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Miamian meets Mariel Boatlift Refugees: A Reevaluation of the Effect of the Mariel Boatlift

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Abstract

In the 1980s, a boatlift brought 125,000 Cuban refugees to Miami, known as the Mariel Boatlift. Previous studies have shown there is no effect of the Mariel Boatlift on wages, except for George Borjas' study. Using data from David Roodman's blog and from National Bureau Economic Research and the synthetic control method, I examine the effect of the Mariel Boatlift on low-educated female non-Hispanic ages 18-65's wages. The results suggest there is little to no effect of the Mariel Boatlift on the wages of low-educated female non-Hispanic aged 18-65.

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1 Introduction

Many labor economists have debated the question "Does a sudden inflow of immigrants lower natives' wages?" Prominent labor economists such as David Card (1990), George Borjas (2017), Giovanni Peri and Vasil Yasenov (2019) have debated this topic in the pages of academic journals and in the press by analyzing and re-analyzing data from a famous natural experiment: the sudden arrival of 125,000 new Cuban workers to Miami following the Mariel Boatlift of 1980. This had the effect of suddenly increasing the Miami workforce by 7-8 percent.

Card, Peri, and Yasenov have argued empirically that the large sudden immigrant inflow did not lower wages. However, in a subsequent analysis of the same data, George Borjas carried out analysis, which he demonstrated that wages declined for several subgroups of workers. Given the public salience of the topic of immigration in recent years, the debates over on how to interpret this large natural experiment have drawn the attention not only of academics, but also of the press, politicians, and citizens alike.

Economist Michael Clemens (2017) has helped summarize and interpret the debate. As he points out standard partial-equilibrium economic theory would predict that a sudden inflow of immigrants should lead to a supply shock, a shift out in the supply of labor, and a decline in equilibrium wages at least in the short-run. International economist Robert Feenstra (2017) has pointed out that in a general equilibrium framework the predicted impact is different: wages are determined not locally in Miami but by the much larger USA labor market within which Miami is integrated. Hence the increase in the supply of labor to Miami is not likely to depress wages in the medium or long run (or even in the short-run, depending on the speed of adjustment). According to the

Rybczynski theorem, the increase in labor supply should, however, lead to an increase in employment and output in the more labor-intensive sectors and a decrease in employment and output in capital-intensive sectors.

David Card's original 1990 difference-in-difference study comparing wages in Miami before and after the boatlift to a group of other cities has served as controls and offered support for the position that the Mariel Boatlift had no statistically significant effect on lowering unskilled wages. Feenstra provides evidence in his international trade textbook that low-skill intensive industries expanded, whereas higher-skill intensive industries declined, as predicted by the Rybczynski theorem. This provides evidence to support the claim that the wages in Miami did not change prior to and after the Mariel Boatlift.

The debate seemed largely settled until George Borjas (2017) reexamined both Card's results and published work claiming to demonstrate a significant wage drop due to immigrants' employment. Peri and Yasenov (2019) also added to the debate and reanalyzed both studies using the more modern synthetic control method. Their findings support that there is no significant effect on wages, confirming Card's empirical findings. David Roodman (2017) also reanalyzed Borjas' findings and similarly found no effect on wages. Most of these studies therefore point to the finding that the Mariel Boatlift had no effect on wages.

This thesis takes a further look at the evidence on the impact of the Mariel Boatlift. Past studies looked at the effect of the Mariel Boatlift with respect to low-educated non-Cubans (Card 1990, Peri and Yasenov 2019) as well as low-educated male non-Hispanic between the ages of 25-59 (Borjas 2017). However, there has been little research done regarding females in the labor market. According to “Changes in men’s and women’s labor force participation rate” (Bureau of Labor Statistics 2007), men’s labor force participation rate was 80% and women’s participation rate was 42% in the 1970s relative to men’s participation rate of 78% and women’s participation rate of 52% in the 1980s. Based on this statistics, I hypothesize that the wages of female non-Hispanics and the arrival of immigrant labor will have an inverse correlation. The results section provides a detailed explanation of how these immigrants could negatively impact female non-Hispanics in the labor market.

In this thesis I analyze the effects of the Mariel Boatlift with respect to low-educated female non-Hispanic between the ages of 18-65. Using the same datasets used by Roodman coupled with the required Current Population Survey data and Merged Outgoing Rotation Groups data obtained from National Bureau of Economic Research (NBER), I will determine if there is any causal effect of the Mariel Boatlift on females’ wages by applying the synthetic control method (SCM). The results show that the Mariel Boatlift had no significant effect on females’ wages.

2 Literature Review

The impact of the Mariel Boatlift has been a well-explored topic, in which there have been studies that analyzed the wage effects of Cuban immigrants. As discussed above, Card, Peri, Yasenov, and Borjas are well-known studies. Although these studies produced different findings, there were similarities. All three studies focused on low-skilled and low-educated immigrants. Furthermore, all three studies utilized the Current Population Survey data (CPS). The CPS interviews households on various socio-demographic and employment topics. Surprisingly, all three studies led to different conclusions on whether the inflow of immigrants had any effects on wages, while utilizing the same data. The next four sections describe the data, methodology and the findings of each study.

2.1 Card's Study

Card (1990) summarized his findings in the article, "The Impact of the Mariel Boatlift on the Miami Labor Market." In addition to the regular CPS data, he used the March 1985 Mobility Supplement of the CPS. The Mobility Supplement asks respondents where they resided prior to the Mariel Boatlift. Card analyzed the effect of the Mariel Boatlift for low-educated non-Cubans between the ages of 16-61 using a difference-in-difference (DID) research design. According to Woodridge, difference-in-difference (DID) is a quasi-experiment statistical method utilized to identify the treatment effect of a non-randomized intervention. This method calculates the difference between the level of wages in the pre-treatment period relative to the post-treatment period in both the treatment and control group. The difference of these differences is calculated, which Woodridge described as the "average treatment effect" (2013 p.457). This approach relies on a number of assumptions including the "parallel trends" assumption that, in the absence of any intervention, wages in both Miami and the control cities would have moved along similar parallel paths. Card found no causal effect between Mariel Boatlift and low-educated non-Cubans' wages. For further evidence, Card also analyzed the wages for low-educated Blacks, and similarly found no significant wage drop.

2.2 Borjas' Study

Almost two decades after Card's findings were published, economist George Borjas (2017) re-ignited the debate over the impacts of the Mariel Boatlift and immigration more generally after publishing the article, "The wage impact of the Marielitos: A Reappraisal." This article received broad attention in the press and academic community, as we shall see below. Borjas also used the Current Population Survey from 1977-1993, with an emphasis on the March Supplement CPS, also known as Annual Social and Economic Supplement (ASEC). The ASEC reports a person's annual wage or salary income along with the number of weeks worked in the previous calendar year. Borjas analyzed the effects of the Mariel Boatlift on male non-Hispanic high school dropout between the ages of 25-59. Borjas applied the same methodology as Card, however, focused on this narrower subgroup. He found a significant wage drop for these male non-Hispanics following the boatlift. Borjas' findings appeared to stand in sharp contrast to Card's original findings.

