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The Mariel Boatlift- A Natural Experiment in Low-Skilled Immigration and Innovation

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Abstract

This paper evaluates the effect of low-skilled immigration on innovation by using the Mariel Boatlift as a natural experiment for how it affected patenting behavior in Florida. This paper builds on the analysis of the Miami labour market following the Mariel Boatlift by David Card. Card finds that this Cuban migration had no negative effects on the Miami labor market. This finding, along with a large gap in the literature about low-skilled immigration and innovation, led to the main idea for this paper, which finds that the Mariel Boatlift caused an increase in individually assigned patents and in technological categories with low barriers to entry. These results are not only statistically significant, but are also economically significant. I propose that the main mechanism behind this is that, following the Mariel Boatlift, individual inventors had access to a large supply of low-skilled laborers, and were able to hire them to do housework, child care, etc. This allowed these inventors to substitute away from housework and spend more time inventing, thus leading to an increase in patenting.

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Introduction

This paper evaluates the effect of low-skilled immigration on innovation by using the Mariel Boatlift as a natural experiment for how it affected patenting behavior in Florida. The Mariel Boatlift was the unauthorized and unexpected migration of as many as 125, 000 Cubans from their home country to the U.S., primarily southern Florida, between April 15 and October 31, 1980. This paper builds on the analysis of the Miami labour market following the Mariel Boatlift by David Card [Card, 1990]. Card finds that this Cuban migration had no negative effects on the Miami labor market. This finding, along with a large gap in the literature about low-skilled immigration and innovation, led to the main idea for this paper, which finds that the Mariel Boatlift caused an increase in individually assigned patents and in technological categories with low barriers to entry. I propose that the main mechanism behind this is that, following the Mariel Boatlift, individual inventors had access to a large supply of low-skilled laborers, and were able to hire them to do housework, child care, etc. This allowed these inventors to substitute away from housework and spend more time inventing, thus leading to an increase in patenting.

This issue has significant policy implications. Recently, U.S. President Barack Obama has proposed significant immigration reforms. In November 2014, President Obama vowed to protect up to five million illegal immigrants. His plan will shift deportation priority away from families- and to felons and other threats [Politico, 2014]. This is not a widely supported policy as of yet. More evidence is needed to strengthen the case for this policy shift, and I believe this paper can provide a piece of that evidence.

Additional motivation for this paper can be seen in Figure 1. Here we see individual patenting behavior in Florida spike up in the early 1980s. In comparison, an average of the rest of the United States does not show the same trend. Clearly, something is happened in Florida that did not happen elsewhere. In addition, Figure 2 shows corporate and government patenting behavior. The trend between Florida and the rest of the United States looks much more similar. This indicates that the Mariel Boatlift probably did not have an effect on corporate and government patenting behavior.

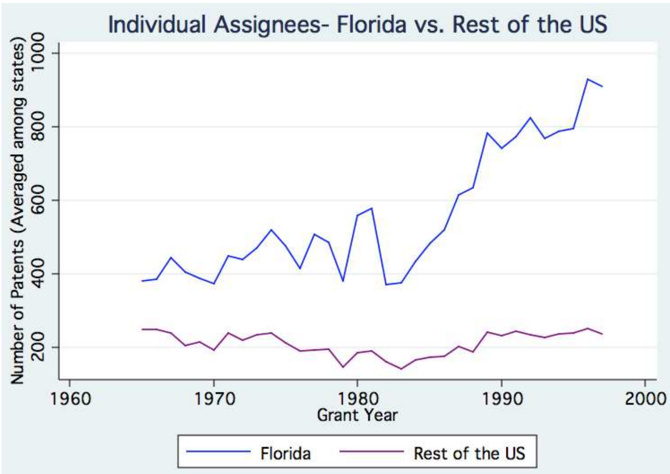

Figure 1: Florida vs. The US

This paper is organized as follows. The first section provides a brief introduction. The next two sections give a preliminary background about the Mariel Boatlift as well as patenting behavior during the 1980s. The fourth section provides summaries of existing literature on the topic. The next section gives a theoretical model to motivate the results. After that, I justify the use of patents as a proxy for innovation. Finally, the last few sections provide the empirical methods, show the results, disprove other

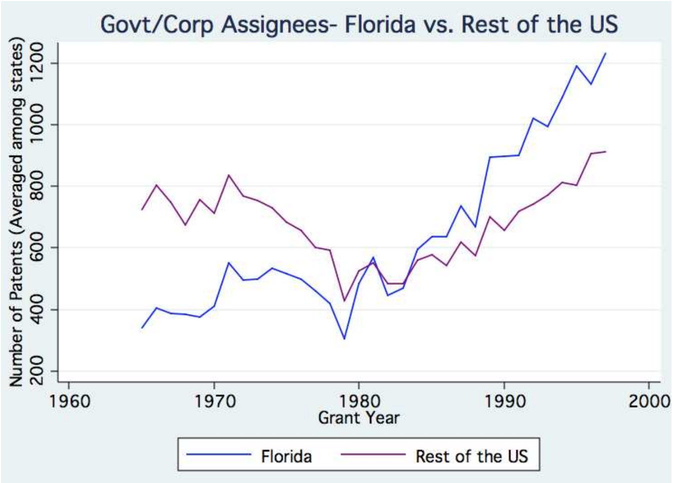

Figure 2: Florida vs. The US

potential mechanisms, and present my conclusions.

The Mariel Boatlift

In April 1980, Fidel Castro allowed anyone who wanted to leave Cuba to do so via the port of Mariel. Hundreds of boats left the port of Mariel and sailed to the American port of Miami. The emigrants chose to leave due to housing and job shortages as well as the weak Cuban economy. The emigration began on April 15, 1980 and ended on October 31, 1980 [Security,].

Since the Mariel Boatlift was unauthorized and unexpected by Americans, little precise information is available on how many people came to the United States or exactly where they settled. Between April 1980 and June 1981, the most reliable sources indicate that 120,000-126,000 Cubans entered the US labor market [Card, 1990]. About half settled in Miami, and the other half dispersed into the rest of Florida [History,].

Three groups of people left Cuba for America. The first group included people with relatives in he United States who rented boats and sailed to the port of Mariel to collect their family members. The second group comprised refugees from the Peruvian embassy. The third group involved those who petitioned for visas from the government. People granted visas were what the government referred to as “escoria,” which included homosexuals, prostitutes, drug users, and enemies of the revolution. Castro used this third category to cleanse Cuba of “scum.” It was hard for emigrants landing in America to be separated into these categories by the locals, and Castro used this to his advantage. If Cubans in Miami noticed that too many criminals or “escoria” were coming over and not enough family members and complained too loudly, Castro would adjust the numbers and send more family members [Ojita, 2005]. This story aligns with Card’s findings; he notes that many of the emigrants were low-skilled and had a low level of English competency[Card, 1990]

The Center for Migration and Development (CMD) conducted a survery and compiled summary statistics [for Migration and Development,]. They interviewed 514 Mariel emigratnts residing in southern Florida in 1983 and then again in 1985 and 1986. Scholars prefer this study over the Current Population Study (CPS), which only interviewed 46 Mariel emigrants in 1985. Although the CMD study only focuses on Mariel emigrants living in southern Florida, it provides a general idea of the overall characteristics of the Mariel emigrants. Table 1 exhibits the summary statistics.

These summary statistics provide some very interesting insights and are very similar to what Card discovered using the CPS data [Card, 1990]. Over half of the respondents said they had very little ability to speak English. Labor scholars consistently use participation in the American food stamp

Characteristic	Percentage
Gender	
Male	64.4
Female	35.6
Self Evaluation of English Knowledge	
Very Good	3.32
Fairly Good	7.62
So-So	22.27
Poor	13.48
Very Bad	53.32
Participation in Food Stamps Program	
Current Participant	22.81
Former Participant	54.19
Never Participated	23
Educational Attainment	
Less Than High School	74.56
High School	7.69
Beyond High School	17.75

Table 1: Summary Statistics

program as a proxy for household income, since participants must be below a certain income to qualify. In the sample, 77.19% of the Mariel emigrants used the food stamp program at some point, indicating low levels of household income. Regarding educational attainment, almost three quarters of the sample did not have a high school degree. All these statistics point to the same conclusion; the Mariel emigrants were ill-suited for the job market as a whole and better suited for domestic job (e.g., nanny, housekeeper, etc.) where educational attainment and English ability were not as large of a concern.

American Patenting Behavior in the 1980s

In the early 1980s, American lawmakers changed patent policies to strengthen the protection that patents provided. In his 2000 paper, Adam Jaffe documents that during this same time, there was also a large increase in patenting all across the U.S. One of the policies causing this surge in patenting was the Federal Courts Improvements Act in 1982. This law was designed to standardize patent laws across the country [Jaffe, 2000].

