,267,792	1,403,835
	1980	1,625,781	1,534,420
African American share (1980)		0.1659	0.1598
Hispanic share (1980)		0.3574	0.0552

Table 48 MSA weights in synthetic control: average rent

	Weight
Baltimore, MD	0.325
Charlotte/Gastonia/Rock Hill, NC/SC	0.171
Las Vegas, NV/AZ	0.363
New York, NY	0.04
San Jose, CA	0.101

Appendix 18: The synthetic control method for the share of employment in industries

Appendix Table 49 shows the synthetic control unit for the employment shares of industries that hire skilled labor intensively. The RMSPE is 0.0002051.

Appendix Table 50 shows weights of each MSA contained in the synthetic control for Miami.

Table 49 Comparison between Miami (treated) and synthetic control

		Treated	Synthetic
Employment shares of industries that hire skilled labor intensively	1940	0.1460	0.1456
	1950	0.1521	0.1637
	1960	0.1987	0.1984
	1970	0.2716	0.2711
	1980	0.3203	0.3201
Share of people with Bachelor's degree or higher in the population aged 25 or older	1970	0.1079	0.1157
	1980	0.1677	0.1767
Share of people didn't graduate high school in the population aged 25 or older	1970	0.4807	0.4835
	1980	0.3600	0.3261
Median family income	1970	9245	9137.941
	1980	18,642	19,682.45
Median home value	1970	19,088	18,462.42
	1980	57,235	56,731.07
Unemployed rate	1970	0.0368	0.0444
	1980	0.0491	0.0530
Total population	1970	1,267,792	1,311,724
	1980	1,625,781	1,580,032
African American share (1980)		0.1659	0.1704
Hispanic share (1980)		0.3574	0.1461

Table 50 Weights of each MSA in the synthetic control

	Weight
Austin/San Marcos, TX	0.057
Hartford, CT	0.051
Lincoln, NE	0.007
Los Angeles/Long Beach, CA	0.046
New Orleans, LA	0.423
Phoenix/Mesa, AZ	0.184
Pueblo, CO	0.009
San Antonio, TX	0.141
San Diego, CA	0.072
San Jose, CA	0.009

Appendix Table 51 shows the synthetic control unit for the share of not-skilled-intensive industries. The RMSPE is 0.0129097. Table H.4 shows weights of cities in the synthetic control.

See Tables 49, 50, 51 and 52.

Table 51 Comparison between Miami (treated) and synthetic control

		Treated	Synthetic
Employment shares of industries not-skilled-intensive industries	1940	0.3710	0.3944
	1950	0.4555	0.4408
	1960	0.3405	0.3486
	1970	0.3608	0.3638
	1980	0.3599	0.3605
Share of people with Bachelor's degree or higher in the population aged 25 or older	1970	0.1079	0.1011
	1980	0.1677	0.1550
Share of people didn't graduate high school in the population aged 25 or older	1970	0.4807	0.4923
	1980	0.3600	0.3359
Median family income	1970	9245	9264.436
	1980	18,642	20,253.74
Median home value	1970	19,088	17,839.99
	1980	57,235	51,512.24
Unemployed rate	1970	0.0368	0.0517
	1980	0.0491	0.0684
Total population	1970	1,267,792	1,362,345
	1980	1,625,781	1,490,644
African American share (1980)		0.1659	0.2030
Hispanic share (1980)		0.3574	0.0500

Table 52 Weights of each MSA in the synthetic control

	Weight
Decatur, IL	0.199
Duluth/Superior, MN/WI	0.151
Los Angeles/Long Beach, CA	0.099
New Orleans, LA	0.501
Norfolk/Virginia Beach/Newport News, VA/NC	0.022
Topeka, KS	0.028

Appendix 19: The synthetic control method for Hispanic share

HUD doesn't provide data on Hispanic share before 1980. Therefore, we use Census data (from 1970 to 2000) from IPUMS. However, we can only identify 111 MSAs (including Miami) from IPUMS data. Therefore, the fit between Miami and the synthetic control unit is worse than the previous results when the share of college graduates was used. However, it still can provide some evidence that Miami experienced a huge increase in the share of college graduates compared to its synthetic control unit. (Pseudo-p-value from *all* donors is very small, less than 0.01 in both 1990 and 2000.) The RMSPE is 0.01107. Table H.1 shows the balance table between Miami and its synthetic control unit, and Table H.2 shows weights of cities in the synthetic control.

See Fig. 30 and Tables 53 and 54.

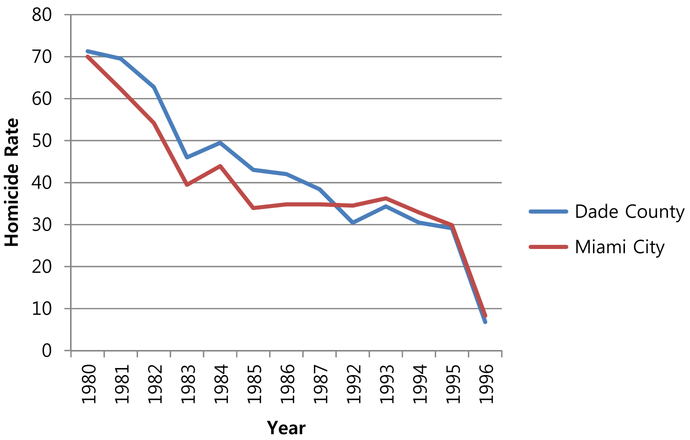

Fig. 30 Homicide rate (Per 100,000) in Miami and Dade County

Table 53 Comparison between Miami (treated) and synthetic control

		Treated	Synthetic
Hispanic share	1970	0.2479	0.2544
	1980	0.3845	0.3703
Share of people with Bachelor's degree or higher in the population aged 25 or older	1970	0.1079	0.1066
	1980	0.1677	0.1541
Share of people didn't graduate high school in the population aged 25 or older	1970	0.4807	0.5041
	1980	0.3600	0.3936
Employment shares of industries that hire skilled labor intensively	1970	0.2759	0.2572
	1980	0.3203	0.2983
Median family income	1970	9245	8608
	1980	18,642	19,807
Median household owner's value	1970	19,088	13,404
	1980	57,235	44,619
Unemployed rate	1970	0.0368	0.0423
	1980	0.0491	0.0475
Total population	1970	1,267,792	1,387,403
	1980	1,625,781	1,567,489
The average Fahrenheit (Celsius) temperature in Jan		67.9 (19.94)	57.06 (13.92)

Table 54 Weights of each MSA in the synthetic control

	Weight
Corpus Christi, TX	0.749
Houston, TX	0.101
Los Angeles/Long Beach, CA	0.138
San Antonio, TX	0.012

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