Borjas' findings led to many debates specifically economists and politicians. Politicians have used Borjas' study in order to implement and support policy decisions relating to immigrants. According to Elizabeth Koh (2017), Stephen Miller, a senior advisor for president Donald Trump, used Borjas' findings to support the RAISE Act. The purpose of this Act is to reduce immigration by "imposing a merit-based system." Miller believes these low-skilled or unskilled immigrants will hurt native workers in finding employment and reduces their wages. This is not the first time that politicians have used the Mariel as supporting evidence. President Ronald Regan also used the Mariel's findings to stop Cuban immigrants from coming (Julio Capo Jr. 2017). Although some politicians seem to favor Borjas' work, economists, on the other hand seem to question Borjas' findings. In general, most economists believe Borjas' findings are biased due to sample selection. Nonetheless, economists and politicians have different perspectives when it comes to analyzing Borjas' results.

2.3 Peri and Yasenov's Study

The studies described thus far relied on a difference-in-difference (DID) methodology, which in turn rests on the choice of comparison control cities. Card (1990) compared Miami to Atlanta, Los Angeles, Houston, and Tampa-St. Petersburg. Card focused on these cities because they have "large populations of Blacks and Hispanics and exhibited a pattern of economic growth similar to Miami in the late 1970s and early 1980s" (1990 p.249). Borjas (2017) compared Miami with Houston, Los Angeles, Gary, and Indianapolis. Borjas focused on these cities based on their "pre-Mariel growth for low-skill employment" (2017 p.1089). The results are sensitive to the choice of cities. Peri and Yasenov (2019) entered the debate with the more recent "synthetic control method" that is more popular for case-study events and/or interventions. This method is similar to difference-in-difference in calculating the treatment effect for the treated unit, whereas the DID approaches described above used a few carefully selected large metropolitan areas as their control group, the synthetic control method uses data from more cities around the country to build a 'synthetic control Miami' as the counterfactual for what might have happened in Miami in the absence of the Mariel Boatlift. They summarized their findings in the article, "The Labor Market Effects of a Refugee Wave: Synthetic Control Method Meets the Mariel Boatlift."

Like the first two studies, they also used the Current Population Survey—specifically the May extracts from 1973-1978 and the Merged Outgoing Rotational Group from 1979. The May Merged Outgoing Rotational Group measures average weekly wage figures in metropolitan areas. In contrast to the other papers they employed measured average hourly and weekly wages, unemployment rate and wages at different percentiles for workers in all major metropolitan areas in the United States to build their counterfactual. Their sample was non-Cuban high school dropouts between the ages of 19-65. In addition, they "sliced" their sample. Clemens (2017) defined "slicing" as looking at certain groups separately. This included high school dropouts, men, women, Hispanics, and African-American. All their results support Card's findings. They also reanalyzed Borjas' sample, but broadened the age range to 19-65. Again, they do not find any significant effect of the Mariel Boatlift on wages, confirming Card's results.

2.4 Roodman's Study

Economist David Roodman (2017) added new insights on the Mariel Boatlift in his blog post entitled "Four Points on the debate over the impact of the Mariel Boatlift." Roodman reanalyzed Borjas' sample using both ASEC and ORG data. Roodman focused on weekly earnings for Borjas' sample. To quantify, Roodman analyzed average weekly earnings, average adjusted weekly earnings, and average adjusted 3-year weekly earnings from 1977-1989. Roodman plotted and graphed the trend of the percentage change of the weekly earnings and found that wages had not plunged. Roodman also analyzed the importance of Blacks. This is because Borjas dropped about half or more Blacks observations from his sample. Prior to dropping, Roodman analyzed how frequent Blacks were in Borjas' sample in both data. Afterwards, Roodman excluded Blacks from the sample and compared the difference between the full sample size and the reduced sample size. Roodman plotted and graphed the trend of the percentage change of weekly earnings for "low-educated non-Black non-Hispanic men." His findings show a significant wage effect, similar to Borjas' findings. Roodman stated that by reducing the sample size would make the results less accurate. As Clemens (2017) stated, Borjas had a full sample, but subsequently dropped most of them meaning Borjas only analyzed a subset in his research. Peri and Yasenov (2019) also articulated that by restricting attention to a sub-sample, results are more sensitive to measurement error. Therefore, many economists argued and questioned about Borjas' results since his findings are bias due to sample selection. After revaluating Borjas' findings, Roodman was not convinced that the Mariel Boatlift had a significant effect on wages. [1]

3 Data

3.1 Data Description

The data used in this study was compiled from two sources. The first source includes three datasets that came from Roodman's file (Roodman Borjas-Card replication 2) located in his blog. These three datasets are "CPI," "smsacode," and "cps62-14." The "CPI" contains data on consumer price index (CPI-U) from Bureau of Labor Statistics website (BLS). The "smsacode," which was obtained from Borjas, contains data on Miami and other metropolitan areas. Lastly the "cps62-14,"—extracted from Integrated Public Use Microdata Series (IPUMS)—contains data on Annual Social and Economic Supplement (ASEC) (Roodman 2017).

According to Roodman, the second source is the National Bureau of Economic Research (NBER), which contains the other required datasets. These are the "CPSMAY" data, or Current Population May Extracts and "MORG" data or Merged Outgoing

[1] Refer to: Roodman David (2017). "Four points on the debate over the impact of the Mariel Boatlift." Access 1 Feb 2020. https://davidroodman.com/blog/2017/05/25/four-points-on-the-debate-over-the-impact-of-mariel-boatlift/ for tables and graphs.

Rotation Groups. The CPS May extracts reports information from households interviewed in May on employment status such the usual weekly hours, earnings, and union coverage. (NBER). The Merged Outgoing Rotation Groups (MORG) contains Outgoing Rotation Groups (ORG) data (Roodman 2017). The CPS interviews households on employment status for four months, and afterward, the CPS ignores the households for eight months, and then conducts subsequent interviews again for four more consecutive months. The CPS will ask weekly hours and earnings in month four as well as in the second round of month four, following the break. The responses of weekly hours and earnings mention in the two rounds of month four are mentioned in the Outgoing Rotation Groups (NBER).

Once the datasets were obtained, I replicated Roodman's results by running his STATA code (Roodman Borjas-Card replication). [2] His scripts merge the datasets into one big dataset. In addition, while using this data and adapting Roodman's scripts, I set out to replicate Card's and Borjas' findings. This step was crucial because it provides a better understanding of the methods and sensitivity of results by changing the sample characteristics. It is important to note that the script abruptly stopped with respect to Card's replication. Therefore, I was not able to replicate and analyze Card's results. As a result of this issue, the dataset I with which worked consists of 32 variables and 603,044 observations. For further exploration, I used the merged dataset and applied the synthetic control method (SCM) for each samples in earlier studies—low-educated non-Cubans

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[2] Refer to: Roodman David (2017). "Roodman Borjas-Card Replication.do" Retrieved from https://davidroodman.com/blog/2017/05/25/four-points-on-the-debate-over-the-impact-of-mariel-boatlift/ for complete codes. This was my starting point in exploring the data.