Another shift that happened in patenting policy during the 1980s was with respect to publically funded research. Up until this time, there was no consistent policy across all the states. Most universities during this time patented inventions that had at least some federal grant money. Beginning in the early 1980s, a set of policy changes made almost all public research subject to the possibility of private patents. Previous to these changes, university patenting would have been patented under the university's name, not the individual's name [Jaffe, 2000]. Since individuals could now get credit for their inventions, university patenting became much more attractive.

Also occurring at the same time was a large change in what could be patented. The U.S. patent office interpreted many of these new laws very broadly and all of a sudden allowed many new subject matters to be patented. An example of this is genetically altered mice. Previous to 1980, this unique idea would probably not have been granted a patent [Jaffe, 2000].

In summary, right around the time of the Mariel Boatlift, there was a huge change in patenting behavior. The entire United States saw a large surge in patenting during the early 1980s. Figure 3 shows the number of domestic patents granted across the U.S. from 1970 until 2000. As is obvious from the graph, during the early 1980s, domestic patenting spiked. This figure differs from Figure 1 because it shows the number of patents summed across states. Figure 1 paints a different picture because it shows the number of patents averaged among states. Despite these changes, this paper argues that Florida saw a much larger increase in patents applied for by individuals and in industries with low barriers to entry than would have been the case had there not been the Mariel Boatlift.

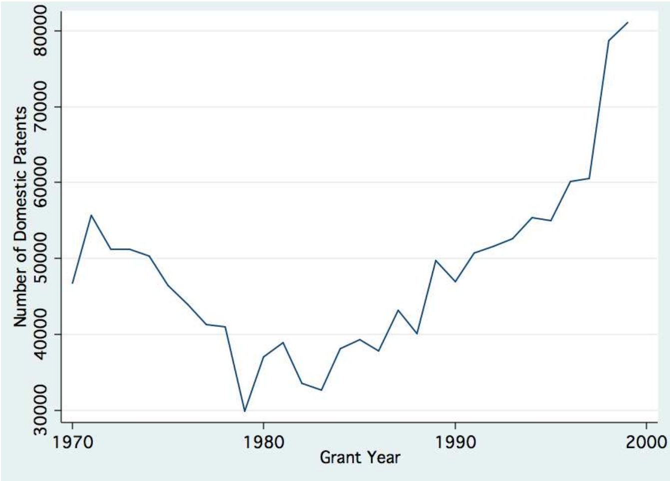

Figure 3: US Patenting Behavior from 1970-2000

What Else Was Happening in Florida during This Time?

From 1972 until 1981, the United States Immigration and Naturalization Service (INS) documented that more than 55,000 Haitians arrived in Florida. The INS also noted that possibly more than half of these immigrants avoided detection, so the actual number was more likely over 100,000. However, the story of the Haitian "boat people" is not similar to that of the Mariel emigrants, since the Haitians were often literate and skilled. About 85% settled in Miami [Hai,]. However, I do not believe the Haitian immigration had much of an effect on patenting behavior for two reasons. The first is that the immigration happened over nine years. If one assumes at least 110,000 Haitian boat people, then on average just over 12,000 Haitians arrived in

Florida each year. The second is that the magnitude is not large enough to cause a large effect. Approximately 125,000 Mariel emigrants came to Florida in one year, while 12,000 Haitians arrived in Florida in that same year.

Another important event was the Miami riots of 1980. In December 1979, police kill an African American after a high-speed chase. The victim, Arthur McDuffie, was a Marine Corps veteran and prominent salesman. At first, the information released said that McDuffie had died due to his injuries resulting from a motorcycle crash. However, an elaborate cover-up was later revealed that the police actually beat him to death. Despite the evidence, the officers were cleared of all charges after a court hearing in front of an all-white jury. The community was outraged by the court's decision and began rioting on May 17, 1980, burning cards and attacking whites. The riots lasted for around three days, with 17 dead, 100 arrested, and more tham $100 million in damages. Despite the protests, the McDuffie family and black community never received justice [PBS,]. I believe that this event may have hindered innovation during this time. Times of unrest and rioting can be detrimental to people entering the workforce as well as the safety of their property. If anything, this event would cause my estimate of patenting estimates in Florida and specifically Miami to be conservative.

Literature Review

This section provides an overview of the current literature on immigration and technological innovation. Most of the work already conducted has focused on highly skilled labor and innovation or low-skilled labor and direct entrepreneurship. For example, Mueller[Mueller, 2011] looks at technology entrepreneurship possibilities with and without immigration. He specifically examines how immigrants from southern and southeast Europe have contributed to entrepreneurship in Germany. Typically, immigrants coming from these areas to Germany have a low level of education and get hired in the industrial sector. His results show that immigrants are less than half as likely to found a knowledge-intensive company than Germany locals are. Mueller suggests that education is a barrier to entry into knowledge-intensive industries [Mueller, 2011].

In a study conducted by the National Domestic Workers Alliance titled "The Invisible and Unregulated World of Domestic Work," the authors provide a summary of the importance of domestic workers [Alliance, 2012]. Domestic workers help families operate more efficiently and can free up valuable time. The authors propose that domestic workers "free the time and attention of millions of other workers, allowing them to engage in the widest range of socially roductive pursuits with undistracted focus and commitment" [Alliance, 2012]. This finding is the cornerstone of my paper.

Another related paper focuses on highly skilled immigration and patenting. Hunt et al [Hunt, 2008] look at how skilled immigration affects patenting in the United States. Using a 1950-2000 state panel, they show that a one percentage point rise in the share of immigrant college graduates increases patents per capita by 6%. They hypothesize that this number would be overstated if immigrant inventors crowd out native inventors and understated if there are spill-over effects. Using the same data set, they prove that immigrant inventors do not crowd out natives and that there are in fact positive spill-overs [Hunt, 2008].

The paper that comes closest to documenting a casual effect between low-skilled immigration and patents is “The Effect of (Mostly Unskilled) Immigration on the innovation of Italian Regions” by Massimiliano Bratti and Chiara Conti[Massimiliano and Conti, 2014]. They find a positive relationship between high-skilled immigrants and patents and a negative relationship between low-skilled immigrants and patents. However, this paper differs from mine in several ways. First, they are looking at Italian immigration and patenting behavior. Immigrants who choose to settle in Italy may not be similar to immigrants who exogenously moved to America. Secondly, Italian patenting behavior may not be comparable to American patenting behavior. Finally, and most importantly, this paper does not spilt up the patents into those applied for by individuals[Massimiliano and Conti, 2014]. Therefore, I see my paper as a more comprehensive look at low-skilled immigration and innovation.

Overall, there is an obvious gap in the literature regarding low-skilled immigration and innovation that this paper hopes to fill.

Theory

In this section, I propose a theoretical model to explain the mechanism behind the results. This model is an adaptation of the standard leisure-work model, popular in labor theory. Consumers have two main tasks and two decisions to make. The two tasks are: work production (e.g., inventing, producing patents, etc.) and home production (e.g., cleaning the house, taking care of children, etc.). The first decision consumers need to make is whether to do home production themselves or whether to hire someone to do home production. The second decision is how much time to spend at work (inventing) and how much time to spend on home production (or how much home production to outsource).

Assume that L_0 is the number of hours in a day, Z_1 is the total amount of home production and Z_2 is the total amount of work production. Also, assume that W_2 is the market wage for work production, W_1 is the cost of obtaining a unit of home production and P_1 is the quantity of home production that someone can produce themselves in an hour. L_0, W_2 *and* P_1 are all determined exogenously. Z_1 *and* Z_2 are determined in the model. If the consumer choose to produce home production himself, then the budget constraint is:

$$Z_2/W_2 + Z_1/P_1 = L_0 \tag{1}$$

If the consumer chooses to pay for home production, the budget constraint is:

$$Z_2 + W_1 Z_1 = W_2 L_0 \tag{2}$$

The consumer will choose to hire someone to do home production if the following exogenously determined condition holds:

$$(W_2/W_1)L_0 > P_1 L_0 \tag{3}$$

If this condition holds for the consumer, then the problem that needs to be solved is:

$$U = (Z_1, Z_2) \quad s.t \quad .Z_2 + W_1 Z_1 = W_2 L_0 \tag{4}$$

In order to simplify this explanation, assume that utility is cobb-douglas and so the problem becomes:

$$U = Z_1^{\alpha} Z_2^{\beta} \quad s.t \quad Z_2 + W_1 Z_1 = W_2 L_0 \tag{5}$$

Where $\beta = 1 - \alpha$. Maximizing this with respect to Z_1 *and* Z_2 yields the following results:

$$Z_1 = (\alpha W_2 L_0)/W_1 \quad and \quad Z_2 = (1 - \alpha)W_2 L_0 \tag{6}$$

If equation 3 does not hold, then the consumer chooses to do home production themselves and they must solve the following problem:

$$U = Z_1^{\alpha} Z_2^{\beta} \quad s.t \quad Z_2/W_2 + Z_1/P_1 = L_0 \tag{7}$$

Again, where $\beta = 1 - \alpha$. Maximizing this with respect to Z_1 *and* Z_2 yields the following results:

$$Z_1 = \alpha P_1 L_0 \quad and \quad Z_2 = (1 - \alpha)L_0 W_2 \tag{8}$$

Thus, if equation 3 holds ($W_2/W_1 > P_1$), consumers choose to hire home production and will have higher levels of Z_1. The consumer will also have higher levels of Z_2 in this case, since $L_0 = Z_1 + Z_2$. Therefore, when equation 3 holds, the consumer is able to reach a higher budget constraint, as can be seen in figure 4.