(Card 1990, Peri and Yasenov 2019) and low-educated male non-Hispanic between the ages of 25-59 (Borjas 2017)—to determine if I can get results concordant with these economists' earlier findings. Ultimately, the replication for each of the different samples yielded results concordant with these economists' earlier findings. My replicated synthetic control figures for low-educated non-Cubans illustrate that the Mariel Boatlift had no effect on low-educated non-Cubans, whereas it did have an effect on low-educated male non-Hispanics.

Using the synthetic control method (SCM), I analyze the effects of the Mariel Boatlift on low-educated female non-Hispanic aged 18-65. This is to determine if my findings either support Card's findings or Borjas' findings.

3.2 Number of Observations

Table 1 provides the number of observations in Miami. Column 1 displays the number of observations for the entire Miami population. The entire population for Miami consists of 8138 observations. Column 2 displays the number of observations for low-educated workers. There is a total of 2717 low-educated worker observations in Miami. This total reflects 33% of the entire Miami population. Column 3 displays the number of observations for my preferred sample. There is a total of 345 low-educated female non-Hispanic aged 18-65 observations in Miami. This total reflects close to 4% of the entire Miami population.

3.3 Summary Statistics

Before analyzing the impact of the Mariel Boatlift on low-educated female non-Hispanic aged 18-65, I looked at the wage trends in Miami. Feenstra argued that prior to the boatlift Miami had already started to respond to "technological change" and rising demand for computers, which led to an "increase in demand of high-skilled workers and a reduction in the employment of low-skilled workers." (2017 p. 238). The Mariel Boatlift however, could be understood as an increase in the city's relative endowment of less-skill labor. According to Feenstra, the Rybczynski trade theorem would predict that in an economy that is integrated into the large US and global economy (i.e. where something close to 'factor price equalization' holds so that wages and other factor prices are determined more in these larger markets than by changes in local relative factor supply), one might expect the local economy to absorb the increase supply of unskilled labor by increasing the size of industries that are intensive in the use of that factor. Although this expands the production of relatively labor-intensive industries, these industries do however still need some more skilled labor (e.g. managers, accountants, specialists). Based upon this, this should result in a contraction of the skill-intensive industries in Miami as those more skilled workers are drawn away. Feenstra showed evidence consistent with the view that the influx of Mariel refugees resulted in changes of this sort. Feenstra utilized and followed Ethan Lewis's research (2004) to further explain the Rybczynski theorem. In this case, Feenstra replicated and analyzed two graphs from Lewis's research that illustrates the real value added per capita for the apparel and high-skilled industries in Miami as well as in other comparison cities from 1972-1996. [3] The comparison cities mentioned by Lewis include the following: Cincinnati, Cleveland, Minneapolis-St. Paul, Rochester, Chicago, Pittsburgh, Nashville, Greensboro-Winston, Richmond-Petersburg, Nassau-Suffolk, and Riverside-San Bernardino. These cities were

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[3] Refer to: Original Data Gathered From Lewis Ethan (2004). "How did the Miami Labor Market Absorb the Mariel Immigrants?" Federal Reserve Bank of Philadelphia. Work Paper No. 04-3. Reprinted from Feenstra Robert and Taylor Alan (2017) *International Trade*. 4th edition. Worth Publishers (p.237) for graphs.

chosen because “they had similar trends in output to Miami in four broad skill-rated manufacturing aggregates during the 1970s” (Lewis 2004 p. 8). According to Feenstra, the real value added per capita in Miami had a slower rate of decline relative to the decline in real value added per capita in comparison cities for the apparel industry. The real value added per capita had a faster rate of decline in Miami compared to the decline in the real value added per capita in comparison cities for high-skilled industries. Therefore, with more low-skilled workers in Miami, it should have led to an increase in output in the apparel industry and a decrease in output in industries using a high proportion of skilled workers. Feenstra concluded that the Rybczynski theorem explains how the rate of decline of real value added per capita differs in Miami and other comparison cities regarding the apparel and high-skilled industries.

Column 1 of Table 2 shows the average log wage in Miami for the entire population. The earliest year is 1977. The Mariel Boatlift occurred in 1980, which is a 3-year difference. The average log wage will be compared over 3-year intervals; i.e (1977-1980 and 1980-1983). The average log wage in 1977 is 1.68. The average log wage in 1980 is 1.59. The average log wage in 1983 is 1.63. The average log wage in 1986 is 1.68. The average log wage in 1989 is 1.68. From 1977-1989, the average log wage remains the same. Overall the trend from 1977 to 1991 shows that the wages had decreased from 1.68 to 1.63. Figure 1 is a line graph reflecting Column 1.

This study focused on the impact of the arrival of low-educated immigrants on the labor market for other low-educated workers. Column 2 of Table 2 shows the average log wage in Miami for low-educated workers. The average log wage in 1977 is 1.46. The average log wage in 1980 is 1.42. The average log wage in 1983 is 1.36. The average log wage in 1986 is 1.36. The average log wage in 1989 is 1.39. The average log wage from 1977-1989 shows a decline from 1.46 to 1.39. The difference is .07, which is insignificant. Overall the trend from 1977 to 1991 shows that the wages had decreased from 1.46 to 1.39, which is also statistically insignificant. Figure 2 is a line graph reflecting Column 2.

Column 3 of Table 2 displays the average log wage for low-educated female non-Hispanics. The average log wage in 1977 is 1.25. The average log wage in 1980 is 1.22. The average log wage in 1983 is 1.48. The average log wage in 1986 is 1.33. The average log wage in 1989 is 1.27. The average log wage from 1977-1989 shows a rise from 1.25 to 1.27. The difference is .02, which is insignificant. Overall the trend from 1977 to 1991 shows that the wages have increased from 1.25 to 1.53. Figure 3 is a line graph reflecting Column 3.

These tables and graphs are used to determine what the average wages are like in Miami. Essentially, these results seem to visually corroborate Feenstra's argument and Card's findings that the wages in Miami did not changed over time from 1977-1991.

We cannot make firm conclusions yet until we have a good measure of what would have happened in the absence of the Mariel Boatlift. Perhaps wages nationwide were on an upward trend but the Mariel boatlift had the effect of depressing Miami wages relative to what they might have been. To be able to say anything about this we must compare trends in Miami to trends in other metro areas. The method of synthetic control attempts to build such a counterfactual.

4 Methodology

The synthetic control method (SCM) developed by Abadie, Diamond, and Hainmueller (Abadie et al. 2010) is an ever more popular statistical technique that focuses on case studies. In the original formulation Abadie considered the case of a single unit, region, or city exposed to an intervention, which is considered the treated unit. The remaining units, regions, or cities do not experience the intervention are considered part of the 'donor pool' that will help establish a "synthetic control." A weighted average of observable characteristics and other relevant variables from the cities in the donor pool are used to construct a synthetic counterfactual, chosen to closely fit the pattern of wages in Miami prior to the intervention. This serves as a synthetic counterfactual prediction of what wages in Miami would have been in the absence of the intervention in the post-intervention period. The measured difference between the observed wages in the treated unit and its synthetic counterfactual is what Abadie, Diamond, and Hainmueller described as the "effect estimation." In this case, the intervention is the Mariel Boatlift. The city that experienced the Mariel Boatlift is Miami, which is the treated city. The remaining 43 cities used in my data are in the donor pool. Synthetic Miami was constructed as a "convex combination" of the cities in the donor pool that closely resembled Miami in the pre-treatment period by using relevant predicators. Synthetic Miami estimates what wages would have been like in the absence of the Mariel Boatlift. The effect of the Mariel Boatlift is the difference between Miami and Synthetic Miami. Table 3 describes the weights of each control cities in the Synthetic Miami. The weights reported in Table 3 suggests that the average log wage in Miami prior to the Mariel Boatlift is best reproduced by a combination of Birmingham (38.7%), Sacramento

(32.6%), Tampa (19.5%), and Cincinnati (4.1%). Other cities have either 0 or low weights. [4]

The following variables were used in this study: log of wages from (1977-1979) and the average hours worked per week last year. These two variables are important in predicting future wages for low-educated female non-Hispanics. Peri and Yasenov articulated that it is vital to allow for a long pre-treatment period. Abadie's case study (2010) focused on 19-year pre-treatment period, and Peri's and Yasenov's case study (2019) focused on 6-year pre-treatment period. However, I was limited to a 3-year pre-treatment period because my earliest year is 1977. Table 4 summarizes the variables used in this study. Based on this table, Synthetic Miami provides means that are close to Miami, which indicates Synthetic Miami, could be a good match in estimating the wage level compare to Miami in the pre-treatment period. To further determine if Synthetic Miami is a good match relative to Miami in the pre-treatment period, I looked at the root mean squared prediction error (RMPSE). According to Abadie, the RMPSE has to be minimized to determine how close Miami and Synthetic Miami track each other. The RMSPE is roughly .00003 also indicating a good match between Miami and Synthetic Miami in the pre-treatment period.

5 Results

Figure 4 shows the output for low-educated female non-Hispanic aged 18-65. The vertical dashed line in 1980 is the treatment period. The dash line shows synthetic Miami, an approximation of what wages would be like if the Mariel Boatlift never happened. The

[4] According to Peri and Yasenov (2019) the SCM is an improvement method from DID and that no decision was made to see which cities enter the control to produce Synthetic Miami. This is why my comparison cities are different from previous studies (Card 1990, Borjas 2017, Peri and Yasenov 2019).

solid line shows real Miami, the actual wages due to the occurrence of the Mariel Boatlift. As stated earlier, the effect of the Mariel Boatlift is the difference between Miami and synthetic Miami. Although the two lines diverge, the difference is not significant with the exception of 1981 and 1985.

As most studies have posited, the Mariel Boatlift had no effect on natives. This means that the treatment effect has to be close to 0. Figure 5 illustrates the treatment effect. Most years have treatment effects close to 0 except 1981 and 1985. The treatment effect in 1981 is roughly -.2 implying a negative effect of the Mariel Boatlift and the treatment effect in 1985 is .2 implying a positive effect after a couple years after the Mariel Boatlift occurred. With the exception of these two years, the Mariel Boatlift does not have any significant effects on low-educated female non-Hispanics' wages.

To evaluate the significance of our estimates, a placebo test is used. As Abadie (2010) stated, this is done by iteratively applying the SCM used to estimate the effect of an intervention, which is the Mariel Boatlift in Miami to all other cities in the donor pool. This is done by reassigning data to one of the 43 cities, shifting Miami to the donor pool. As a result, the treatment effect is calculated for all the cities. Abadie stated that the iterative process provides a "distribution of estimated gaps for the states where no intervention took place." Figure 6 shows the placebo test. The dark line represents the treatment effect for Miami, while the shaded gray line represents the treatment effect for one of the 43 cities in the donor pool. My output is similar to Peri and Yasenov (2019), where Miami is an average city in the pre-intervention. However, from 1980-1981, the average log wage had a negative derivation from its control. After 1980, the figure shows that the estimated gap for Miami is within range compare to the distribution of gaps for the cities in the donor pool.

It is interesting to see that the Mariel Boatlift had an immediate effect on female non-Hispanics. As discussed in the introduction section, an inflow of immigrants should lead to a supply shock, where labor increases and equilibrium wages decline in the short run. The negative derivation in 1981 is consistent with labor and capital mobility. It is plausible that with more labor, the wages for females should decline. Also mentioned in the introduction, women's labor force participation rate was only half as much compared to men's participation rate. In "The gender gap in employment: What's holding women back?" (2017-2018), it is stated that the difference in the participation rate between men and women is due to "socio-economic constraints" and "traditional gender roles." Women were seen as housewives while men were seen as workers. Based on this sociological concept and the fact that Mariel Boatlift was male dominant (Clemens 2017), Mariel refugees could have replaced females.

It cannot be fully determine if labor and capital mobility caused a negative deviation in 1981. This is because the SCM does not provide any evidence to justify that labor and capital mobility reduce females' wages in 1981. Another plausible reason is "measurement noise." Peri and Yasenov (2019) posited that having measurement noise in data makes it hard to identify deviations of average log wages in Miami and Synthetic Miami. In my case, it is possible that because of measurement noise caused the deviation of average log wage in 1981 to differ from other deviations of average log wages in other years.

6 Limitations

Although much research was utilized for my thesis, there are a few main limitations with respect to data and methodology. As described in the data description section, despite running most of Roodman's code, I was unable to fully replicate Card's results. I ran a majority of Roodman's code, however, encountered complications with Card's Replication[5]. I tried to run the codes individually, but was unable due to coding logic problems. Therefore this issue could potentially affect my results. At best, I analyzed a descriptive summary and applied the SCM for Card's sample to determine if I could get consistent findings. Although my findings were consistent with Cards' findings, the comparison may not be the most complete as two different methodologies were utilized.