Since Equation 3 is exogenous to an individual's choice and will differ for each individual, some consumers will choose to pay for home production and some will choose to do home production themselves. Given certain labor market conditions, the demand and supply schedule for low-skilled labor will look as it does in Figure 5.

When a large influx of immigrants arrives in an economy, labor supply shifts outward. When W_1 equals W_2/P_1, all available low-skilled labor will be hired, with no change in wages or unemployment. This market for

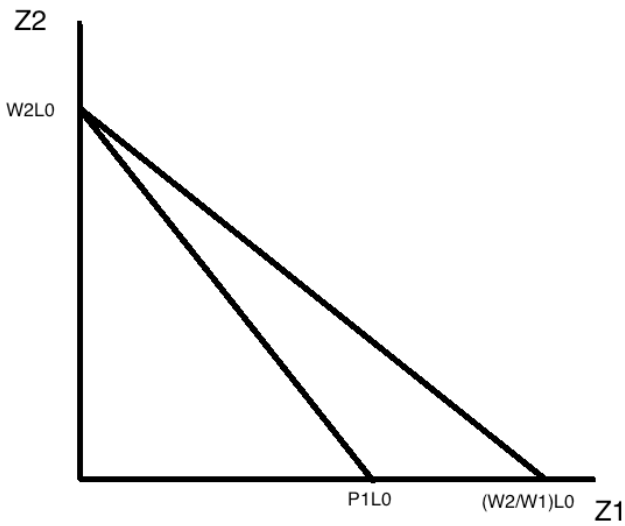

Figure 4: Individual Budget Constraints

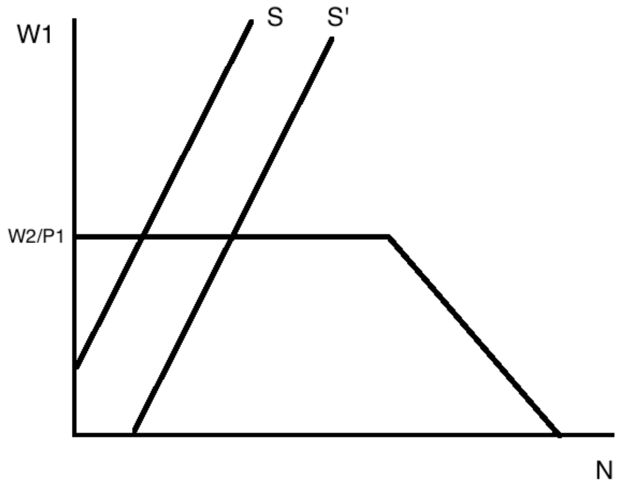

Figure 5: Market Supply and Demand

low-skilled labor is unique in that it is invisible at high levels of W_1. No consumers are willing to pay above W_2/P_1 for home production. This same mechanism is what Card [Card, 1990] observes in his 1990 paper. He documents that the new supply of labor is absorbed by the economy and hired without affecting wages or unemployment levels [Card, 1990]. This implies that previous to the Mariel Boatlift, there were not enough locals willing to work at low skilled jobs for wages equal to W_2/P_1. Therefore, an increase in supply causes an increase in employment (N), without a change in wages.

Patents as a Proxy

For this empirical design, patents are the best available proxy for innovation due to the large amount of information a patent can provide. Each patent contains highly relevant information, including which technological classification it belongs to, where the inventors are from, and the assignee. The assignee category lays out who applied for the patent: the government, a corporation, or an individual. It also gives information on whether the patent was applied for by a foreign or domestic entity.

Of course, there are issues to using patent data. The first is that not everyone chooses to have their invention patented. Applying for patents is expensive and it is time-consuming. In this case, since not every single piece of technology is being patented, using patents as a proxy for innovation will not bias the results unless inventors in the comparison group are more likely to file for patents than people in the treatment group are (and vice versa).

Another potential problem with using patents as a proxy is that not all inventions are granted a patent. All potential patents must pass strict criteria and patents are something rejected for seemingly arbitrary reasons [Bronwyn Hall, 2001]. This issue would only bias the results if patents in the comparison group are more likely to be granted than patents in the treatment group (and vice versa). As long as patenting behavior and application/grant percentages are the same in each state, neither of these potential drawbacks of using patent data will bias the results.

In 1982, individuals filed for 383 patents. Table 1 lists a 5% sample of these patents. Although individuals filed for all of these patents, not all were filed in technological categories with low barriers to entry. This table provides examples of what sort of innovation was happening in Florida two years after the Mariel Boatlift.

Patent Number	Description of Innovation
4354144	transmissionless drive system
4359870	apparatus for producing solar electricity from solar energy
4369922	sprinkler head for a center pivot irrigation system
4378214	multi-purpose educational device
4378611	multifunction cleaning and drying device
4378678	turbine system
4379708	process for tanning fish skins
4380090	hip prosthesis
4380227	grinding wheel dressing apparatus
4381649	CO.sub.2 snow producer with heat exchanger
4382095	pharmaceutical methods and compositions using parabenzoquinone
4385672	feed level indicator
4386480	simulated tree trunk for supporting vines or vine-like plants
4388185	electric oil refiner
4391706	filter element dealing device for filter pan
4393150	adhesive bandage material
4393986	surfboard carrying rack
4395030	quick action vise
4395975	method for desulfurication and oxidation of carbonaceous

Table 2: Sample of Individual Patents in 1982

Data

This paper utilizes data from the NBER patent citations data file, which contains patent information on over three million United States patents granted between January 1963 and December 1999. It contains all utility patents filed for during this period but does not include the three other minor patent categories (design, reissue, and plant patents). The majority of patents filed for fall into the utility category. For example, in 1999, 153,493 utility patents were granted, while only 14,732 design, 448 reissue, and 421 plant patents were granted [Bronwyn Hall, 2001]. The NBER dataset also includes all citations made to these patents between 1975 and 1999, greatly facilitating my analysis for three main reasons. The first is that it provides a wealth of information about each patent such as where the patent was filed, what technology it concerns, and the name of the inventor. Another is that it provides at least ten years of patent information from before and after the treatment date. Finally, it contains many helpful, constructed variables such as a measure of “generality” and a measure of “originality” [Bronwyn Hall, 2001].

At the end of the paper, an additional analysis uses state level population data gathered by the United States Census Bureau [Bureau, 2014].

Using a 1990 demographic profile generator, I am able to discern average income and age of the inventor. The data provided by the NBER lists zipcode, so I am able to look up this zipcode and get average demographic information for the zipcode. Information was not available for 1980, so I have used 1990 averages. Using common sense and a name lookup, I am able to discern sex of the inventor. I have only generated these averages for a subset of the data; comparison and treatment groups for individual assignees in 1982. Table 3 lists the results. These findings indicate that individuals patenting in Florida are, on average, older and earn less. They also show that there are more female inventors in Florida.

	Age (mean)	Income (mean)	Women (count)
Florida	39.71	31,154.25	32
Synthetic Control	34.83	35,886.79	20

Table 3: Inventor Statistics

Empirical Methods

In order to discern the treatment effect of the Mariel Boatlift on innovation in Florida, a state needs to be chosen that will serve as a “synthetic Florida” or comparison state. A comparison state should be chosen that, previous to the treatment, followed the same timeline as Florida with respect to number of patents produced. This paper proposes a new way to choose this comparison group. Here, Florida is the treatment group, but 49 states and one district serve as potential comparison states. In this case, a weighted combination of states may be a better comparison group than a single state would be. Following the work that Abadie et al conduct in their 2003 [Alberto Abadie, 2003] and 2010 [Alberto Abadie and Hainmueller, 2010] papers, the comparison group for each sample is chosen using the synthetic control method (SCM).