Another main limitation was having a long pre-treatment period. As mentioned above, Abadie (2010) focused on 19-year pre-treatment period, and Peri and Yasenov (2019) focused on 6-year pre-treatment period. Abadie (2010) stated a long pre-treatment period provides a "reasonable limit on the span of plausible prediction" of the effect of the Mariel Boatlift. Peri and Yasenov (2019) further articulated that a short pre-treatment period could produce large differences between Miami and Synthetic Miami. Large differences indicate that Synthetic Miami is not a good match in estimating the wage level compare to Miami in the pre-treatment period. In my case, I was limited to a 3-year

[5] Roodman's STATA codes provide details to replicate Borjas' and Card's findings. There is a part of his script intended to replicate Card's findings. However, as stated, the script abruptly stopped. Despite having the data, I was unable to replicate Card's results. Furthermore, using the merged dataset, I attempted to run codes individually, but encountered continued coding problems with respect to Card's replication (i.e some codes were not able to work in the merged dataset.)

pre-treatment period because my earliest year is 1977. Although, I was able to obtain a good match between Miami and Synthetic Miami in the pre-treatment period, a longer pre-treatment period would have provided me with a more plausible prediction of the effect of the Mariel Boatlift.

7 Conclusion

This thesis reexamines the effect of the Mariel Boatlift on natives' wages. The impacts of the Mariel Boatlift have been a well-researched topic. Existing studies have mixed findings even when using the same data. The two ethnicities compared were non-Cubans and non-Hispanics. The findings for non-Cubans were agreed upon, in which Card (1990), Peri and Yasenov (2019) show no significant wage effect. The findings for non-Hispanics differ. Borjas (2017) found a significant wage drop, but Roodman (2017) and Peri and Yasenov (2019) claimed otherwise. Additionally, the Mariel Boatlift consisted of mostly male immigrants (Clemens 2017), which all of these papers focused on. Roodman (2017) mentioned that Card analyzed both males and females and Peri and Yasenov (2019) looked at women for further evidence, however, both studies did not provide an in-depth research on females. This paper provides an in-depth look at the effect of the Mariel Boatlift with a specific focus on female non-Hispanics. The results indicate that the Mariel Boatlift consistently had no significant medium or long-term wage effect on female non-Hispanics.

It is interesting to see how my sample, data and methodology were similar to Borjas' but resulted in different findings. Both of our subgroups consisted of non-Hispanics, but Borjas focused on low-educated males, whereas I focused on low-educated females. Furthermore, I used the ASEC data, which is the same data that Borjas used in his research. Lastly, I applied the SCM, whereas Borjas utilized the DID to analyze the effect of the Mariel Boatlift. However, despite utilizing similar data and methodology, I found that there was no significant medium or long-term wage effect. To summarize, my findings support Card's findings.

8 Tables

Table 1: Number of Observations in Miami

	(1) Entire Population	(2) Low-educated	(3) Low-educated Female non-Hispanics
1977	443	162	23
1978	493	182	24
1979	538	189	26
1980	543	207	19
1981	547	205	27
1982	528	199	21
1983	529	176	18
1984	526	162	17
1985	532	130	16
1986	565	140	17
1987	550	148	21
1988	570	165	27
1989	606	186	28
1990	586	162	19
1991	582	304	42
Total	8138	2717	345
N	8138	2717	345

count coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2:Average Log Wage in Miami

	(1) Entire Population	(2) Low-educated	(3) Low-educated Female non-Hispanics
1977	1.68	1.46	1.25
1978	1.66	1.49	1.44
1979	1.63	1.46	1.32
1980	1.59	1.42	1.22
1981	1.59	1.41	1.00
1982	1.54	1.29	1.27
1983	1.63	1.36	1.48
1984	1.61	1.26	1.26
1985	1.69	1.32	1.44
1986	1.68	1.36	1.33
1987	1.67	1.35	1.37
1988	1.65	1.34	1.24
1989	1.68	1.39	1.27
1990	1.62	1.35	1.14
1991	1.63	1.39	1.53
Total	1.64	1.38	1.31
N	8138	2717	345

mean coefficients; sd in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3:City Weights in the Synthetic Miami

Metropolitan Area	Weight
Akron, OH	.004
Albany-Schenectady-Troy, NY	.001
Atlanta, GA	.002
Baltimore, MD	.001
Birmingham, AL	**.387**
Boston, MA	.001
Buffalo-Niagara Falls, NY	.004
Chicago-Gary-Lake IL	.001
Gary-Hamond-East Chicago, IN	.001
Cincinnati-Hamilton,OH/KY/IN	**.041**
Cleveland, OH	.001
Columbus, OH	.001
Dallas-Fort Worth, TX	.002
Fort Worth-Arlington, TX	.003
Denver-Boulder-Longmont, CO	.002
Detroit, MI	.001
Greensboro-Winston Salem, NC	.001
Houston-Brazoria,TX	.002
Indianapolis, IN	.002
Kansas City, MO/KS	.002
Los Angeles-Long Beach, CA	.001
Anaheim-Santa Ana- Garden Grove, CA	.001
Milwaukee, WI	.001
Minneapolis-St. Paul, MN	.001
New Orleans, LA	.001
Nassau-Suffolk, NY	.001
Bergen-Passaic, NJ	0
Newark, NJ	.001
New York, NY	0
Norfolk-Virginia Beach-Newport News, VA	.003
Philadelphia, PA/NJ	.001
Pittsburg, PA	.001
Portland-Vancouver, OR/WA	.002
Riverside-San Bernadino, CA	.002
Rochester, NY	0
Sacramento, CA	**.326**
St. Louis, MO/IL	.002
San Diego, CA	.002
San Francisco-Oaklan-Vallejo, CA	0
San Jose, CA	.001
Seattle-Everett, WA	.001
Tampa-St. Petersburg-Clearwater, FL	**.195**
Washington, DC/MD/VA	.001

Table 4:Average Log Wage Predictor Means

Variables	Miami	Synthetic Miami
Log Wage (1977)	1.38	1.39
Log Wage (1978)	1.43	1.44
Log Wage (1979)	1.46	1.47
Log Wage (1977-1979)	1.42	1.43
Usual hours worked per week (Last year)	36.89	36.15

9 Figures

Figure 1

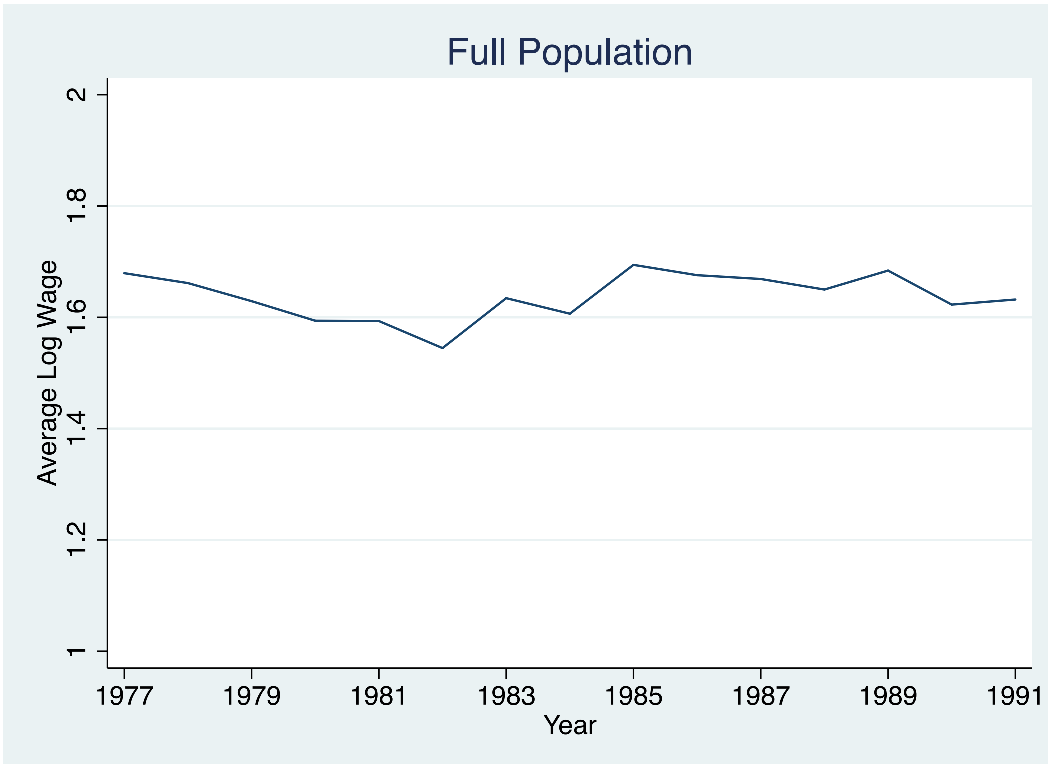


Figure 2

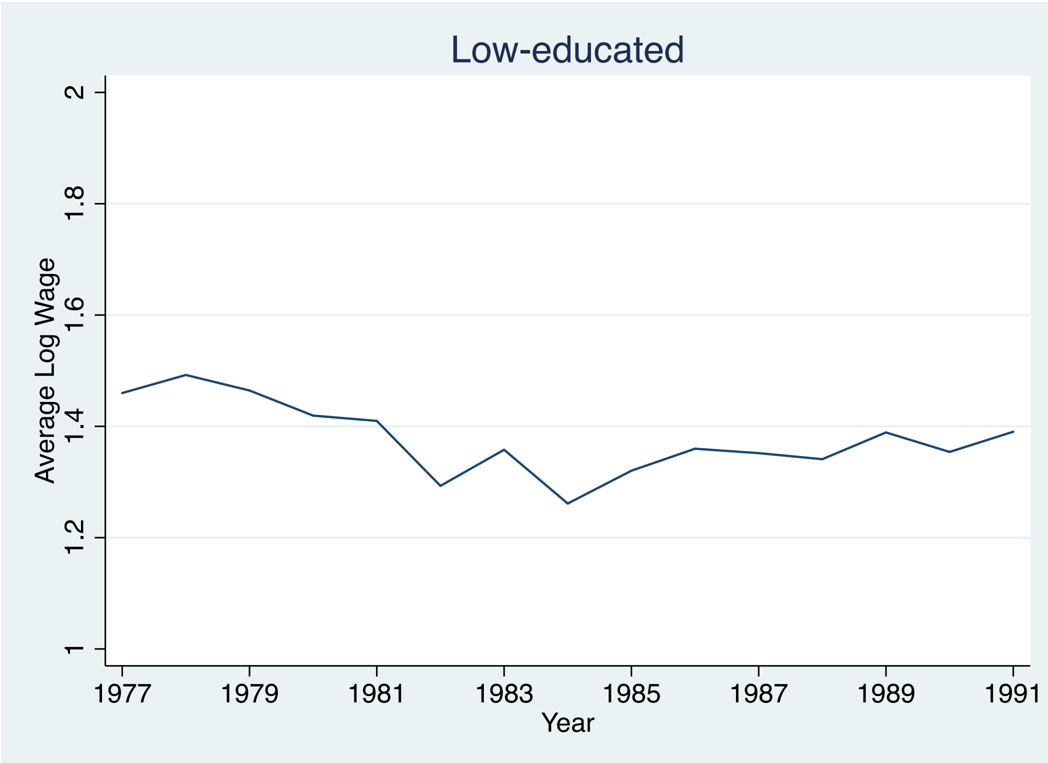

Low-educated
Average Log Wage
1
1.2
1.4
1.6
1.8
2
1977
1979
1981
1983
1985
1987
1989
1991
Year

Figure 3

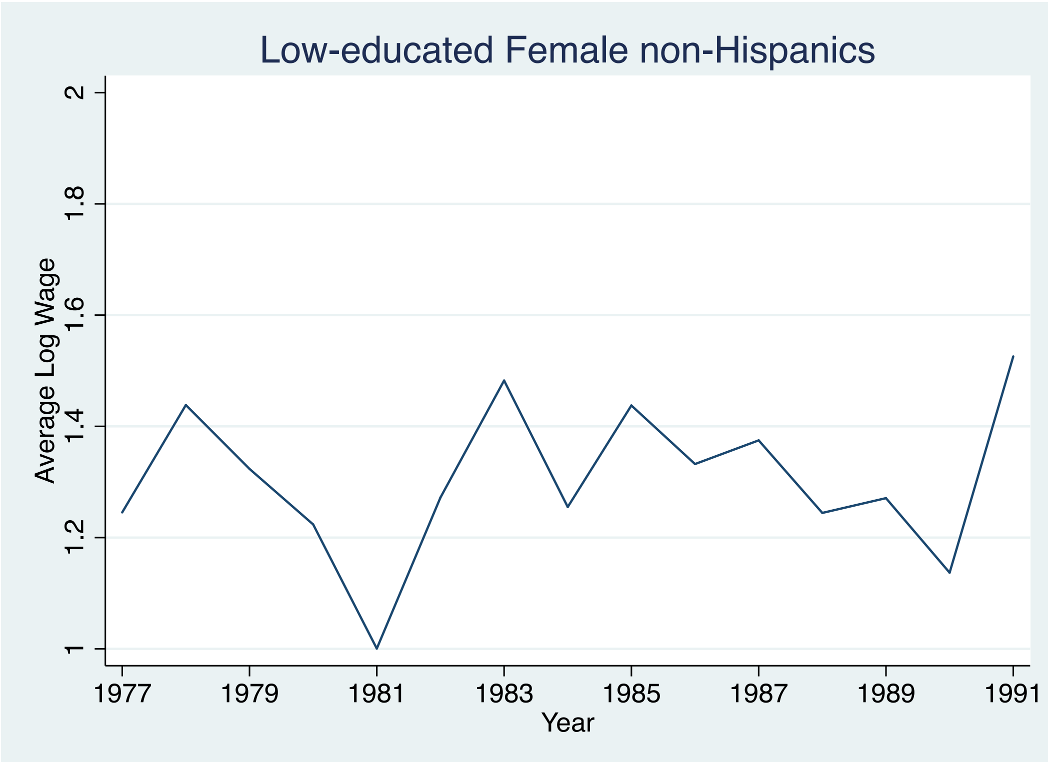

Low-educated Female non-Hispanics
Average Log Wage
1
1.2
1.4
1.6
1.8
2
1977
1979
1981
1983
1985
1987
1989
1991
Year