Abadie et al first propose the synthetic control method in a 2003 paper that examines terrorism in Basque country [Alberto Abadie, 2003]. In a 2010 paper, Abadie et al refine the SCM method and look at the effects of Proposition 99 on smoking rates in California. Proposition 99 was a 1988 California law, that essentially added a 25 cent excise tax to each package of cigarettes sold. The authors construct a weighted average of states that can be considered a synthetic California, or suitable comparison group, because up until the time of the treatment, the time trend of packs of cigarettes sold was almost identical to California’s. They then compare the two timelines to see what would have happened in California if Proposition 99 had not passed [Alberto Abadie and Hainmueller, 2010].

This paper will follow a slightly different method. The synthetic control method will be used to choose the comparison group, but a difference-in-difference calculation will be used to discern the treatment effect. Thus, for each sample being tested, a different set of states will comprise the comparison group. This paper will use this unique way of choosing a comparison state to increase transparency and remove the potential for human error.

The potential error is perfectly captured in Card's initial paper documenting the Mariel Boatlift. In order to strengthen his argument, Card tests the treatment group against several comparison groups by manually choosing each comparison group to try and emulate a synthetic treatment group. In comparison, my synthetic control method uses a data-driven procedure to find the best possible weighted average of potential comparison states. This removes the ambiguity from choosing comparison units, while also increasing transparency [Alberto Abadie and Hainmueller, 2010].

Following the work done by Abadie et al in 2003 [Alberto Abadie, 2003] and in 2010 [Alberto Abadie and Hainmueller, 2010], I now describe the theory behind the SCM. Although this theory directly follows the work done by Abadie et al [Alberto Abadie and Hainmueller, 2010], it has been slightly adapted to this particular case. Assume Y_{it} is the outcome observed for region i at time t in the absence of treatment. Also assume there are $J + 1$ states, with one state receiving the intervention and J states that could be used as possible controls. Assume T_0 is the number of pre-intervention periods. Assume Y_{it}^I is the outcome for state i if it is exposed to the treatment in period $T_0 + 1$ and that Y_{it}^N is the outcome for state i if it is not exposed to the treatment. In this case Florida is the treatment state and all other states (conditional on having enough data points) are included in the pool to be used as potential control states.

Assume that $\alpha_{it} = Y_{it}^I - Y_{it}^N$ and that α_{it} is the effect of the Mariel Boatlift on Florida. D_{it} is a dummy variable and will take the value of 1 if the state is exposed to the intervention and 0 otherwise. The observed outcome for unit i at time t is the following:

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it}. \tag{9}$$

From this, we have to estimate $(\alpha_{1T0+1}, ..., \alpha_{1t})$. For any $t > T_0$:

$$\alpha_{1t} = Y_{1t}^I - Y_{1t}^N = Y_{1t} - Y_{1t}^N. \tag{10}$$

Since only the first state (Florida) will be receiving the intervention, Y_{1t}^I is thus observed and only Y_{1t}^N is left to estimate in order to determine the effect of the intervention. Assume that Y_{it}^N is given by the following factor model:

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \epsilon_{it}. \tag{11}$$

Where δ_t is common to all units, Z_i are obersved covariates not affecting the intervention, θ_t is a vector of unknown paratmeters and ϵ_{it} is the unknown error term. Next, assume there is a vector of J weights such that they all sum to 1. Each weight will signify a potential sythetic control state and thus the synthetic control unit will be a weighted average of each potential state. Follwing equation (3), the value of the outcome variable for each synthetic control is:

$$\sum_{j=2}^{J+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{j=2}^{J+1} w_j Z_j + \lambda_t \sum_{j=2}^{J+1} w_j \mu_j + \sum_{j=2}^{J+1} w_j \epsilon jt \tag{12}$$

Assume that there are weights such that:

$$\sum_{j=2}^{J+1} w_j^* Y_{j1} = Y_{11}, ..., \sum_{j=2}^{J+1} w_j^* Y_{jT0} = Y_{1T0}, and \sum_{j=2}^{J+1} w_j^* (\epsilon_{jt} - \epsilon_{1t}) \tag{13}$$

Abadie et al [Alberto Abadie and Hainmueller, 2010] prove that as long as $\sum_{t=1}^{T0} \lambda_t^{'} \lambda_t$ is non-singular, then:

$$Y_{1t}^N - \sum_{j=2}^{J+1} w_j^* Y_{jt} = \sum_{j=2}^{J+1} w_j \sum_{s=1}^{T0} \lambda_t (\sum_{n=1}^{T0} \lambda_n^{'} \lambda_n)^{-1} \lambda_s^{'} (\epsilon_{js} - \epsilon_{1s} - \sum_{j=2}^{J+1} w_j^* (\epsilon_{jt} - \epsilon_{1t}) \tag{14}$$

As an estimator of α_{it}, Abadie et al. [Alberto Abadie and Hainmueller, 2010] suggest using:

$$\hat{\alpha_{1t}} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{15}$$

Equation (5) can hold only if $(Y_{11}, ..., Y_{1T0}, Z_1^{'})$ belongs to the convex hull of $(Y_{21}, ..., Y_{2T0}, Z_2^{'}), ..., (Y_{J+1T0}, ..., Y_{J+1T0}, Z_{J+1}^{'})$. Usually, there is no set of weights such that equation (5) will hold exactly, so it is enough that it holds approximately [?]Abadie2010). This implies that the future time path of the synthetic control group should imitate the time path of Florida, had Florida not been exposed to the Mariel Boatlift. The full, in depth explanation of this method can be found in Abadie et al's 2010 paper [Alberto Abadie and Hainmueller, 2010].

My outcome variable is the number of patents. In order to construct the synthetic Florida using the SCM, I must choose indicator variables that predict the number of patents. I have decided to use patent levels in previous years to predict future values of patents, post treatment. Therefore, my predictors for number of patents are: number of patents in 1965, number of patents in 1966, number of patents in 1967, etc., including every year right up until the year of the treatment in 1982. The data is separated into several samples based on technological category and assignee, so each separate sample has its own comparison group calculated using the SCM.

The first sub-samples to be tested are individual assignees, and corporate and government assignees. Each sample has a comparison group chosen using the SCM. The states and weights for these two categories are shown in Tables 4 and 5. Figures 6 and 7 show how well the comparison group matches the pre treatment time trend of the treated group. The states, weights, and graphs for all remaining sub samples are listed in the appendix.

The next set of sub samples to be tested are chemical, computer/communications, drugs/medical, electrical/electronic, mechanical, and other. The final set is the sub-samples within drugs/medical. Drugs and medical contains four sub-categories, but only two of them have at least one patent being filed each year in Florida. Therefore, the two categories that will be tested are drugs and surgery/medical instruments.

State	Weight
AZ	0.837
CA	0.163

Table 4: State Weights- Individual Assignees

Results

The purpose of this paper is to test the significance of the Mariel Boatlift on patenting behavior in Florida. The entire sample is split up into many