Figure 4

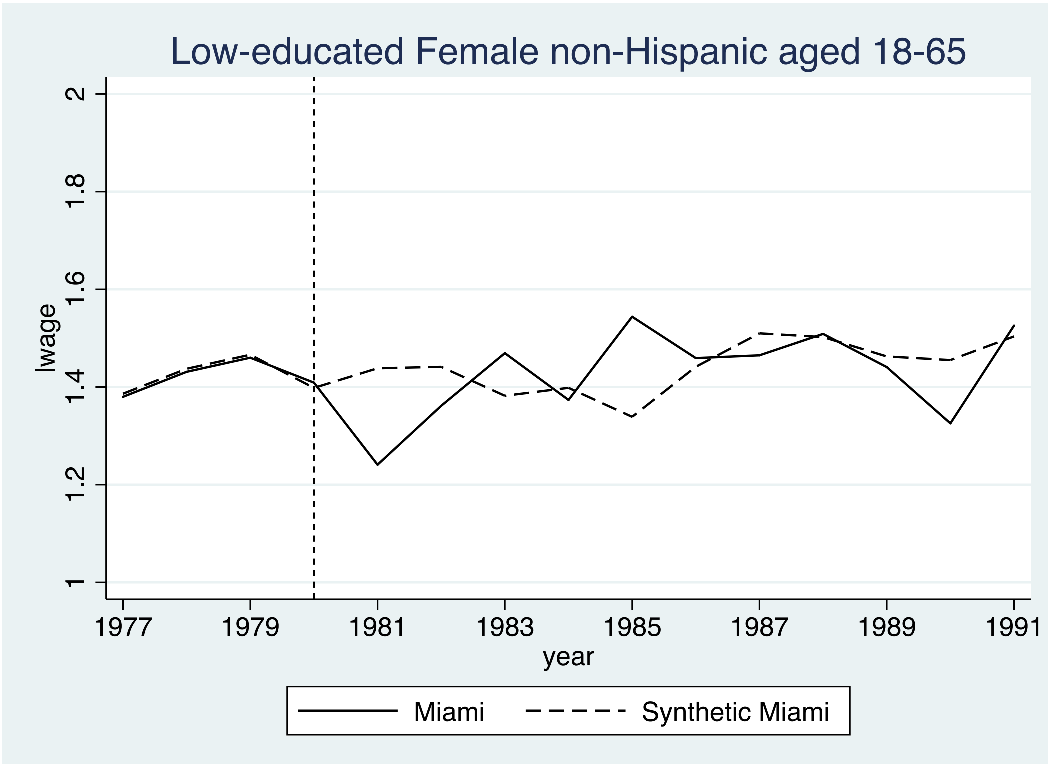
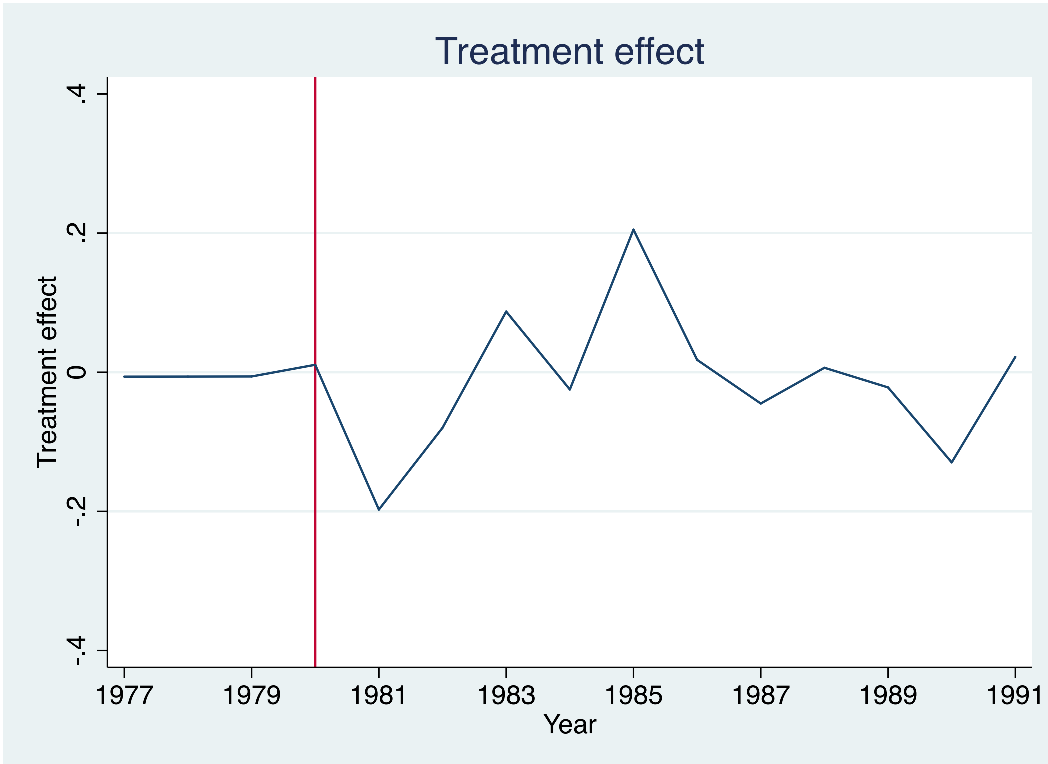
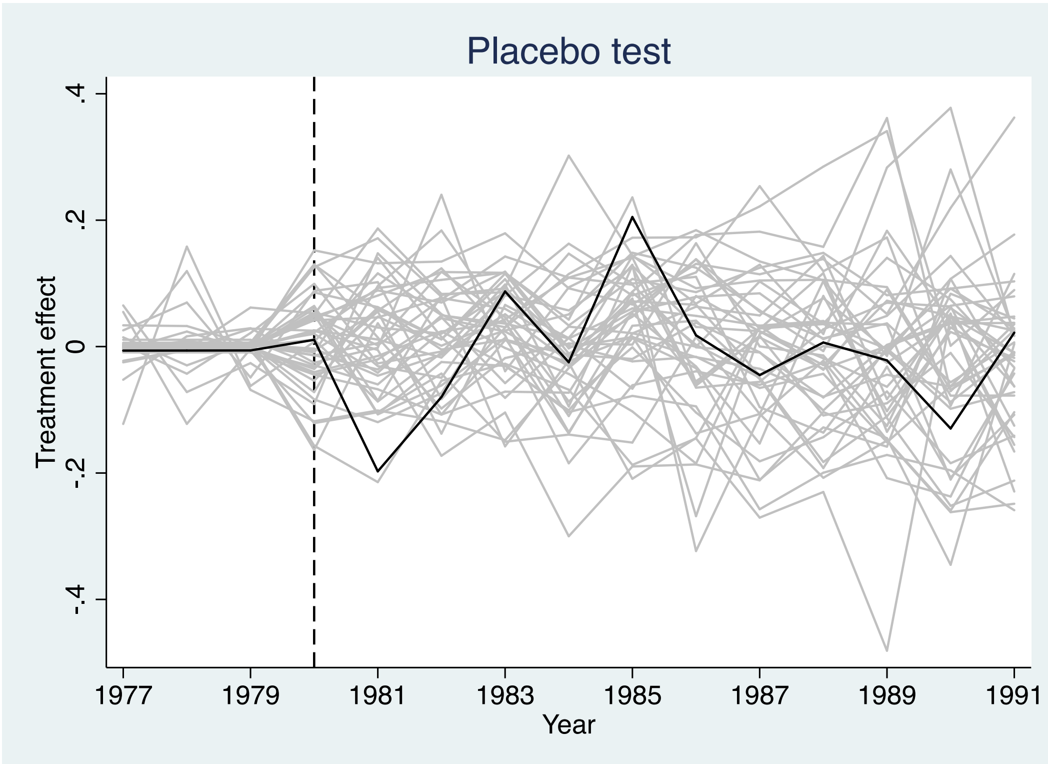