State	Weight
C0	0.171
NH	0.11
TX	0.211
UT	0.263
WA	0.222
WI	0.023

Table 5: State Weights- Corporate and Government Assignees

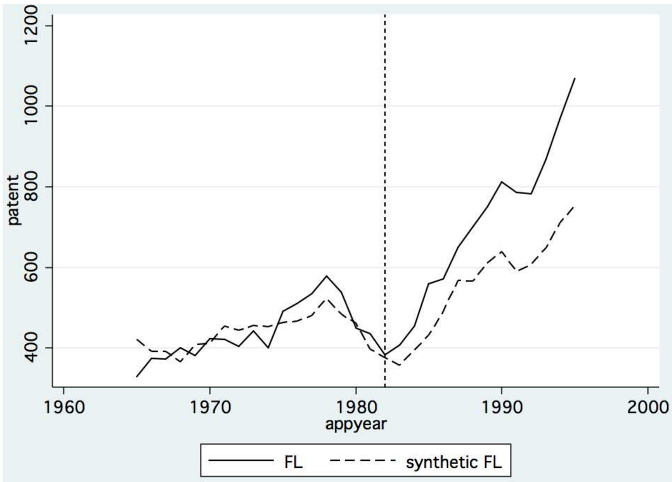

Figure 6: SCM- Individual Assignees

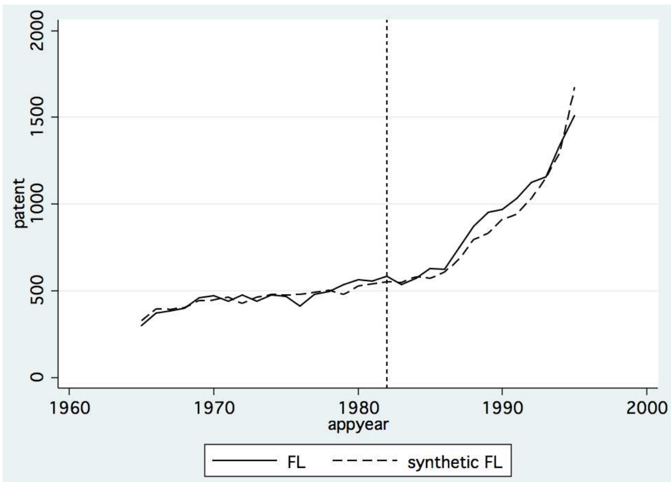

Figure 7: SCM- Corporate and Government Assignees

different categories in to see where exactly this natural experiment had an effect. First, the sample is split into patents assigned to individuals and patents applied for by government agencies and corporations. Next, it is split up into six different technological categories: chemical, computers/communications, drugs/medical, electrical/electronic, mechanical, and other. Other contains patents filed in the following sub-categories: agriculture, husbandry/food, amusement devices, apparel/textile, earth working/wells, heating, pipes/joints, receptacles, and miscellaneous [Bronwyn Hall, 2001]. Next, the drug/medical sample is split up into the two subsections with enough observations, drugs and surgery/medical instruments, and tested individually. Finally, mechanical and other are split up into smaller groups of patent classifications.

Table 6 lists all categories tested. To discern a treatment effect, I use a difference-in-difference method. This method compares the category in Florida against the category in the counter factual (found using the SCM). The first important point to note is that patents applied for by individuals has a significant treatment variable (post*treatment). This coefficient can be interpreted as follows. The Mariel Boatlift increased individual patenting behavior by 153 patents. On average, between 1965 and 1995, individuals applied for around 555 patents per year. An increase of 153 patents is not only statistically significant at the 1% level but also economically significant. The treatment variable for patents applied for by government agencies and corporations was not statistically significant.

Table 7 tests individual and corporate/government patenting using a slightly different method. Here, I use a triple difference-in-differences. All this does is increase the number of observations and adds an additional com-

Table 6: Main Effects by Category

	Individuals	Govt./Corp.	Chemical	Computers	Drugs	Electrical	Mechanical	Other
Post	130.57	463.48	45.88	161.52	116.54	164.22	38.36	87.94
	(40.66)***	(78.05)***	(10.88)***	(32.26)***	(19.35)***	(22.88)***	(16.47)**	(25.17)***
Treatment	0.8251	-28.17 7	-2.41	-0.1103	0.8378	0.1812	1.38	-0.2672
	(37.24)	(71.48)	(9.97)	(29.54)	(17.72)	(20.95)	(15.08)	(23.05)
Post*Treatment	153.93	3.22	4.84	-18.09	47.36	-49.69	64.43	100.44
	(57.5)***	(110.38)	(15.39)	(45.62)	(27.37)*	(32.36)	(23.29)***	(35.59)***
Observations	62	62	62	62	62	62	62	62
R-Squared	0.53	0.55	0.4	0.44	0.66	0.57	0.47	0.56

Standard errors are listed in the brackets
* -10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level.

parison group. For regression (1), individuals in Florida are compared to individuals in the synthetic control group as well as non-individuals in Florida. Since each group has a distinct synthetic control group, I run regressions (1) and (2) separately. In regression (1), I usethe synthetic control group of part Arizona and California and for regression (2), I use a separate synthetic control group. In Table 8, the results from the difference-in-difference in Table 5 are validated. The treatment effect is determined by the variable "post*individual*treatment." In regression (3), the treatment effect can be read that the treatment caused individual patenting to increase by 276 patents when compared to non individuals. In regression (4), the treatment effect measures the effect of the treatment on non-individuals compared to individuals. Thus, I expect to see a negative number.

I

Table 8 lists the results of the triple difference-in-difference by technological category. I have only included the variable of interest, "post*category*treatment," but each regression includes a full set of dummy and interaction terms. Regressions (7-12) include a full set of year dummies, and standard errors are robust. Here, I must choose which category will be the comparison group. For regressions (1, 3, 6 and 8), the comparison (or group left out) is mechan-

Table 7: Diff-in-Diff-in-Diff by Assignees

			Year Dummies Robust SEs	Year Dummies Robust SEs
	Individuals (1)	Non-Individuals (2)	Individuals (3)	Non-Individuals (4)
Individual	-364.81	273.07	-364.81	273.07
	(106.41)***	(56.03)***	(13.28)***	(12.95)
Post	601.71	98.01	1313.464	667.85
	(601.71)***	(61.19)	(305.58)***	(170.28)***
Treatment	-355.04	255.51	-355.04	225.51
	(75.24)***	(56.04)***	(16.99)***	(16)***
Post*Treatment	-122.46	198.93	-122.46	198.94
	(116.19)	(86.53)**	(93.35)	(53.84)***
Treatment*Individual	355.87	-253.68	355.87	365.57
	(106.41)***	(79.25)***	(22.19)***	(64.01)***
Post*Individual	-471.13	365.57	-471.13	-253.68
	(116.19)**	(86.53)***	(109.61)***	(20.47)***
Post*Individual*Treatment	276.39	-195.72	276.39	-195.72
	(164.32)*	(112.38)	(116.79)**	(72.65)***
Observations	124	124	124	124
R-Squared	0.65	0.68	0.9	0.94

* -10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level.

Table 8: Diff-in-Diff-in-Diff by Technological Category

	Chemical (1)	Computers (2)	Drugs/Medical (3)	Electrical (4)	Mechanical (5)	Other (6)
Post*Category*Treatment	-79.49	-3.21	-73.01	-5.4	66.27	120.6
	(37.55)**	(43.7)	(38.51)*	(46.06)	(41.07)	(49.19)**
Observations	372	372	372	372	372	372
R-Squared	0.79	0.74	0.81	0.75	0.77	0.71
Year Dummies and Robust SEs						
	Chemical (7)	Computers (8)	Drugs/Medical (9)	Electrical (10)	Mechanical (11)	Other (12)
Post*Category*Treatment	-79.49	-265.5	-73.01	-5.4	66.27	120.6
	(20.21)***	(161.38)	(19.85)***	(20.64)	(20.02)***	(24.96)***
Observations	372	372	372	372	372	372
R-Squared	0.95	0.94	0.95	0.94	0.95	0.93

* -10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level

ical. Those regressions are testing the effect of chemical and drugs/medical patents, which I have already argued are high barries-to-entry categories. Therefore, the comparison group should be a category with a low barrier to entry, such as mechanical. For all the other regressions, the omitted/comparison group is chemical. Since these regressions are all examining a category with a low barrier to entry, they should be compared to a category with a high barrier to entry, such as chemical.

As is similar to Table 7, each regression is run separately, with its own pre-determined synthetic control group. For example, for regression (1), the synthetic control group is part Alabama, Arizona, Colorado, Iowa, North Carolina, New Hampshire, Oklahoma and Texas. The appendix shows the full details of all the particular synthetic control groups.

The results in Table 8 reflect those in Table 6 and further validate my previous results. The other difference in Table 8 is that the variable measuring the treatment effect for chemical is now significant. This is because the comparison group has changed. The treatment effect in regression (1) of Table 8 measures the effect of the treatment on patents in the chemical category in Florida, compared to patents in the chemical category in the synthetic control state as well as patents in the mechanical category in Florida, whereas the treatment effect in regression (1) of Table 6 measures the effect of the treatment on patents in the chemical category in Florida compared to patents in the chemical category in the synthetic control state.

Table 9: Drugs and Medical- Subcategories

	Drugs (1)	Surgery/Medical Instruments (2)	Biotechnology (3)	Miscellaneous (4)
Post	25.72 (6.22)***	54.28 (10.22)***	16.63 (3.22)***	8.26 (1.84)***
Treatment	-18.28 (5.69)***	8.36 (9.36)	-1.66 (3.22)	1.78 (1,69)
Post*Treatment	6.42 (8.79)	48.8 (14.45)***	-5.48 (4.73)	8.25 (2.61)***
Observations	62	62	62	62
R-Squared	0.49	0.71	0.42	0.67

* -10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level

The only technological categories that have a statistically significant and positive treatment variable are drugs/medical, mechanical, and other. Ta-

Table 10: Mechanical- Subcategories

	Materials (1)	Metalworking (2)	Moters/Engines/Parts (3)	Optics (4)	Transportation (5)	Miscellaneous (6)
Post	0.7	8.45	1.6	4.05	9.77	13.45
	(4.63)	(2.11)***	(2.7)	(1.8)**	(4.53)*	(5.23)**
Treatment	-0.68	0.24	-5.71	6.35	-8.21	9.67
	(4.24)	(1.93)	(2.47)**	(1.64)***	(4.53)*	(4.79)**
Post*Treatment	7.04	6.36	13.73	-0.11	16.74	21
	(6.54)	(2.99)**	(3.82)***	(2.54)	(7)**	(7.4)***
Observations	62	62	62	62	62	
R-Squared	0.05	0.54	0.36	0.38	0.36	0.57

* -10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level

Table 11: Other- Subcategories

	Agriculture (1)	Amusement Devices (2)	Apparel/Textiles (3)	Earth Working (4)	Furniture (5)
Post	5.91	9.33	4.87	1.45	13.43
	(3.32)*	(3.78)**	(2.17)**	(2.77)	(3.51)***
Treatment	22.85	5.22	8.91	-56.38	12.28
	(3.04)***	(3.46)	(1.98)***	(2.54)***	(3.21)***
Post*Treatment	4.6	11.51	1.52	6.63	14.07
	(4.7)	(5.34)**	(3.06)	(3.92)*	(4.96)***
Observations	62	62	62	62	62
R-Squared	0.67	0.47	0.48	0.93	0.69

* -10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level

Table 12: Other- Subcategories (Continued)

	Heating (6)	Pipes/Joints (7)	Receptacles (8)	Miscellaneous (9)
Post	-2.29	-0.26	14.66	40.99
	(2.32)	(1.31)	(3.52)***	(10.69)***
Treatment	-2.64	-9.64	3.57	13.19
	(2.12)	(1.2)***	(3.22)	(9.79)
Post*Treatment	8.12	7.82	10.03	35.99
	(3.28)**	(1.86)	(4.97)**	(16.12)**
Observations	62	62	62	62
R-Squared	0.11	0.58	0.57	0.58

* -10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level

bles 9, 10, 11, and 12 provide a breakdown of these technological categories. This breakdown intends to provide a clearer picture of exactly what sort of inventions happened during this time. To allow me to test each category and not be restricted by number of observations, I have used the same synthetic control group for each sub-category as the main technological category. For example, the synthetic control group for "metalworking" is what it is for "mechanical"- parts Michigan, Missouri, Texas and Washington.

On the surface, mechanical and other seem to have low barriers to entry and drugs/medical does not. An industry with low barriers to entry is defined here as one that does not require a large amount of capital to enter. The drugs/medical category at first seems like an industry with high barriers to entry; however, when looking at sub-categories, a different story emerges. Drugs/medical is split up into four sub-categories: drugs, surgery/medical instruments, biotechnology and miscellaneous. All four subcategories are tested, and Table 8 shows the results. The treatment variable for drugs and biotechnology are not statistically significant but the treatment variable for surgery/medical and miscellaneous is at the 1 percent level.

Intuitively, the sub-categories of drugs and biotechnology have high barriers to entry but surgery/medical, and miscellaneous do not. In order to patent a new drug, large amounts of capital are required. In order to patent a new surgical instrument, much less is needed. Although some patents for surgery and medical instruments do require FDA approval, this can be applied for after the initial patent application, with the FDA guaranteeing a 90-day turn around period for most approvals [Emergo,]. Medical devices are not subject to the same rigorous approval process that drugs are. In addition, class 1 medical devices generally defined as low risk, such as gauze, do not need FDA approval. Class 2 medical devices, which are not life-sustaining or threatening, do not need to submit their devices for clinical trials but do require FDA approval. Class 3 medical devices, which are life-sustaining or threatening, require a more intense approval process [Today, 2014]. Therefore, for the majority of medical devices, FDA approval is given and is not an extremely time-consuming or capital-intensive process. Table 13 provides a sample of patents in the surgery/medical instruments subcategory.

Patent Number	Description of Innovation
4383531	compact hygienic syringe apparatus
4389573	method of using a surgical drape
4385628	new way for fracturing lateral walls of bony vault of the nose
4387715	shunt valve
4390018	method for preventing loss of spinal fluid after spinal tap
4392852	tamper-altering hypodermic syringe
4397644	sanitary napkin with improved comfort
4397647	catheter stabilization fitting having a snap-over cover
4399816	wound protector with transparent cover
4401107	intestinal control valve

Table 13: Sample of Surgery and Medical Instruments Patents in 1982

For mechanical, the treatment effect variable is significant for metalworking, motors, engines/parts, transportation, and miscellaneous. For other, the significant sub-categories are amusement devices, earth working, furniture, heating, receptacles and miscellaneous. I believe all these subcategories to be low barrier to entry, thus further validating my argument of the Mariel Boatlift only affecting industries with low barriers to entry.

It is hard to discern where exactly the emigrants settled and where they found work. Card documents that 50% stayed in Miami and the rest dispersed into Florida [Card, 1990], although this is only an estimate. In 1980, central and southeastern Florida was almost twice as populous as northern and southwestern Florida. However, northern Florida's population was quickly increasing during this time, as was central and southeastern Florida [Smith, 2005]. The cities that saw big increases in patenting around the time of the boatlift were Miami (southeastern Florida), Naples (southwestern Florida), Sarasota (central Florida), Jacksonville (northern Florida) and Orlando (central Florida). Thus, if I assume the Mariel emigrants followed dispersion patterns similar to other immigrants, then I can infer that cities with increased migration saw increased patenting. The only city that doesn't follow this pattern is Naples. However, Naples is only a two-hour drive from Miami, and it is reasonable to assume it was easy for the Mariel emigrants to settle there. With the Naples population being much smaller than Miami, a smaller number of Mariel emigrants would have had an effect.

Ideally, I would be able to collect information on where each migrant settled and test to see if those cities increased their patenting. Unfortunately this data is not available and even the assumptions that Card makes are taken from the consumer population survey that surveyd less than one hundred Mariel emigrants.

Robustness Check

This section provides a robustness check, to further validate my results. I change the comparison group to a single state and test the treatment effect for individually assigned patents. When using the SCM, I use a combination of Arizona and California to form the control group. Since the majority of the control group is formed using Arizona, I use Arizona as the control group. Figure 8 shows individual patenting behavior in Florida and in Arizona. Patenting behavior prior to the treatment looks very similar in both states. Following the treatment, Florida sees a much larger increase in patenting behavior than Arizona does.

Table 14 shows the results of testing this formally. We can interpret the

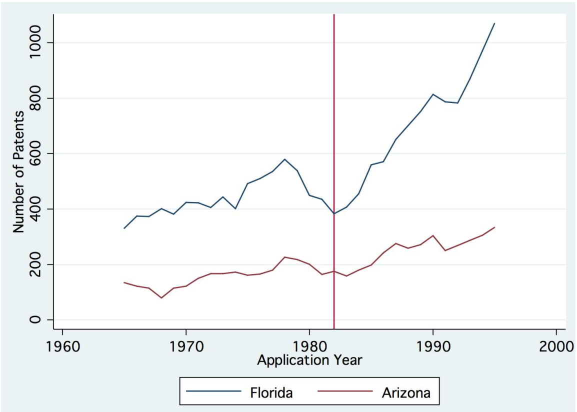

Figure 8: Individual Patenting Levels

"post*treatment" variable as: the Mariel emigration cauing an increase of 185 patents in Florida. Remember that when the synthetic control group is used, the effect of the treatment is only 153. Using a synthetic control method provides a more conservative and arguably a more accurate estimate of the treatment effect.

Table 14: Results- Individual Patenting Using Arizona As The Comparison Group

Variable	Coefficient
Post	98.75
	(36.37) ***
Treatment	279.94
	(33.3)***
Post*Treatment	185.75
	(51.43)***

Standard errors are listed in the brackets
* -10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level.

As another robustness check, I change the year of the treatment from 1970 to 1994 and estimate the treatment effect. Since 1980 was the year of the Mariel Boatlift and, for my purpose, 1982 is the treatment year, we should see a much larger treatment effect (economically larger and more statistically significant) around these years. I only do this for the sub sample of individually assigned patents, as I believe this result provides the strongest argument. I use the same comparison group of 83.7% Arizona and 16.3% California and list the results in Table 15.

Table 15: Robustness Check

Year	Treatment Effect
1970	103.55
1971	110.7
1972	118.81
1973	122.73
1974	133.12*
1975	132*
1976	130.92*
1977	129.17*
1978	128.28*
1979	128.8*
1980	138.88**
1981	143.69**
1982	153.93***
1983	160.18***
1984	166.7***
1985	165.35***
1986	173.27***
1987	183.64***
1988	188.29***
1989	195.71***
1990	190.94***
1991	202.8**
1992	220.55**
1993	236.35*
1994	257.58

Note two caveats. The first is that although the treatment effect is significant at the 10% level before 1980, it becomes more statistically significant at the time of the treatment (1982). Although a statistically significant treatment effect persists into the 1990s, it starts to become less significant and is not statistically significant by 1984. The second caveat is that after

1980, the treatment effect increases steadily. Before 1980, the treatment effect is steadier. The economic significance of the changing treatment effect can be seen in Figure 9, where the two red lines signify the time of the Mariel Boatlift and the "treatment" date.