Low-educated Female non-Hispanic aged 18-65
lwage
1
1.2
1.4
1.6
1.8
2
1977
1979
1981
1983
1985
1987
1989
1991
year
Miami
Synthetic Miami

Figure 5



Treatment effect
Treatment effect
.4
.2
0
-.2
-.4
1977
1979
1981
1983
1985
1987
1989
1991
Year

Figure 6


Placebo test
Treatment effect
.4
.2
0
-.2
-.4
1977
1979
1981
1983
1985
1987
1989
1991
Year

10 References

Abadie Alberto, Diamond Alexis, Hainmueller Jen (2010). "Synthetic Control Methods for Comparative Studies: Estimating the Effect of California Tobacco Control Program". Journal of the American Statistical Association, Vol.105, No. 490, 493-505

Borjas George J (2017). "The Wage Impact of the Marielitos: A Reappraisal." Industrial and Labor Relations Review, Vol.70, No.5, 1077-1110.

Bureau of Labor Statistics, U.S. Department of Labor, The Economics Daily (2007). "Changes in men's and women's labor force participation rate." Access May 31. 2020. https://www.bls.gov/opub/ted/2007/jan/wk2/art03.htm

Card David (1990). "The Impact of The Mariel Boatlift on the Miami Labor Market." Industrial and Labor Relations Review, Vol 43, No.2, 245-257.

Clemens Michael (2017). "There's no evidence that immigrants hurt any American workers. The debate over the Mariel Boatlift, a crucial immigration case study, explained." Vox. Access 19 April 2020. https://www.vox.com/the-big-idea/2017/6/23/15855342/immigrants-wages-trump-economics-mariel-boatlift-hispanic-cuban

Feenstra Robert and Taylor Alan (2017). *International Trade*. 4th edition. Worth Publishers.

Hainmueller Jen. "Synth Package". Access 19 April 2020. https://web.stanford.edu/~jhain/synthpage.html

"Index of/morg/annual." Access 15 Feb 2020. https://data.nber.org/morg/annual/

Jr. Julio Capo (2017). "The White House Used This Moment as Proof the U.S. Should Cut Immigration. Its Real History is More Complicated." Time. Access May 31 2020. https://time.com/4888381/immigration-act-mariel-boatlift-history/

Koh Elizabeth (2017). "Why the Mariel Boatlift has become a Trump talking point on immigration." Miami herald. Access May 31 2020. https://www.miamiherald.com/news/local/immigration/article165148372.html

Lewis Ethan (2004). "How did the Miami Labor Market Absorb the Mariel Immigrants?" Federal Reserve Bank of Philadelphia. Work Paper No. 04-3.

"NBER's CPS May Extracts"—1969-1987. Access 15 Feb 2020. https://data.nber.org/data/cps_may.html

Peri Giovanni & Yasenov Vasil. (2019). “The Labor Market Effects of a Refugee Wave: Applying the Synthetic Control Method to the Mariel Boatlift.” Journal of Human Resources, Vol. 54, No. 2, 267-309

“Replication code for Bonander (2017). "Estimating the population-level impact.." published in Injury Prevention.”

Roodman David (2017). *CPI Data*. Retrieved from https://davidroodman.com/blog/2017/05/25/four-points-on-the-debate-over-the-impact-of-mariel-boatlift/

Roodman David. (2017). *CPS62-14 Data*. Retrieved from https://davidroodman.com/blog/2017/05/25/four-points-on-the-debate-over-the-impact-of-mariel-boatlift/

Roodman David (2017). “CPS ORG labels. do” Retrieved from https://davidroodman.com/blog/2017/05/25/four-points-on-the-debate-over-the-impact-of-mariel-boatlift/

Roodman David (2017). “Four points on the debate over the impact of the Mariel Boatlift.” Access 1 Feb 2020. https://davidroodman.com/blog/2017/05/25/four-points-on-the-debate-over-the-impact-of-mariel-boatlift/

Roodman David (2017). “Roodman Borjas-Card Replication 2”. Retrieved from https://davidroodman.com/blog/2017/05/25/four-points-on-the-debate-over-the-impact-of-mariel-boatlift/

Roodman David (2017). “Roodman Borjas-Card Replication. do” Retrieved from https://davidroodman.com/blog/2017/05/25/four-points-on-the-debate-over-the-impact-of-mariel-boatlift/

Roodman David (2017). *SMSACODE Data*. Retrieved from https://davidroodman.com/blog/2017/05/25/four-points-on-the-debate-over-the-impact-of-mariel-boatlift/

Roodman David (2017). “Why a new study of the Mariel Boatlift has not changed our views on the benefits of immigration.” Access 11 July 2020.https://blog.givewell.org/2015/10/21/why-a-new-study-of-the-mariel-boatlift-has-not-changed-our-views-on-the-benefits-of-immigration/

Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 7.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V7.0

“Synth—Synthetic control methods for comparative case studies”. Access 19 April 2020. https://fmwww.bc.edu/RePEc/bocode/s/synth.html

"The gender gap in employment: What's holding women back?" (2017-2018) ILO. Access May 31 2020. https://www.ilo.org/infostories/en-GB/Stories/Employment/barriers-women#intro

Woodridge Jeffrey (2013). *Introductory Econometrics A Modern Approach*. 5th Edition. Cengage Learning.