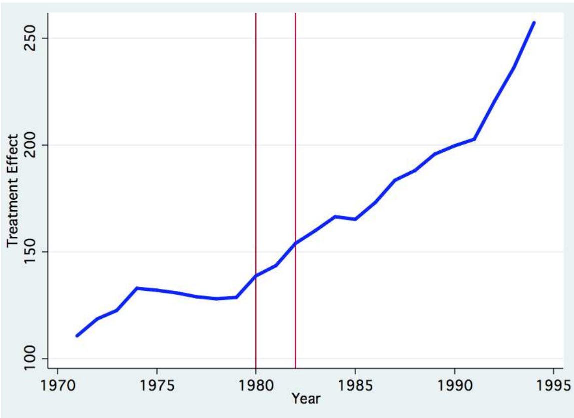

Figure 9: Robustness Check

Other Mechanisms

This section addresses and discounts an other plausible mecahnisms them using various techniques. The first potential mechanism is that the Cuban emigrants arrived in America, the land of opportunity, and were able to pursue their dreams of inventing. To test this, I have gathered over 400 of the most common Cuban last names in Florida and matched these to my sample of patents [Club,]. I have also collected over 1000 of the most common Spanish last names in the United States and matched these with my sample [Mongabay,]. Figure 10 displays the results. As a comparison, I also include the number of patents applied for by individuals.

The number of patents applied for by inventors with a Cuban last name are negligible and do not increase after the treatment. Patents applied for

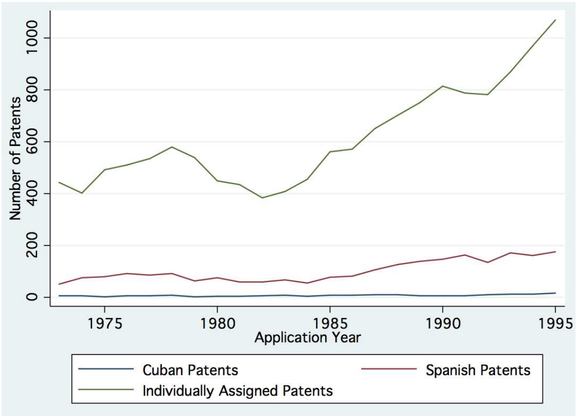

Figure 10: Hispanic Inventors

by inventors with a Spanish last name do increase slightly after the time of the treatment. However, in comparison to the overall number of individually assigned patents, the number of Spanish patents is almost trivial. I believe this test shows definitive proof that it was not the Cubans themselves applying for patents once they arrived in Florida.

Another possible mechanism is that the Cubans came to Florida and stole locals' jobs. This would provide the opportunity for all these recently unemployed locals to start tinkering in their garage and potentially apply for a patent. If this was increasing the number of patents, then we would see an increase of first-time inventors after the treatment. I have calculated the number of multiple inventors (whohave filed for more than one patent) and first-time inventors (between 1970 and 1996) and have taken the difference between the number of first-time inventors and the number of multiple inventors; Figure 11 shows the results.

Although there are more first-time inventors than multiple inventors, the difference between these two numbers stays fairly consistent after the treatment. It does increase slightly, but this could be because people whom I am counting as first-time inventors may actually be multiple inventors who

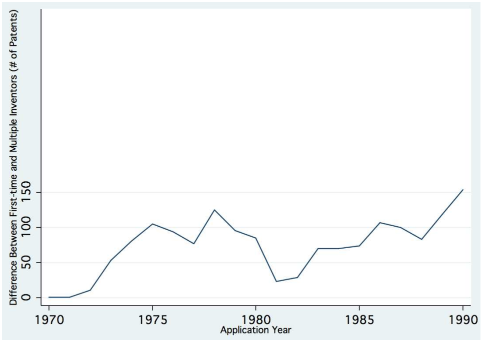

Figure 11: Multiple-Single Inventors

have applied for additional patents outside of the time period in question. There are not enough new inventors after the treatment to validate this mechanism.

Another possibility is that during 1980, in addition to the Mariel Boatlift Cubans, Florida received other immigrants from neighboring states or other countries. These individuals could have been highly skilled and contributed to the increase in patenting behavior. If this was a viable mechanism, I would expect to see a significant increase in population around the time of the treatment. As can be seen in Figure 12, Florida's population steadily increases from 1975-1985 and does not experience a large spike in population around the time of the treatment.

In addition, I also test the treatment effect on individuals using patents per capita as the dependent variable and show the results in Table 16. The variable of interest is again "post*treatment" and is not only statistically significant but is also economically significant. To put these numbers in perspective, the number of individual patents per capita in 1982 in Florida is 0.0000582. I strongly believe that Figure 12, and especially Table 16, are able to provide proof that an increase in population was not the cause of

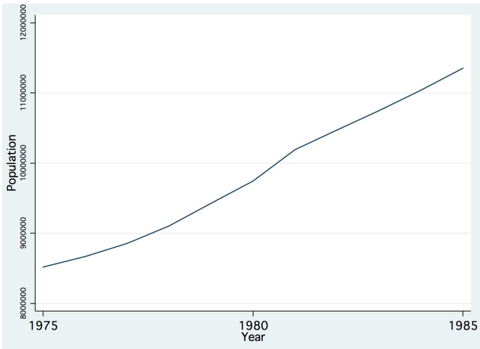

Figure 12: Florida Population

this surge in patenting.

In sum, once examined more closely, none of these potential mechanisms are significant enough to explain the large increase in individual patenting behavior after the Mariel Boatlift.

Table 16: Results- Individual Patenting Using Patents Per Capita

	(1)	(2)
Post	-0.00000925	-0.0000348
	(0.00000372)**	(0.0000022)***
Treatment	-0.0000279	-0.0000279
	(0.00000363)***	(0.00000144)***
Post*Treatment	0.0000135	0.0000135
	(0.00000512)**	(0.00000204)***
Year Dummies	N	Y
Observations	56	56
R Squared	0.58	0.97

Robust standard errors are listed in the brackets
* -10 percent significance level, ** - 5 percent significance level, *** - 1 percent significance level.

Conclusion

Discerning the effect that low-skilled immigration can have on an economy is very important. Unfortunately, this subject is under-researched. This paper starts to fill the gap in this area of literature by looking at the effect of he

Mariel Boatlift on levels of innovation in Florida. I am able to conclude that the Mariel Boatlift indeed affected different types of innovation differently. In some areas of patenting, there was little to no effect, while in others, there was an economically and statistically significant increase in patenting. Overall, patenting by individuals and in industries with low barriers to entry increased. I hope this paper will not only aid current policy making but also spark new research surrounding this issue.

Appendix

State	Weight
AL	0.065
AZ	0.144
C0	0.258
IA	0.124
NC	0.085
NH	0.068
OK	0.11
TX	0.145

Table 17: State Weights- Chemical

State	Weight
AL	0.009
AZ	0.061
CA	0.063
CO	0.1
IA	0.214
TX	0.179
UT	0.375

Table 18: State Weights- Computers and Communications

State	Weight
CA	0.022
DE	0.026
IN	0.005
MN	0.26
NJ	0.087
OK	0.472
TX	0.127

Table 19: State Weights- Drugs and Medical

State	Weight
AZ	0.351
TX	0.308
VA	0.037
WA	0.304

Table 20: State Weights- Electrical and Electronic

State	Weight
MI	0.043
MO	0.08
TX	0.133
WA	0.744

Table 21: State Weights- Mechanical

State	Weight
AZ	0.343
CA	0.063
C0	0.436
TX	0.158

Table 22: State Weights- Other

State	Weight
DE	0.099
IL	0.075
MA	0.136
NC	0.322
VA	0.159
WI	0.21

Table 23: State Weights- Drugs

State	Weight
IL	0.11
MI	0.078
MN	0.17
MO	0.191
NC	0.06
NJ	0.142
NY	0.036
UT	0.213

Table 24: State Weights- Surgery and Medical Instruments

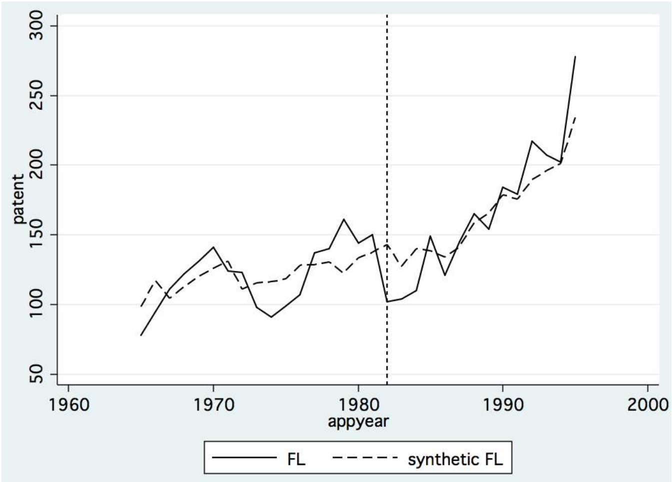

Figure 13: SCM- Chemical

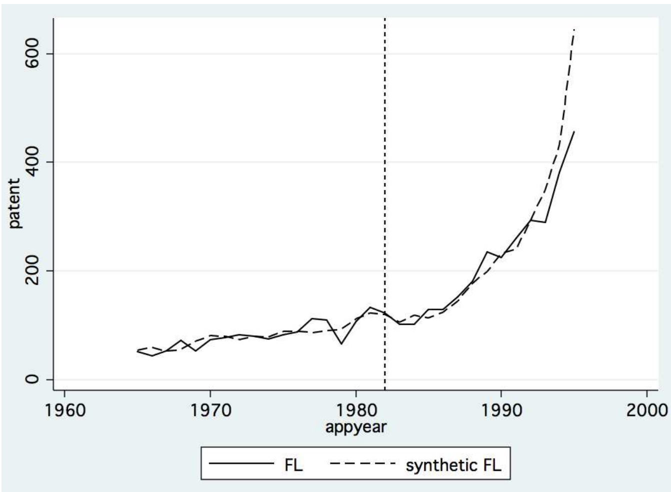

Figure 14: SCM- Computers and Communications

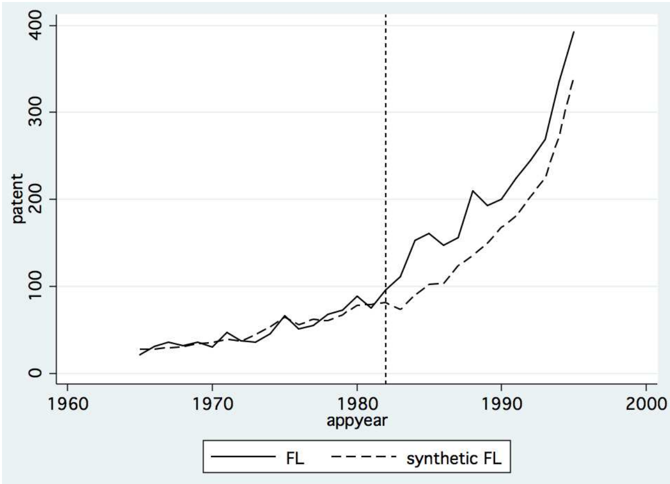

Figure 15: SCM- Drugs and Medical

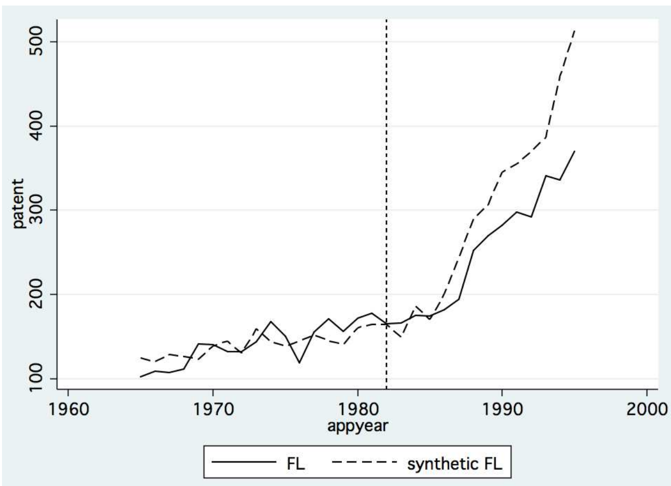

Figure 16: SCM- Electrical and Electronics

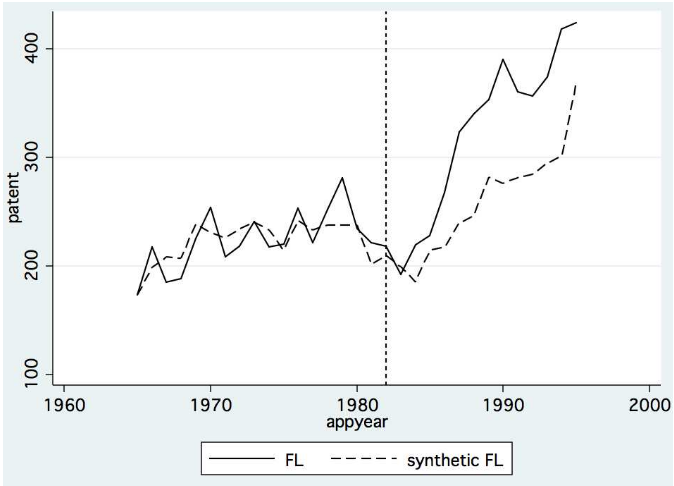

Figure 17: SCM- Mechanical

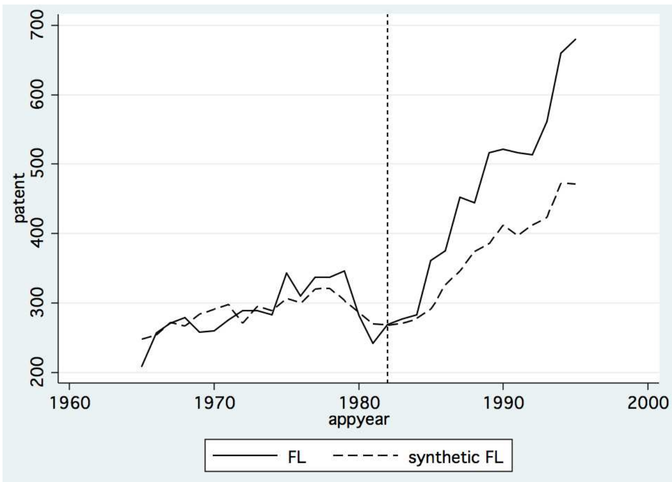

Figure 18: SCM- Others

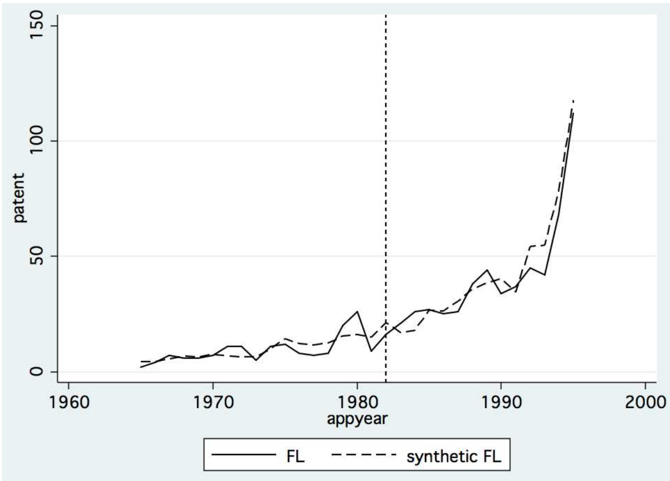

Figure 19: SCM- Drugs

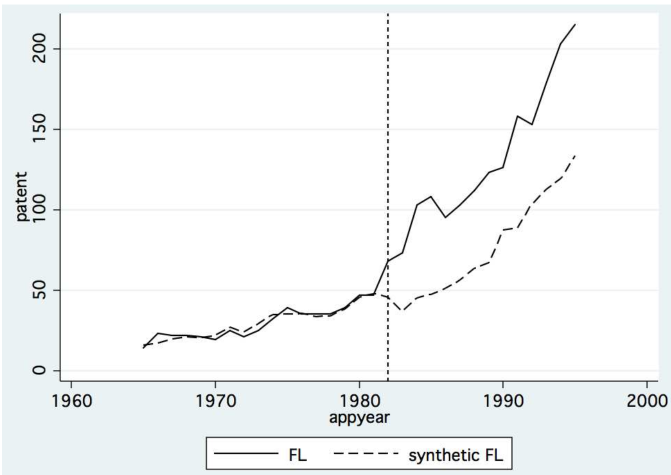

Figure 20: SCM- Surgery and Medical Instruments

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